Journal of Environmental Radioactivity 164 (2016) 377–394

Contents lists available at ScienceDirect

Journal of Environmental Radioactivity

journal homepage: www.elsevier.com/locate/jenvrad

Inverse modelling for real-time estimation of radiological consequences in the early stage of an accidental radioactivity release

Petr Pecha*, Václav Šmídl

Institute of Information Theory and Automation of the Czech Academy of Sciences, v.v.i., Pod Vodarenskou vezi 4, 182 08, Prague 8, Czech Republic

ARTICLE INFO

Article history:
Received 8 October 2015
Received in revised form
14 May 2016
Accepted 19 June 2016
Available online 15 September 2016

Keywords:
Radioactivity release
Assimilation of measurements
Ill-posed inversion problem
Measurement noise
Urgent emergency

ABSTRACT

A stepwise sequential assimilation algorithm is proposed based on an optimisation approach for recursive parameter estimation and tracking of radioactive plume propagation in the early stage of a radiation accident. Predictions of the radiological situation in each time step of the plume propagation are driven by an existing short-term meteorological forecast and the assimilation procedure manipulates the model parameters to match the observations incoming concurrently from the terrain. Mathematically, the task is a typical ill-posed inverse problem of estimating the parameters of the release. The proposed method is designated as a stepwise re-estimation of the source term release dynamics and an improvement of several input model parameters. It results in a more precise determination of the adversely affected areas in the terrain. The nonlinear least-squares regression methodology is applied for estimation of the unknowns. The fast and adequately accurate segmented Gaussian plume model (SGPM) is used in the first stage of direct (forward) modelling. The subsequent inverse procedure infers (re-estimates) the values of important model parameters from the actual observations. Accuracy and sensitivity of the proposed method for real-time forecasting of the accident propagation is studied. First, a twin experiment generating noiseless simulated "artificial" observations is studied to verify the minimisation algorithm. Second, the impact of the measurement noise on the re-estimated source release rate is examined. In addition, the presented method can be used as a proposal for more advanced statistical techniques using, e.g., importance sampling.

1. Introduction

Measured and calculated doses/dose rates of external irradiation induced by radioactive cloud propagation are basic inputs to the objective analysis of the data assimilation (DA) techniques. The aim of DA is modification of the internal parameters of a dispersion model in order to obtain a good fit of the model predictions with observations incoming from the terrain. The task is solved as an inversion problem when the values of certain model parameters must be refined inversely from the observed data. The inversion of the original forward problem is a valuable tool for improvement of the important model parameters, primarily for the source strength re-estimation and the parameters controlling the recursive tracking of the plume progression at small distances from the source. Source term analysis based on operational conditions can occasionally be impossible due to the potential blackout of a nuclear power station, in which case the inverse modelling based on the radiation monitoring becomes a sole solution. The uncertainty in the source term dominates among all other uncertainties of an accidental release scenario. Estimated radiological values can differ from the true ones by a factor of 10 or more. Proper re-estimation can significantly contribute to more accurate localisation of the most impacted areas in the terrain. In principle, the assimilation procedures require the most accurate data possible, to be obtained from measuring devices (sensors) located on the terrain around the perimeter of a nuclear facility and an additional network of the measuring devices at outer distances (fixed stations, apparatus deployed temporarily on terrain in case of emergency, monitoring vehicles, aerial monitoring and other possible unmanned aerial vehicles).

We have examined the inversion problem for the category of parameter estimation where the system characteristics are inferred from the experimental data. Inverse problems are often mathematically ill-posed (improperly posed) due to an information deficit (e.g., http://www.waterloo.ca, Kabanikhin, 2008). It is called an inverse problem because it starts with the effects and then

* Corresponding author.
E-mail address: pecha@utia.cas.cz (P. Pecha).

http://dx.doi.org/10.1016/j.jenvrad.2016.06.016

calculates the causes. This is the inverse of the original forward problem, which starts with the causes and then calculates the effects. The solution of an ill-posed problem is often not unique and gives rise to instability with respect to measurement errors or small changes in the data. When sufficiently informative measurements are available, the inversion step typically provides a unique solution. However, this is not guaranteed for extreme cases of the parameter correlations. Only their ratios and not their individual values can be determined then.

An overview of the assimilation methods capable of solving the inverse modelling task is given in Chapter 3. Section 3.1 provides a motivation for simple data assimilation from the perspective of advanced statistical assimilation techniques. A dispersion model can provide predictions for multiple (Monte Carlo) runs of the pollution trajectories. The likelihood of the trial for different parameterisations of the dispersion models (e.g., source term, wind velocity vector, potential precipitation, etc.) can be summarised in the form of the posterior probability distribution. The methods for nuclear source estimation are summarised, e.g., in (Rao, 2007). Some specific applications are examined using the inverse modelling technique which is widely defined (Rao, 2007) as any technique used for identifying the source from the corresponding category of measurements (e.g. dose rates). Targeting of observations using the inverse modelling technique is presented in (Abida and Bocquet, 2009) with a design strategy to seek the optimal location of mobile monitors. A semi-automatic method based on inverse modelling, proposed in (Winiarek et al., 2011), is designed for assessment of a newly planned surveillance network covering large observational errors and analysing outlying situations where the inversion could fail. The source reconstruction of an accidental radionuclide release on a continental scale is examined in (Krysta and Bocquet, 2007) where a generalised classical variational least-squares assimilation technique is tested on a set of TWIN experiments. The authors stated that a truly successful three-dimensional inversion is still far out of reach using existing computer capability.

Several remarkable articles deal with the latest experience with the Fukushima accident. In (Saunier et al., 2013) the inverse modelling procedure is combined with an attempt at reconstruction of the isotopic composition of the discharge. Examination of the emissions of two isotopes into the atmosphere, the noble gas ^{133}Xe and the aerosol-bound ^{137}Cs, was accomplished in (Stohl et al., 2012). The first guess was subsequently improved by inverse modelling, which combined the results of an atmospheric transport model FLEXPART with measurement data from several dozen stations in Japan, North America and other regions. An application to the real nuclear disaster of the Fukushima Daiichi plant is presented in (Winiarek et al., 2012). An efficient inverse modelling method is proposed there to reconstruct the Fukushima Daiichi source from the long-range transport data. The maximisation of the likelihood of publicly released measurements of the air activity concentration of radionuclides was applied. Following these top scientific activities we have obtained experience in the field. The assimilation subsystem (ASIM (2013)) in conjunction with the probabilistic version of the segmented Gaussian dispersion model SGPM has been developed and the first applications addressing the advanced Particle Filter (PF) were tested (e.g., Pecha et al., 2009; Šmídl et al., 2014). The high computational cost of the Monte-Carlo techniques can be significantly reduced when an optimisation-based first guess is used to design the proposal function (Šmídl and Hofman, 2014). In this paper, we propose an optimisation approach for the SGPM.

In Section 3.2 of this article, we propose a nonlinear least-squares regression scheme which optimises the agreement between the measured values and model prediction. Computational efficiency of the SGPM enables generation of results in real-time mode. The use of nonlinear regression analysis for integrating pollutant concentration measurements with an atmospheric dispersion model for source term estimation can be found in (Edwards et al., 1993). The inverse model as a nonlinear least squared estimation is presented in (Kathirgamanathan et al., 2003a) where an attempt to stabilise the ill-posed minimisation problem is described. A certain extension of the dimension of the input parameter vector entering the minimisation approach is examined in (Kathirgamanathan et al., 2003b). In the paper (Gab-Bock Lee et al., 2013) the measured air dose rates from the Fukushima accident are compared with the same values calculated by the optimised estimation using nonlinear minimisation. An extension of analysis on the measurement errors is given in Section 4.4.3. An extensive simulation experiment covers 1196 sets of the randomly perturbed measurements, each set for all 84 sensors on the terrain, is described in Section 4.4.4.

2. Prediction of random output fields using parametrised dispersion model SGPM

We have adopted a special modification of the dispersion model with the acronym SGPM based on the segmented Gaussian plume model. It can account approximately for dynamics of the released discharges synchronised with the short-term forecast of the hourly (half-hourly) changes of meteorological conditions. This model is able to describe the random nature of the problem and simulate the uncertainty propagation of the input model parameters. The distinction between variability and uncertainty of a certain input parameter is taken into account. Variability reflects changes of a certain quantity over time, over space or across individuals in population. Variability represents diversity or heterogeneity in a well-characterised population. The term "uncertainty" covers stochastic uncertainties, structural uncertainties representing partial ignorance or incomplete knowledge associated with the lack of perfect information about poorly-characterised phenomena or models, uncertain (ill-defined) release scenario or input model uncertainties. For purposes of the assimilation procedures, the sampling of fluctuations of input parameters repeatedly entering the SGPM model is internally driven by the algorithm for optimisation of the corresponding cost function.

In the following text, the upper case symbols are related to the random variables and lower case symbols stand for the actual values generated from the corresponding random distributions. The vector $\boldsymbol{\Theta}$ of M random input model parameters Θ_m can be schematically written as:

$$\boldsymbol{\Theta} = [\Theta_1, \Theta_2, \ldots, \Theta_M]^{\mathrm{T}} \quad (1)$$

Their specific realisations are generated with a corresponding sequence of random distributions $D_1, D_2, \ldots, D_M$ which are usually formulated on the basis of consensus among experts (range, type of distribution, and potential mutual dependencies). The model parameters usually have a physical meaning, such as the amount of discharged radioactivity, atmospheric stability characteristics, dispersion parameters, uncertainties related to dry and wet radioactivity fallout, wind field components, etc. The input parameters enter the SGPM model, which generates dispersion outputs submitted for further processing in the subsequent parts of the environmental model. Specifically in our case, the SGPM model is nested inside the environmental program system HARP (online access in (HARP, 2013)). The HARP system addresses all resulting meaningful output entities $\boldsymbol{X}_j$ being subject of interest, which can be formally collected into the output vector Λ with components $\boldsymbol{X}_j$, $j = 1, \ldots, J$. The multidimensional output $\Lambda(t)$ related to the time t