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EVALUATION OF DETECTION ABILITIES OF MONITORING NETWORKS USING DIFFERENT ASSESSMENT CRITERIA

Radek Hofman, **Petr Pecha** and **Václav Šmídl**
Institute of Information Theory and Automation, Prague, Czech Republic, pecha@utia.cas.cz

Motivation

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**. In this contribution, we investigate evaluation of a network using **Bayesian assimilation**,which is capable to comply with uncertainty of the release and evaluate predictions of its evolution. We provide tools for evaluation of design extensions of selected fixed configurations of a 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 is used in Bayesian assimilation. The adaptive strategies are applied to improve convergence properties of the sequential Monte Carlo (Smidl, V. and R. Hofman, 2011). Quality of a network is studied via two loss functions:

- Spatial coverage of the affected area
- Misclassification of inhabitants (Heuvelink, G.B.M. et al., 2010).

Decision theory framework

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 minimizes the expected value of the chosen loss function

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

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.

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 D in the whole area,

$$L(n, X) = (D(X) - \hat{D}(X))^2, \qquad (2)$$

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

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

where $I_{fp} = \sum_j P_j \times (\hat{D}_j > \overline{D} \,\&\, D_j < \overline{D})$, 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 level.

Key element of the loss is the estimate of the radiation dose $\hat{D}$. This is a result of assimilation with measurements y provided by the configured data. 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 $\hat{D}$. These parameters will be denoted by θ_{asim}. The estimate of the radiation dose is provided by an analytical atmospheric model $\hat{D} = D(\theta_{asim}(y), \theta_{other})$.

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 $\theta^{(i)}$. These samples are used to generate the twin model from which is generated the twin deposition $D^{(i)}$ 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, $\theta^{(k,i,n)}$ $k = 1, \dots, K$. Each of the samples have 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. Evaluation of the network performance criteria (2) is then approximated by

$$E(L(n, X)) \approx \sum_{i=1}^{I} \sum_{k=1}^{K} w^{(k,i,n)} (D^{(i)} - D(\theta^{(k,i,n)}_{asim}))^2, \qquad (4)$$

and equivalently for the misclassification loss (3).

Determination of external irradiation dose rates

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. 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 .

Time dynamics of the released material is partitioned into a number of fictitious one-hour segments with equivalent homogeneous release source strength. Each segment subsequently spreads according to given meteorological conditions. The movement is simulated numerically by means of a large number of elemental shifts.

Model parametrization. There are many model parameters that influence the shape of the plume. From these parameters, we consider only the release source strength of activity Q [Bq.s$^{-1)}$] 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 (launching of the spectral sensors is so far hardly practicable) . However, the knowledge of the release composition is important for wet and dry deposition.

Calculation of dose rates. The sensors register sum of cloudshine and groundshine dose rates. The groundshine is computed as a supperposition of contributions from all hourly segments with index s denoting the time of the segment release. The groundshine dose is sum of contributions during the whole trajectory of the segment. Just at time T, each released segment s has relative index of its history $\tau = s, ..., T$.

$$\begin{aligned} RATE_{ground}(l;T) &= \sum_{(r)} \sum_{s=1}^{s=T} \sum_{\tau=s}^{\tau=T} RATE^{r}_{ground}(l; s, \tau) \cdot \exp\left[-\lambda_r \cdot (T-\tau)\right] \cdot 3600 \\ RATE_{cloud}(l;T) &= \sum_{(r)} \sum_{s=1}^{s=T} RATE^{r}_{cloud}(l; s, T) \end{aligned} \qquad (5)$$

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

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 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.

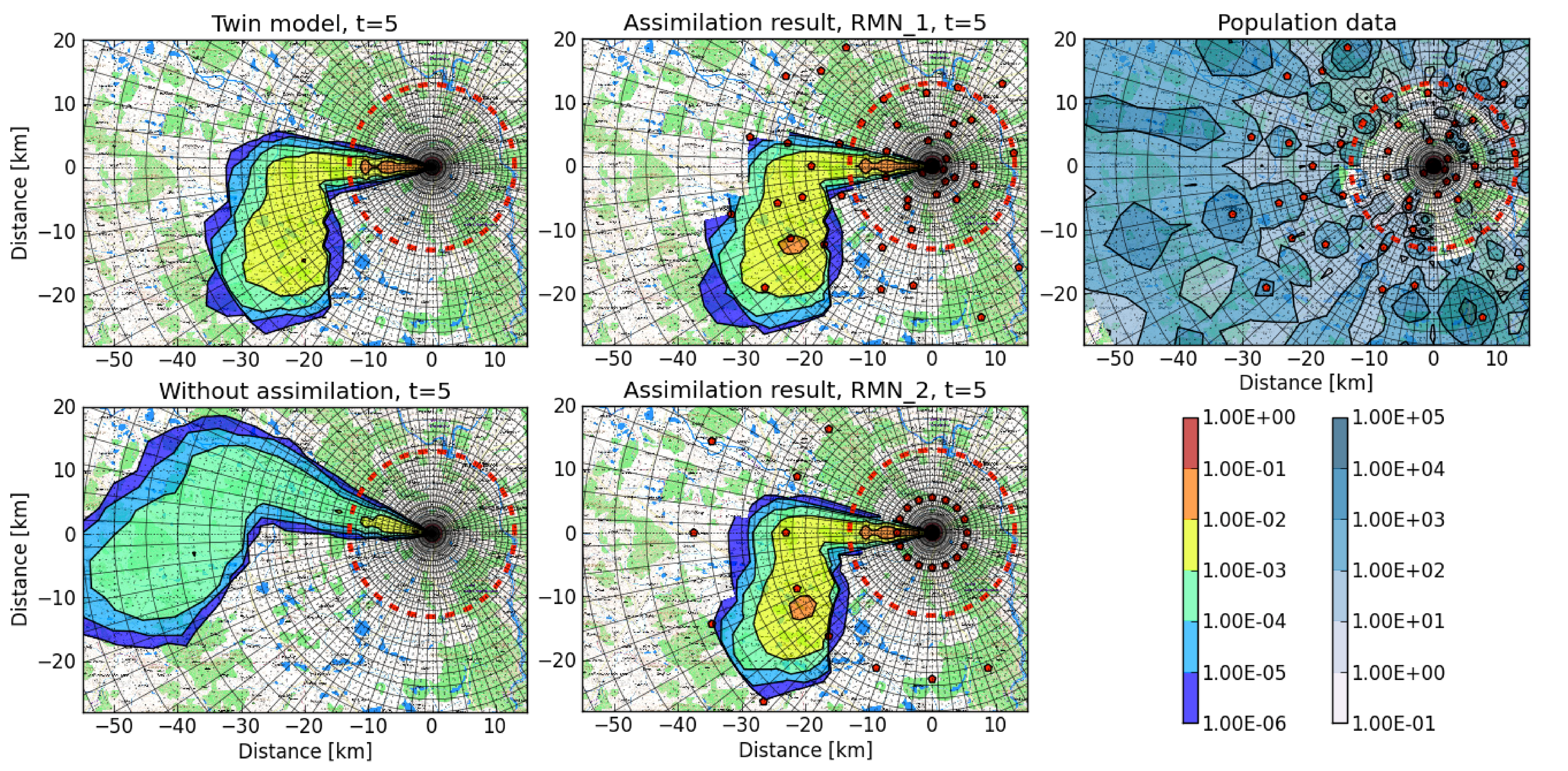

Figure 1: Comparison of twin model and data assimilation results. **Top left:** Twin model: 5.0E+15 Bq.h^{-1}. **Bottom left:** Simulation based on initial deterministic calculations with nominal inputs 1.0E+15 Bq.h^{-1}. **Top** and **bottom middle:** Assimilation results based on RMN_1 and RMN_2 candidate 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.

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.

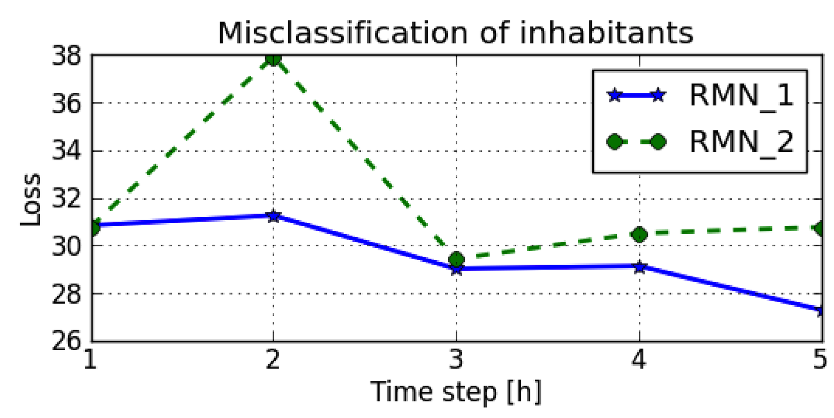

Figure 2: Comparison of performance of monitoring networks RMN_1 and RMN_2. Loss function weighted by population data for respective grid cells.

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.

REFERENCES: See extended abstract H15-333

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Appendix: STEPWISE SEQUENTIAL ASSIMILATION SCHEME

Steps:

- Simulation of artificial "measurements" based on TWIN model
- Setup of best estimate of dispersion model parameters
- Selection of the most important of random model parameter subset:

C$_{rand}$ ...... Release source strength (Bq/hour)
ϕ_{rand} .... Wind direction (deg)
U10$_{rand}$ .... Wind velocity (at 10 meters height) (m/s)
Meteorological data archived for the year 2009 are available.
JREAL means JREAL-th random realisation of the plume trajectory.
f ..... hour of propagation from the same release beginning, the release is segmented to consecutive one-hour segments
JREAL=1
f = 1
S0: running model for successive hours (phases) g from 1 ... f
g = 1
S1: IF (g = f) goto S3
S2: Plume propagation in the next phase f (hour f of propagation from beginning):

- Load former estimated parameters from INTERCOM.ASI :

^{est}C(f=1) , $^{est}\phi$(g), ^{est}U10(g);

- Run dispersion model SGPM from for g
- g= g+1
- GOTO S1

S3:

- Generation of random realization for phase f:

ϕ_{rand} (JREAL,f),U10$_{rand}$ (JREAL,f))

- The single trajectory from f=1 up to f-1 is now propagated in the new phase f. The plume segment in the phase f is randomly split into bunch of random "beams" JREAL (JREAL=1, . . . , JREAL$_{max}$) . The particular beam belongs to parameters:

^{est}C(f=1) , ϕ_{rand} (JREAL,f), U10$_{rand}$ (JREAL,f);

- Sum of cloudshine and groundshine deposition rates is added into the output matrix IMPLICIT.OUT

JREAL=JREAL+1
IF (JREAL.GT. JREAL$_{max}$) GO TO S4 - Bayesian estimation of $^{est}\phi$ (f), ^{est}U10 (f) results
from application of the assimilation cycle S4.
GO TO S3
S4:
Assimilation subsystem: Processing of JREAL$_{max}$ random matrices stored
In IMPLICIT.OUT

- Bayesian estimation of "best" matrices (2-D trajectories) on bases of likelihood relation between model and simulated measurements.
- Estimation of best beam(s) $^{best}\phi_{rand}$ (phase=f), ^{best}U10$_{rand}$ (f); are stored into file INTERCOM.ASI
- f= f+1

IF (f GT fmax) GOTO S5
CONTINUE TO S0 - propagation in the next phase f
S5: END