Evaluation of detection abilities of monitoring networks using multiple assessment criteria

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Abstract: The problem of evaluation of radiation monitoring network quality is considered. The comparison of possible network configurations is performed on simulated experiments where a twin model is used to simulate observed data. An assimilation procedure based on the particle filter approach is run for each configuration of the network. Specifically, multiple realisations of segmented Gaussian plume models are computed, each with different parameters. The simulated measurements from the network sensors are used to weight the likelihood of the parameter realisations, providing an empirical posterior distribution of the parameters. The quality of the network is then evaluated as an expected value of multiple loss functions with respect to the empirical posterior distribution. Our goal is to provide a tool that allows the decision-makers to compare the proposed configurations from various points of view. The results for a hypothetical discharge of radioactivity are presented.

Keywords: dispersion modelling; dose rates; assimilation; monitoring network.

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Biographical notes: Radek Hofman received his MS in 2007 and PhD in 2011. His postdoctoral activities are concentrated on development of advanced Bayesian statistical assimilation and on approximations of posterior probability density function for the state in non-linear and non-Gaussian filtering problems. He participates in projects of safety research, and development of a user-friendly interactive software tool for an assimilation subsystem of the HARP system.

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Václav Šmídl is a Research Fellow. His main research interest is connected to Bayesian techniques for data assimilation and their efficient computation. His active research is concentrated on model-based algorithms for active learning; sensor positioning and experiment design; development of computationally efficient algorithms based on variational Bayes, importance sampling and adaptive Monte Carlo. He has introduced a methodology for assessment of a network monitoring capability based on particle filtering techniques.

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1 Introduction

Sensors of radiation monitoring networks are nowadays scattered around the world and monitor the global radiation situation for any severe radiation event. These sensors are so sensitive that it is possible, despite the initial high degree of uncertainty, to reconstruct the significant scenario parameters by means of optimal blending with corresponding measurements. However, these measurements are too coarse for small-scale events that may occur after a minor accident in a power plant. For this reason, every power plant has its own radiation-monitoring network that is connected to its control system. With increasing demands for radiation safety, the monitoring networks are expanded to improve their detection capabilities. Testing of the radiation networks is done in simulation mode when a hypothetical release of radioactivity is generated artificially by means of a twin model. A twin model is a mathematical model with simulated (artificial) 'true' parameter values.

A lot of work has been invested into the research of detectability of a small release (Urso et al., 2012). Optimal configuration of monitoring networks was also considered (Zidek et al., 2000; Abida et al., 2008; Baume et al., 2011; Melles et al., 2011), using simulated annealing to minimise a chosen loss function. Since the optimisation should be performed over all possible uncertainties in weather conditions and conditions of the release, the computation needs to be simplified to achieve tractability. The most common simplifying step in the optimisation is the assimilation procedure. In the case of detectability, the assimilation procedure is a simple thresholding. It aims at situations where only one radiation sensor detects the release. In the simulated annealing optimisation, it is usually spatial interpolation or kriging (Heuvelink et al., 2010), with weather- and space-independent variograms. This simplification approach is suitable when the network is dense enough that the interpolation provides sufficiently accurate results.

In this contribution, we investigate evaluation of a network using Bayesian assimilation. The main advantage of Bayesian assimilation is that it is capable of representing uncertainty of the release and evaluating predictions of its evolution. The disadvantage is its computational cost, which is prohibitive in demanding applications of network optimisation. Therefore, we do not use the simulation annealing for optimal positioning of all sensors in a network, but provide only tools for evaluation of selected fixed configurations of a network. Thus, the resulting algorithm serves as a support for human decision-makers who design extensions of the network.

To achieve computational feasibility we use a combination of a sequential Monte Carlo method with an analytical dispersion model (Johannesson et al., 2004; Hiemstra et al., 2011). Specifically, we use the segmented Gaussian plume model (SGPM) which was used in Bayesian assimilation in Pecha et al. (2009). Parameters of this model are estimated by adaptive sequential Monte Carlo assimilation (Smidl and Hofman, 2013). Quality of the estimation for a selected network is compared using two principal criteria:

1 error of spatial coverage of the dose after assimilation

2 impact of the error of assimilation for the inhabitants (Heuvelink et al., 2010).

2 Decision theory framework

The principal framework of network evaluation is the statistical decision theory which is commonly used in this context. The main result of decision theory under uncertainty is formally simple (Berger, 1985). If we are to choose which network, n^*, from a given set of candidates, $n \in \{1,\dots, N\}$, is best, we are to choose the one that minimises the expected value of the chosen loss function

$$n^* = \arg\min_{n\in N} \; E_X\left(L(n,X)\right), \tag{1}$$

where X models all uncertainty of the release, $L()$ is the chosen loss function and $E_X()$ is the operator of expected value

$$E_X\left(L(n,X)\right) = \int p(X \mid n)\, L(n,X)\, dX..$$

The space of uncertainty X contains the following:

1 uncertainty of the release, given by its parameters θ

2 uncertainty in the weather conditions, typically modelled by corrections of the numerical weather forecast ψ

3 uncertainty in realisations of the measurements of the monitoring network, y.

Naturally, the number of measurement points and their positions are influenced by configuration of the network, $y(n)$.

We will consider the following loss functions:

1 weighted mean square error

2 correct estimation of the dose given by the factor of two metrics.

The weighted mean square error is defined on the assimilated radiation dose rate D,

$$L_{mse}(n,X) = \sum_j w_j \left(D_j(X) - \hat{D}_j(X)\right)^2, \tag{2}$$

where $D(X)$ is the value of the radiation dose rate of the twin model (i.e., a model with simulated 'true' values of the release and meteorological conditions) and $\hat{D}$ is its estimate based on the observed data $y(n)$. The sum in (2) is over all points of the computational grid. The optional weight w_i is used to take into account the number of inhabitants living in proximity of the grid point. The factor-of-two criterion for correct dose classification is defined as

$$L_{FA}(n,X)=\sum_{j:D_j>0,\hat{D}_j>0}\frac{N(0.5D_j(X)<\hat{D}_j(X)<2D_j(X))}{M}, \tag{3}$$

where M is either the total number of grid points or the total number of inhabitants living in the modelled area, and M(*condition*) is the number of grid points or inhabitants satisfying the condition in the argument.

A key element of both loss functions is the estimate of the radiation dose rate $\hat{D}$. This is a result of assimilation with measurements y. The assimilation procedure thus strongly influences the results. Owing to the small amount of information provided by these measurements, we assume that only a few selected parameters of the release are assimilated to provide $\hat{D}$. These parameters will be denoted by θ_{asim}. The estimate of the radiation dose rate is provided by a numerical atmospheric dispersion model $\hat{D}=M(\theta_{asim}(y),\theta_{other})$ which is provided by the AMIS procedure (Smidl and Hofman, 2013).

3 HARP dispersion model

The environmental code hazardous radioactivity propagation (HARP) with dispersion model based on SGPM was found to be fast enough to be deployed in the sequential data assimilation procedures. The model validation benchmarks have proved sufficient agreement with similar European codes, e.g., COSYMA and RODOS (Pecha and Pechová, 2002). More detailed information is available online (HARP, 2011).

The time dynamics of the discharged radioactive material is partitioned into a number of fictitious one-hour consecutive segments s with equivalent homogeneous release source strength. Each segment of the release is spread during the first hour as a straight-line Gaussian plume. As the material spreads during the hours that follow, the segment is, according to a given set of meteorological conditions, treated as a 'prolonged puff' and its dispersion and depletion during the movement are simulated numerically by means of a large number of elemental shifts.

There are many model parameters that influence the shape of the plume: release source strength of activity Q [Bq.s$^{-1)}$], release height, category of atmospheric stability, height of the mixing layer, terrain parameters, etc. From these parameters, we consider only Q to be assimilated from the measurements. All other parameters are given by their best estimated deterministic values. The weather conditions are supposed to be known from the numerical weather prediction. However, we calibrate the wind direction and wind speed by additive offset a, and multiplicative offset b, respectively, which are assumed to be unknown and different at each time step (Pecha et al., 2009). The composition of discharged radionuclides in the release is assumed to be known and their physical-chemical form is important for determination of wet and dry depositions.

Determination of groundshine and cloudshine dose rates $RATE_{ground}$ and $RATE_{cloud}$ comes from the segmentation scheme of the continuous release. The external irradiation from cloud and from deposition is considered. The cloudshine is computed as a superposition of contributions from all hourly segments which are at time T still drifting over the terrain. The groundshine dose is a sum of contributions from deposition during the whole trajectory of the segment. Just at time T, each released segment s has relative index of its history τ = {s,…, T}.

$$\begin{aligned} RATE_{ground}(l;T) &= \sum_{(r)} \sum_{s=1}^{s=T} \sum_{\tau=s}^{\tau=T} RATE_{ground}^{r}(l;s,\tau) \cdot \exp[-\lambda_r \cdot (T-\tau)] \cdot 3600 \\ RATE_{cloud}(l;T) &= \sum_{(r)} \sum_{s=1}^{s=T} RATE_{cloud}^{r}(l;s,T) \end{aligned} \tag{4}$$

We introduce the sum $D = RATE_{cloud} + RATE_{ground}$ which denotes the total dose rate [mSv.h^{-1}] at location coordinates l exactly at hour T after the release starts. Index r runs over all radionuclides, each nuclide having a decay constant of λ_r [s^{-1}]. The error of measurements is assumed to be relative to the measured dose rates. Here we are using simplified expression (4) for the case of only one-hour release of one nuclide, ^{137}Cs.

4 Evaluation of the expected loss

Evaluation of the expected loss (1) is achieved using importance sampling, where the expected value is replaced by a weighted average of the generated samples. The number of generated samples is I, with a running index i = 1, …, I. The weather conditions are sampled randomly from historical records, forming $\psi^{(i)}$. The release conditions are sampled from available estimates, forming $\theta^{(i)}$ (Pecha et al., 2009). These samples are used to generate the twin model from which are generated the twin dose rates $D^{(i)}$ and samples of the observations of all competing monitoring networks, $y^{(i,n)}$, $n = 1,\dots,N$. The sampled data are then treated as true measurements to obtain the estimate of the assimilated parameters θ_{asim} using a Bayesian assimilation procedure. The parameters θ_{asim} are estimated using importance sampling by generating K samples, $\theta^{(k,i,n)}$, k = 1,…, K. Each of these samples has an associated weight $w^{(k,i,n)} \propto p\left(y^{(i,n)} | \theta_{asim}^{(k,i,n)}, \theta_{other}^{i}, \psi^{(i)}\right)$. For efficient sampling we use the Adaptive Multiple Importance Sampling (AMIS) procedure (Smidl and Hofman, 2013). This procedure is based on generation of multiple populations of samples, where each population is sampled from an adaptively tuned probability density function. This adaptation significantly speeds up the convergence to accurate estimates. Evaluation of the network performance criteria (1) is then approximated for all variants of the loss function (2) and (3) by:

$$E\left(L(n,X)\right) \approx \sum_{i=1}^{I} \sum_{k=1}^{K} w^{(k,i,n)} L(n,X) \tag{5}$$

The whole procedure is summarised by the following pseudo-code:

Initialise: select fixed parameters of the release θ_{other}
For $i = 1, \ldots, I$
Sample meteorological conditions $\psi^{(i)}$ from an archive of meteorological data
For $n = 1, \ldots, N$
- Generate measurements $y^{(i,n)}$ using the twin model (HARP),
- Run a chosen assimilation procedure (e.g. AMIS) using $y^{(i,n)}$,
- Evaluate all loss functions of interest,

Evaluate expected values of all loss functions (5).

5 Results

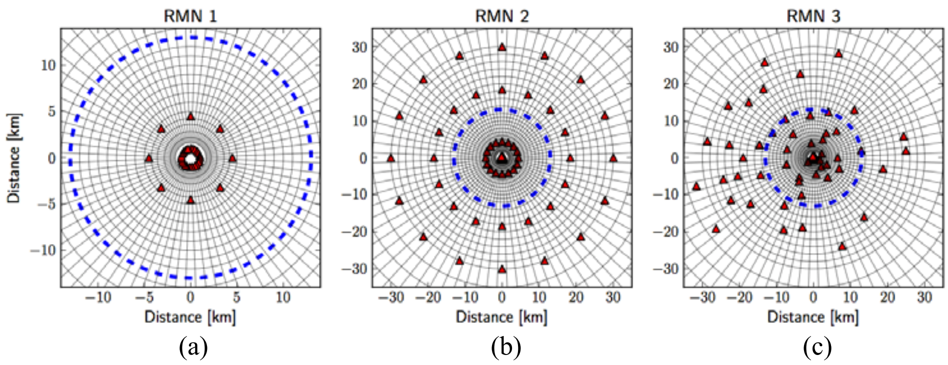
We performed a Monte Carlo study of simulated releases from Czech nuclear power plant (NPP) Temelin under I = 150 different meteorological episodes. A hypothetical release of ^{137}Cs with a one-hour duration is assumed. Starting dates of these historical meteorological sequences were randomly sampled from the whole year 2009. We tested three radiation monitoring networks (N =3) denoted as RMN 1, 2 and 3, see Figure 1. RMN 1 approximates the current monitoring network of NPP Temelin. It is comprised of two receptor circles:

1 an inner circle of on-fence receptors

2 a sparse outer circle in the emergency planning zone (denoted with dashed line).

Two other monitoring networks, RMN 2 and RMN 3, are possible extensions of RMN 1. The total number of receptors in both networks is 64. The number of samples in the AMIS was K =1000.

Figure 1 Assessed radiation monitoring networks. Receptors are denoted with triangles, (a) approximation of current RMN around NPP Temelin (b) extension with uniform spatial coverage (c) extension with new receptors in towns and villages (see online version for colours)



5.1 Setup of the twin experiment

The reference release used in the twin simulation was a one-hour release of ^{137}Cs of total activity Q^{twin} = 5.0E+15 Bq.h^{-1}. Twin simulations were carried out by the HARP model using hourly meteorological measurements from the NPP site that were considered to be spatially homogenous on the modelled domain. The measurements were sampled from the recorded meteorological conditions at the site collected during the year 2009. Release height was assumed to be 150 metres with no thermal uplift. The height of the mixing layer and the dispersion coefficients were selected as their best estimates from the recorded Pasquill's category of stability. Simulated measurements of the cumulative gamma dose rate from groundshine and cloudshine for all tested networks were obtained as samples from the perfect measurements given by the twin model. Measurement error was assumed normally distributed with the standard deviation set to 20% of the measured value. A small offset was added to simulate the natural background radiation level.

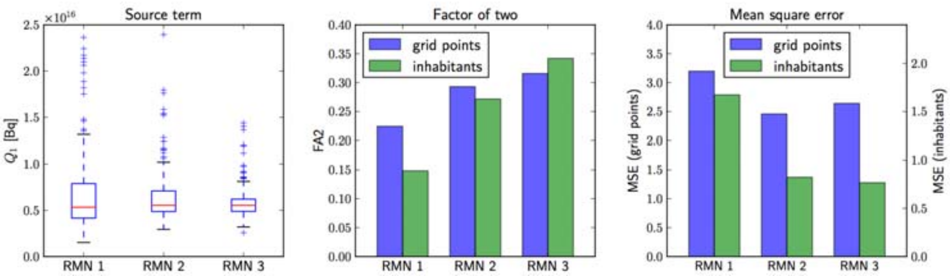
Data assimilation was then performed for all candidate networks and meteorological situations for the first three hours, t = 1,2,3, of the release. To avoid identical twin experiments, assimilated models were propagated using gridded meteorological forecasts shifted one hour forward with respect to the artificial measurements. In each run, parameters estimated by the data assimilation procedure were:

- *Q1* – total activity released during the first hour
- a_t – additive offset of the measured/forecasted wind speed, t =1,2,3.
- b_t – multiplicative offset of the measured/forecasted wind direction, t =1,2,3.

5.2 *Statistical evaluation of performance of candidate grids*

Assimilation results were compared with true releases (twin simulations) using expected values (5) of the loss functions (2) and (3) in two variants. MSE (grid points) is the loss function (2) with unit weight summed over all grid points, MSE (inhabitants) is also (2) with weights w_i set to the number of inhabitants. FA (grid points) is the loss function (3) with M having the meaning of the grid points of the computation grid, FA (inhabitants) is also (3) with M having the meaning of the inhabitants at the grid point.

Figure 2 (a) Boxplots for ensembles of estimates of activity release Q_1 for assessed networks (median, box at 25% and 75% quantile, and crosses denote outlying realisations), (b) Values of the FA2 loss function (c) Values of the MSE loss function (see online version for colours)



(a) (b) (c)

Results of assimilation are presented in Figure 2(a). There are boxplots for estimates of the magnitude of the activity release given by the ensemble for all three monitoring networks. We observe that the median for all networks is sufficiently close to the true value Q_1 = 5.0E+15 Bq.h^{-1}. In the case of RMN 1 we see the increased variability of estimates caused by the lack of gamma dose receptors covering a broader vicinity of the NPP.

Medians of both FA2 loss functions for the tested networks are shown in Figure 2(b). On the one hand, we observe that RMN 2 with regularly spaced receptors attained higher values of the FA2 (grid points) over FA2 (inhabitants). On the other hand, RMN 3 with receptors placed in the inhabited sites attains a higher value of FA2 (inhabitants). A similar trend is evident from the results for the MSE loss functions, Figure 2(c). RMN 2 performs better than RMN 3 in the case of MSE (grid points), but worse in the case of MSE (inhabitants).

6 Conclusions

Various particular problems in the field are addressed by different optimisation tools for monitoring networks. Some of them can only support the planning and optimisation of network configuration (DETECT, 2011), and need to be combined with other methods for the purposes of decision-making. The assessment of monitoring network detection abilities was proposed here by means of comparing the assimilation results with the true values represented by the twin model. We proposed using the sequential Monte Carlo assimilation which fits well into the common Monte Carlo approach. The resulting algorithm is still computationally feasible due to application of the latest adaptive importance sampling techniques, such as the adaptive multi importance sampling (AMIS), and evaluates performance of the selected candidates of a radiation monitoring network. The algorithm will serve as a supporting tool for considerations of potential network extension by human decision-makers.

The sequential Monte Carlo assimilation is an efficient tool for online Bayesian tracking of the radioactive plume propagation and an inverse modelling technique for reconstruction of the significant model parameters initially burdened by large uncertainties. Specifically, the source term re-estimation on the basis of assimilation with observations is mentioned here in the Appendix. It provides a more accurate prognosis for evolution of the radiological situation and a better identification of the most contaminated areas [e.g., comparison shown in Figure 3(a) and Figure 3(b)]. It can support decision-making under nuclear emergency related to the launching of urgent countermeasures on population protection. The threat of possible fatal health and social consequences in case of erroneously classified areas is reduced. Nevertheless, a lot of work should still be done, mainly in the field of multi-segment and multi-nuclide analysis of an accidental scenario.

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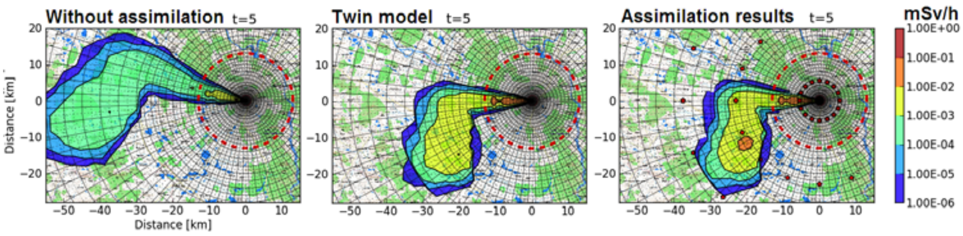
Appendix

An assimilation run for a certain weather episode. Figure 3 demonstrates tracing of the plume up to 5 hours forward and inverse source term modelling.

Figure 3 (a) Simple model prediction of dose rate: $D^{nom} = M(\theta_{nom})$ without accounting of measurements (b) Twin model: $D^{twin} = M(\theta_{twin})$ (c) Assimilation scheme: $\hat{D} = M(\theta_{asim}(y), \theta_{other})$ – assimilation with the true release represented by the twin model (see online version for colours)



(a) (b) (c)

The assimilated parameters include θ_{asim} = [$Q1$, a,b] where $Q1$ is source strength of radioactive release [Bq.h^{-1}], wind direction and wind speed are calibrated by additive offset a and multiplicative offset b, respectively. Magnitude of the release is estimated after the release goes through the time t = 1 hour. Wind speed and wind direction are estimated independently in each step of the assimilation t = 1,…, 5 hours. Assimilation results in Figure 3(c) are compared with the twin model in Figure 3(b). The value $Q1_{nom}$ in D^{nom} is 1.0E+15 Bq, while selected $Q1_{twin}$ in D^{twin} is 5.0E+15 Bq. Estimated value $Q1$ reconstructed from the assimilation process $\hat{D}$ resulted in 5.6E+15 Bq. It represents an example of the inverse modelling technique. A huge error in estimation of the most impacted areas in Figure 3(a) is evident with regard to the improvement based on assimilation in Figure 3(c).