EVALUATION OF DETECTION ABILITIES OF MONITORING NETWORKS USING DIFFERENT ASSESSMENT CRITERIA

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

Key words: *Dispersion modelling, dose rates, data assimilation, monitoring network***.**

INTRODUCTION

Sensors of radiation monitoring networks are nowadays scattered around the world and monitor global radiation situation in the case of severe radiation event. They are so sensitive that it can be possible to reconstruct the significant scenario parameters initially burdened by large uncertainties 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 lot of work has been invested into the research of detectability of a small release (Urso, L. et al., 2012), and optimal configuration of monitoring networks (Zidek, J.V. et al., 2000; Abida, R. et al., 2008; Baume, O.P. et al., 2011; Melles, S.J. et al., 2011).

Simulated annealing is the most commonly used tool for network optimization where a chosen loss function is minimized. Since the optimization is performed over all possible uncertainties in weather conditions and conditions of the release, the computation needs to be simplified to achieve tractability. The most commonly simplified step in the optimization is the assimilation procedure. In the case of detectability, the assimilation procedure is simple thresholding. It aims at situations, where only one radiation sensor detects the release. In the simulated annealing optimization, it is usually spatial interpolation or kriging (Heuvelink, G.B.M. et al., 2010), with weather- and space-independent variogram. 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 to represent uncertainty of the release and evaluate predictions of its evolution. The disadvantage is its computational cost, which is prohibitive in demanding applications of network optimization. Therefore, we do not use the simulation annealing for optimal positioning of all sensors of 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 the combination of a sequential Monte Carlo method with an analytical dispersion model (Johannesson, G. et al., 2004; Hiemstra, P.H. et al., 2011). Specifically, we use the segmented Gaussian plume model which was used in Bayesian assimilation in (Pecha, P. et al., 2009). Moreover, we use adaptive strategies to improve convergence properties of the sequential Monte Carlo (Smidl, V. and R. Hofman, 2011). Quality of the network is studied via two loss functions: (i) spatial coverage of the affected area and (ii) misclassification of inhabitants (Heuvelink, G.B.M. et al., 2010).

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,J.O., 1985). If we are to choose which network,n^*, from a given set of candidates, $n \in \{1, \ldots, N\}$, is best, we are to choose the one that minimizes the expected value of the chosen loss function

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

where X models all uncertainty of the release, $L()$ is the chosen loss function and $E_X()$ is the operator of expected value $E_X(L(n, X)) = \int p\,(X|n) L(n, X)\,dX$.

The space of uncertainty X contains the following: (i) uncertainty of the release, given by its parameters θ, (ii) uncertainty in the weather conditions, typically modeled by corrections of the numerical weather forecast ψ, and (iii) uncertainty in realizations of the measurements of the monitoring network, y. Naturally, the number of the measurement points and their position is influence by configuration of the network, $y(n)$.

We will consider the following loss functions: (i) spatial mean square error, and (ii) misclassification of inhabitants. The spatial mean square error is defined on the assimilated radiation dose rate D in the whole area,

$$L(n, X) = (D(X) - \widehat{D}(X))^2, \tag{2}$$

where $D(X)$ is the spatial distribution of the radiation dose rate for the considered parameters and $\widehat{D}$ is its estimate based on the observed data $y(n)$. The misclassification of inhabitants is

$$L(n, X) = \alpha I_{fp} + \beta I_{fn}, \tag{3}$$

where $I_{fp} = \sum_j P_j \times (\widehat{D}_j > \overline{D} \,\&\, D_j < \overline{D})$, is the number of people incorrectly classified as affected by the release, and analogically I_{fn} is the number of people that are incorrectly classified as unaffected. It is computed as a sum over all inhabited places indexed by j, with the number of inhabitants being P_j. $\overline{D}$ denotes a threshold for the gamma dose rate level.

Key element of both loss functions is the estimate of the radiation dose rate $\widehat{D}$. This is a result of assimilation with measurements y. The assimilation procedure thus strongly influences the results. Due to low informativeness of measurements, we assume that only few selected parameters of the release are assimilated to provide $\widehat{D}$. These parameters will be denoted by θ_{asim}. The estimate of the radiation dose rate is provided by a numerical atmospheric dispersion model $\widehat{D} = M(\hat{\theta}_{asim}(y), \theta_{other})$.

HARP DISPERSION MODEL

The environmental code HARP with dispersion model based on segmented Gaussian plume model (SGPM) showed to be fast enough for its deployment in the sequential data assimilation procedures. Besides that, the model validation benchmarks proved sufficient agreement with similar European codes (e.g. COSYMA, RODOS). This classical Gaussian model is based on Pasquill's stability classification scheme and is consistent with the random nature of turbulence. Proved semi-empirical formulas are available for approximation of various important effects (influence of near-standing buildings, momentum and buoyant plume rise during release, depletion of the plume activity due to removal processes of dry and wet deposition and decay, account for small changes in surface elevation, alternative dispersion formulae for rough or smooth terrain etc.). Implemented numerical difference scheme enables to approximate formation of important parent-daughter pairs of nuclides.

Time dynamics of the released material is partitioned into a number of fictitious one-hour segments with equivalent homogeneous release source strength. Each segment of the release is spread during the first hour as a straight-line Gaussian plume. In the following hours of spreading according to given meteorological conditions, the segment is treated as a "prolonged puff" and its dispersion and depletion during the movement is simulated numerically by means of a large number of elemental shifts. More detailed description of the procedure can be found in (Hofman, R. and P. Pecha, 2011). For the purpose of evaluation of the monitoring network, we review only its essential parts.

1. Model parametrization.

Model parameters that influence the shape of the plume are: 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 speed and wind direction by additive offsets, a, b which are assumed to be unknown and different at each time step. The composition of nuclides in the release is assumed to be known. The sensors of the monitoring networks measure only the total radiation dose rate, hence there is not enough information to distinguish the nuclides. However, the knowledge of the release composition is important for wet and dry deposition.

2. Computation of the groundshine and the cloudshine dose rates $RATE_{ground}$ and $RATE_{cloud}$.

The sensors of the monitoring networks register dose rates from two sources: cloudshine and deposition. The groundshine is computed as a superposition of contribution from all hourly segments with index s denoting the time of the segment release. 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 $\tau = \{s, \ldots, T\}$.

$$RATE_{ground}(l;T)=\sum_{(r)}\sum_{s=1}^{s=T}\sum_{\tau=s}^{\tau=T}RATE^{r}_{ground}(l;s,\tau)\cdot\exp\left[-\lambda_r\cdot(T-\tau)\right]\cdot 3600$$

$$RATE_{cloud}(l;T)=\sum_{(r)}\sum_{s=1}^{s=T}RATE^{r}_{cloud}(l;s,T) \qquad (4)$$

We introduce the sum D = $RATE_{cloud}$ + $RATE_{ground}$ which denotes the total dose rate [mSv.h^{-1}] at location coordinates l precisely at hour T since the release start. Index r runs over all radionuclides in the release, each nuclide having decay constant λ_r [s^{-1}]. The error of measurements is assumed to be relative to the measured dose rates (accuracy about 20%).

EVALUATION OF THE EXPECTED LOSS

Evaluation of the expected loss (1) is achieved using importance sampling, where the uncertainty is represented by empirical density. The number of generated samples is I, with running index $i=1,\dots,I$. The weather conditions are sampled uniformly from historical records, forming $\psi^{(i)}$. The release conditions are sampled from available estimates $\theta^{(i)}$ (Pecha, P. 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, $y^{(\boldsymbol{i},\boldsymbol{n})}$, $n=1,\dots,N$. 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, $\theta^{(k,i,n)}$ $k=1,\dots,K$. Each of the samples has associated weight $w^{(k,i,n)}\propto p(y^{(i,n)}|\theta^{(k,i,n)}_{asim},\theta^{(i)}_{other},\psi^{(i)})$. For efficient sampling we use the adaptive sequential Monte Carlo with the ASIM procedure (Smidl, V. and R. Hofman, 2013). Specifically, the total number of particles is split into several populations, each with adaptively improved proposal functions. This adaptation significantly speeds up the convergence to accurate estimates. Evaluation of the network performance criteria (2) is then approximated by

$$E(L(n,X))\approx\sum_{i=1}^{I}\sum_{k=1}^{K}w^{(k,i,n)}\,(D^{(i)}-D(\theta^{(k,i,n)}_{asim}))^2, \qquad (5)$$

and equivalently for the misclassification loss (3).

RESULTS

As a first step in more demanding simulations, we compared suitability of two designs of a radiation monitoring network (RMN). We evaluated two loss functions for a fixed released scenario (meteorological conditions and a source term). Both candidate networks contain the ring of detectors around a power plant. The first candidate has detectors located in the inhabited places surrounding power plant (RMN_1) while the second candidate has detectors located in regular concentric circles around the power plant (RMN_2).

Simulation setup

The experiment was performed as a twin experiment, i.e. time series of measurements were obtained via perturbation of values sampled from HARP model initialized with nominal inputs. To avoid identical twin experiment, twin model values were simulated using point-wise meteorological data valid over the whole computational domain while more realistic gridded meteorological data enters the data assimilation procedure. Spatially and temporally variable differences of wind speed and direction between point and gridded data were estimated during data assimilation in tandem with the magnitude of release. Accuracy of the radiation dose sensors providing cumulative gamma dose rate from cloudshine and groundshine was 20%. The simulated accident is represented by one hour continuous release of radioactivity 5.0E+15 Bq.h^{-1} of Cs-137. Decay half-life of this radionuclide is approx. 30 years. Assimilation was performed for the first 5 hours of the release. Spatial integration needed for evaluation of cloudshine dose rates is approximated using semifinite cloud model, which is corrected on the finite shape at near distances. Alternative and more convenient approach of the finite cloud model based on the “n/μ” method is successfully tested (Pecha, P. and R. Hofman, 2011) for configuration when the size of the plume is small compared to the mean free path of the gamma rays. Data assimilation is initialized using Monte Carlo procedure for population of 200 particles. Five best fit 2-D trajectories are then resampled and each of them is subsequently adaptively proliferated to the new populations in the next hourly steps.

Assimilation results

The assimilated parameters are $\theta_{asim}=[Q,a,b]$ where Q is source strength of radioactive release [Bq.h^{-1}], a is the correction of the predicted wind direction (in degrees), and b is the correction of the wind speed. Magnitude of release is estimated after the release goes through the time t=1. Wind speed and wind direction are

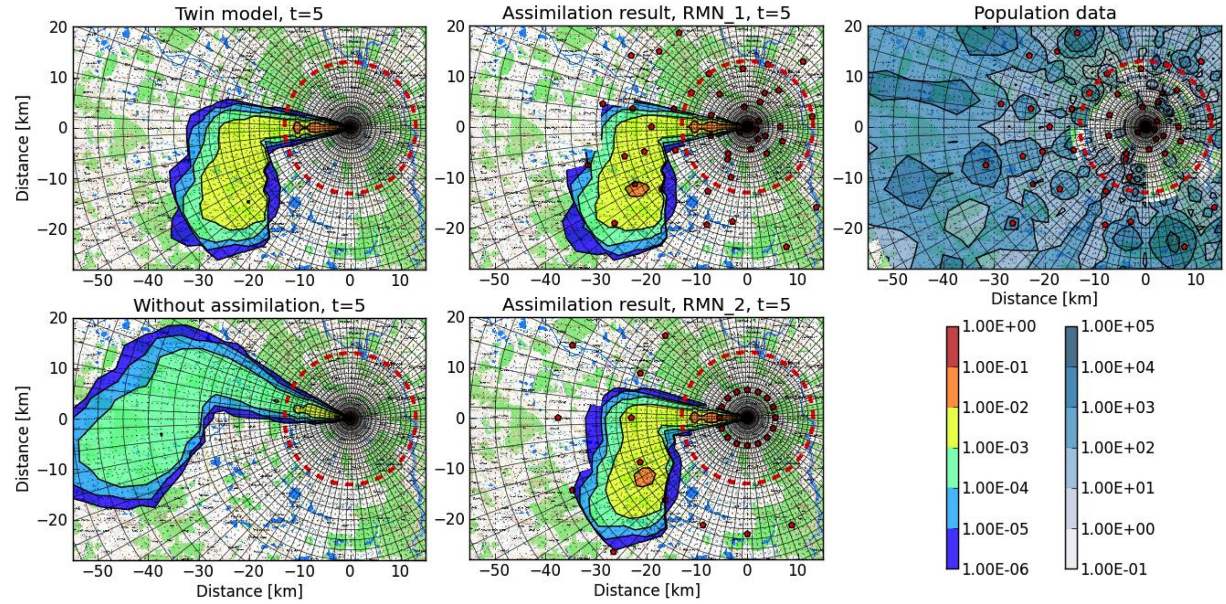

Figure 1: Comparison of twin model and data assimilation results. **Top left:** Twin model: 5.0E+15 Bq.h^{-1}. **Bottom left:** Simulation based on initial deterministic calculations with nominal inputs 1.0E+15 Bq.h^{-1}. **Top** and **bottom middle:** Assimilation results based on RMN_1 and RMN_2 candidate networks. Visualized quantity is cumulative gamma dose rate from cloudshine and groundshine [mSv.h^{-1}]. **Top right:** Visualization of population data from 2003 census used for construction of RMN_1.

estimated independently in each step of the assimilation t=1,…,5. Assimilation results are compared with the twin model in Figure 1. We see that both the radiation monitoring networks produced almost equal results well comparable to the twin model.

Estimated values of magnitude of release were 5.6E+15 Bq and 6.7E+15 Bq for monitoring network configurations RMN_1 and RMN_2, respectively. The fact that Q was estimated with successful accuracy in both experiments is justified by the presence of the teledosimetric system-the first ring of receptors around a power plant. The slight overestimation of Q along with underestimation of wind speed during time step 4 caused overall overestimation of the gamma dose rate in time 5, see Figure 1.

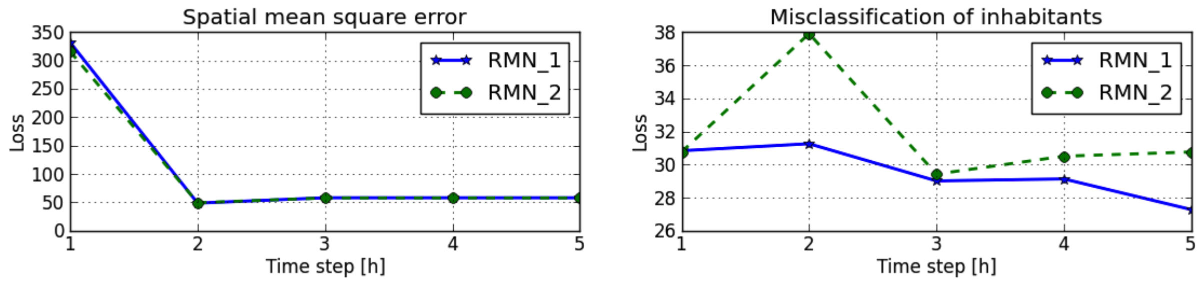

Figure 2: Comparison of performance of monitoring networks RMN_1 and RMN_2 in terms of two loss functions evaluated in time steps t=1,…,5. **Left:** Loss function measuring mean square error (MSE) between assimilation results and twin model. **Right:** Loss function measuring MSE weighted by population data for respective grid cells.

Loss evaluation

The main objective of this paper-the comparison of suitability of different monitoring network configurations-is achieved via assessment of capability of Monte Carlo data assimilation procedure to reconstruct an accident. The assessment is performed by the means of comparison of an assimilation result with the true release represented by the twin model in term of a loss function. In Figure 2, data assimilation results using the two candidate networks are compared in term of a loss function measuring mean square error (MSE) of the assimilation result (Left) and MSE weighted by the number of people living in grid cells.

We observe that performance of data assimilation procedure for both candidate networks is almost equal in terms of MSE. RMN_2 performs slightly better because it regularly covers the computational domain. More interesting results we obtain for the second loss function measuring the discrepancy between the twin model and assimilation result in terms of misclassified people. We observe that RMN_1 performs much better since it covers the inhabited locations-the grid points with highest contributions to the overall loss. MSE in these grid points is significantly reduced in case of RMN_2 due to presence of receptors providing direct information of radiation levels.

CONCLUSION

Performance of a radiation monitoring network is typically evaluated via Monte Carlo study over the weather and release conditions to simulate all potential events. However, the ability of the network to help the decision makers strongly depends on the quality of the assimilated results. This aspect is often overlooked and networks are optimized using very simple assimilation procedures, in order to keep reasonable computational cost. In this paper, we proposed to use 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. Demo of the tool is available online at http://dss.utia.cas.cz.

Finally, we should point out further significant feature of the proposed technique. It represents efficient advanced tool for online Bayesian tracking of the radioactive plume propagation. It provides more accurate prognosis of evolution of radiological situation and better identification of the most contaminated areas (e.g. see top left and bottom left pictures in Figure 1). It can support decision making under nuclear emergency related to the introduction of urgent countermeasures on population protection. It restricts threat of possible fatal health and social consequences in case of erroneously classified areas. Nevertheless, a lot of work should be done, mainly in the field of multi-segment and multi-nuclide analysis of an accidental scenario.

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