Optimization for the design of environmental monitoring networks in routine and emergency settings

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Abstract. The design of radiation monitoring networks were optimized by combining a geostatistical assessment of routine prediction error with simulation modelling to assess network signalling function in emergency settings. A physical atmospheric dispersion model was used to simulate radioactive releases throughout the study area under different accident scenarios and varying weather conditions (e.g. small nuclear power plant accidents and mock human-caused radioactive emissions). Network signalling function was defined as the ability to detect radioactivity above a critical threshold within 3 hours of a nuclear release. Spatial simulated annealing was used to obtain optimal monitoring designs by moving stations around and accepting those designs that reduced a weighted sum of two criteria (prediction error of mean annual background radiation and network signalling function). Results were promising and the method should prove useful for assessing the efficacy of hazard monitoring networks designed to detect the unlikely event of a nuclear emergency.

1 INTRODUCTION

Radiation monitoring networks are designed to detect gamma dose rates emitted by both natural and artificial radionuclides. The importance of these networks is without question given the potential for accidents like the radioactive release at Three Mile Island in Pennsylvania (1979) and the Chernobyl nuclear power plant (NPP) accident in the Ukraine (1986). Currently there are 436 NPPs operating worldwide [8] and that number is set to increase. The probability of an attack with a dirty bomb is difficult to estimate, but may be even higher than the probability of an NPP type accident [8]. In addition, public fears related to the risks of radiation tend to be amplified [8].

The National Institute for Public Health and the Environment (RIVM) operates the Dutch National Radioactivity Monitoring network, and in Germany, the Federal Office for Radiation Protection (BfS) is the agency responsible for the German network. Monitoring stations are more or less uniformly spread across the two countries, with increased densities near nuclear power plants and along country borders [6]. However, there is a need to coordinate the sampling design of radiation monitoring networks amongst these and other countries because hazard releases have trans boundary properties [7].

In order to optimize a sampling design, one must first select an appropriate criterion with which to evaluate the suitability of a given design. Also referred to as the objective function, the criterion must encompass the sometimes conflicting objectives of a monitoring network. In cases where environmental variables are being mapped, it is generally appropriate to use model-based geostatistical approaches that rely on a pre-specified

Table 1: Release characteristics and example meteorological data used with NPK-PUFF to generate plumes shown in Fig. 1

Release	Hr	Wd10	Ws10	Wd300	Ws300	Wd500	Ws500	P	HM	Obukv
5.00	8	165	2.88	223	3.99	232	4.66	0	150	-24.9
E+13 Bq	9	175	3.13	215	4.23	224	4.74	0	150	-27.4
Cs-137	10	182	3.46	209	4.52	215	4.92	0	150	-31.7
5-Apr-05	11	189	3.85	204	4.86	208	5.2	0	150	-39.1
1.36	7	301	3.59	307	7.27	313	8.65	0.02	1618	-121.5
E+16 Bq	8	301	3.94	305	7.23	310	8.46	0.02	1768	-91.1
Kr-88	9	301	4.31	303	6.92	305	7.81	0.01	250	-80.2
9-Aug-05	10	301	4.68	301	6.94	303	7.72	0.01	250	-77.1

Hr = hour; Wd10, Wd300, Wd500 = wind direction at 10 m, 300 m, and 500 m; Ws10, Ws300, Ws500 = wind speed at 10 m, 300 m, 500 m; P = precipitation (mm); HM = mixing layer height; Obukv = Monin Obukhov length (a measure of atmospheric stability).

model of underlying spatial variation in the variables sampled [2, 6]. Some studies have used the average prediction error variance as a criterion to obtain an optimal sampling design [1, 9]. Though methods that use the average prediction error variance [3] can help to improve the design of radiation monitoring networks under routine conditions [7], such an approach neglects to consider the prime objective of these networks: that is, they must be designed to quickly detect accidental or purposeful radioactive releases in emergency situations. We examine the question of how to optimize the permanent, fixed, network for monitoring both background radiation and the detection of an accidental or purposeful radioactive release. The novelty of our approach is that radioactive releases were tracked through time and were simulated throughout the area of interest, given a modifiable probability distribution for the release locations.

2 METHODS

The NPK-PUFF model [10] simulates emissions from a radioactive source in hourly releases (or puffs), and NPK-PUFF trajectories are estimated using meteorological forecasts such as wind fields [4]. This model is part of a GIS-based decision support system used by the RIVM and the model has been actively developed and improved over the past 15-20 years. We used a beta version of NPK-PUFF (v.4.0) to simulate the release of radioactive plumes in the study area with a magnitude of either a small NPP accident or a mock human-caused radioactive accident (GEN, Fig. 1, Table 1[1]). Meteorological conditions during simulations were sampled from representative hourly weather conditions for the area from a weather station at De Bilt, NL (Table 1). Radioactive plumes were delineated as areas with gamma dose rates (GDR) above critical thresholds. The threshold was set high enough to trigger emergency response procedures under normal circumstances ($\geq$ 100 nSv/hr increase).

2.1 Optimization criterion

Two criteria were combined in the objective function: the mean kriging standard deviation and network signalling function. Kriging prediction error variance was calculated using

[1] developed in consultation with the Back Office for Radiological Information, RIVM

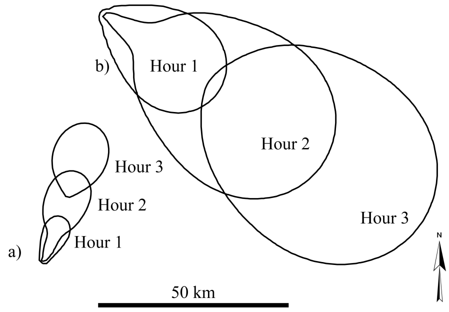

Figure 1: Example radioactive plumes ($> 100\ nSv/hr$ GDR) simulated using the atmospheric dispersion model NPK-PUFF for a) GEN type accident, and b) small NPP type accident. Refer to Table 1 (*upper* and *lower* respectively) for release characteristics.

spatial interpolation of (mean) annual GDRs with known predictor variables as in [7]. Signalling function was calculated as the average cost of failing to detect a plume by a minimum of two detectors within three hours of a release. A look up table was used to weight the costs of failing to detect a spreading radioactive plume (Table 2). The cost of signalling function failure was further weighted by population density such that highly populated areas were associated with higher costs if network signalling function failed (Fig. 2). If a plume followed a trajectory that carried the radioactivity entirely outside the study area, signalling function cost was set to zero. These weights and probabilities can easily be varied and should be set by expert judgment. All analyses and simulations were performed using a package of functions written in the R language for statistical computing (R 2008). The two criteria ϕ were combined into a single objective function as follows:

$$min[\sum_i (w_i \phi_i)]\ , \quad (1)$$

where w is the relative weight assigned to each criterion (e.g., signalling function may be 5 times more important than monitoring background radiation, but for the purposes of this research, equal weights were assigned to both criteria).

Spatial simulated annealing (SSA) is the spatial counterpart to simulated annealing, which is a random search technique commonly used to solve nonlinear optimization problems. For the present study, the procedure began with the current monitoring network design. Optimization proceeded iteratively by randomly moving monitoring stations one by one, simulating nuclear accidents with varying weather conditions (n = 1000), and accepting improved designs over a set number of SSA iterations ($k \leq 8000$). With SSA, worsening designs are accepted with a decreasing probability (here set to $p \leq 20\%$), and the 'cooling schedule' of SSA dictates the rate at which p decreases to zero. We used a simple cooling schedule whereby p was set to exponentially decrease as a function of number of iterations, in order to both avoid the selection of local optima and to ensure convergence [5].

3 Results and Discussion

Optimized sampling designs are presented for both small NPPs and GEN radioactive releases in Fig. 2. It is immediately apparent that a monitoring network designed to detect

Table 2: A) Weights used to determine mean cost of signalling function failure. B) Weights for densely populated areas and probabilities associated with start locations.

A)	hour 1	hour 2	hour 3	B) population density	weight	probability
undetected	2	2	2	1-500	0.25	0.0000001
single	1	1	1	501-3,000	0.33	0.0003
two	0	0	0	3,001-6,000	0.5	0.28
multiple	0	0	0	>6000	1	0.7

general nuclear emissions (e.g., dirty bombs) will be substantially different from networks designed to detect emissions at nuclear power plants (compare Fig. 2ab to 2cd). The design for GEN nuclear accidents was strongly influenced by both the probability distribution of start locations and by the weather conditions at the time of release. This is evident in Fig. 2ab as optimal station locations closely match densely populated areas and are generally situated in the direction of advancing plumes, leaving some directions under-sampled and indicating that 1000 simulated accidents was perhaps inadequate.

Perhaps not surprisingly, optimized results for the small NPP accident scenario did not change markedly over the current network design. Moreover, though a consistent improvement in the objective function was observed over several replications of the small NPP accident scenario (Fig. 3a), the relative improvement was not nearly as great as that observed for the GEN accident scenario (data not shown). This finding suggests that the current network has adequate coverage for both mapping routine radioactivity levels and for detecting small NPP releases with the release characteristics tested here, all within a reasonable amount of time. Noteworthy, however, was how tightly network stations were spaced around NPPs in optimal designs (e.g. Fig. 2c), as well as the decrease in the number of monitoring stations at the border between the Netherlands and Germany.

Finally, Fig. 3b shows how criterion one and two changed as SSA progressed. There was general improvement in both criteria with the small NPP accident scenario, but this was not the case for the GEN accident scenario. Given the costs associated with failing to detect a radioactive release in densely populated areas, signalling function dominated the change in the objective function at the expense of mean kriging standard deviation. That is to say, predictive accuracy for mapping annual background GDR levels decreased overall as stations became more clustered around urban areas, but this decrease was very slight (e.g., for the GEN scenario in Fig 3b, criterion 1 ranged between 8.218 and 8.233). The clustered design was a response to the higher likelihood of a 'dirty bomb-like' attack in urban areas under the GEN scenario.

3.1 Conclusions

The methodology applied here was computationally demanding. However, our results suggest that the method may prove useful as an exploratory tool available to network designers challenged with the task of assessing the efficacy of hazard monitoring networks. Improvements are envisioned that would allow varying weather station data to be used in NPK-PUFF simulations. Moreover, extensions that allow users to build up the network using a subset of stations to optimize the network for NPP type accidents first, and then using additional stations to optimize for detection of human caused radioactive releases.

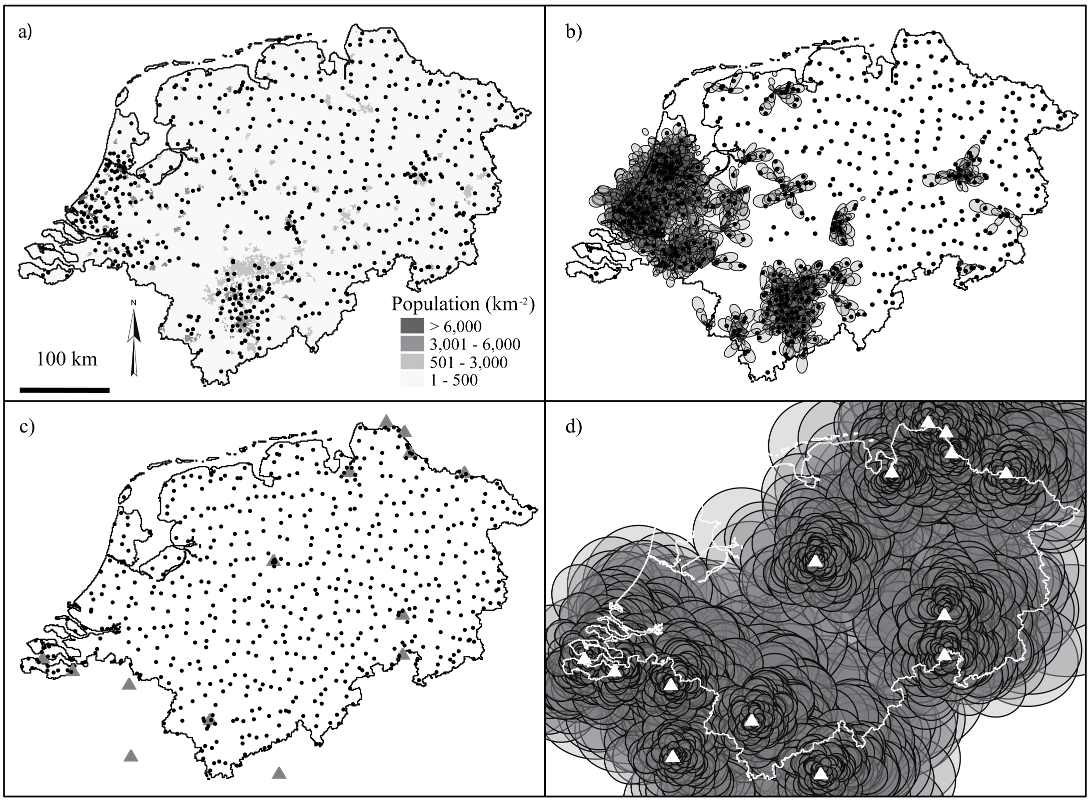

Figure 2: Optimized sampling designs and maps of simulated accident scenarios. a) Sampling design for a GEN radioactive emission scenario depicting population density classes (*grey*). b) Map of the GEN radioactive emission scenario (*plumes*) used to optimize stations shown in a). c) Sampling design for the small NPP accident scenario with weightings for population density as in a) and Table 2, and d) the simulated NPP radioactive plumes.

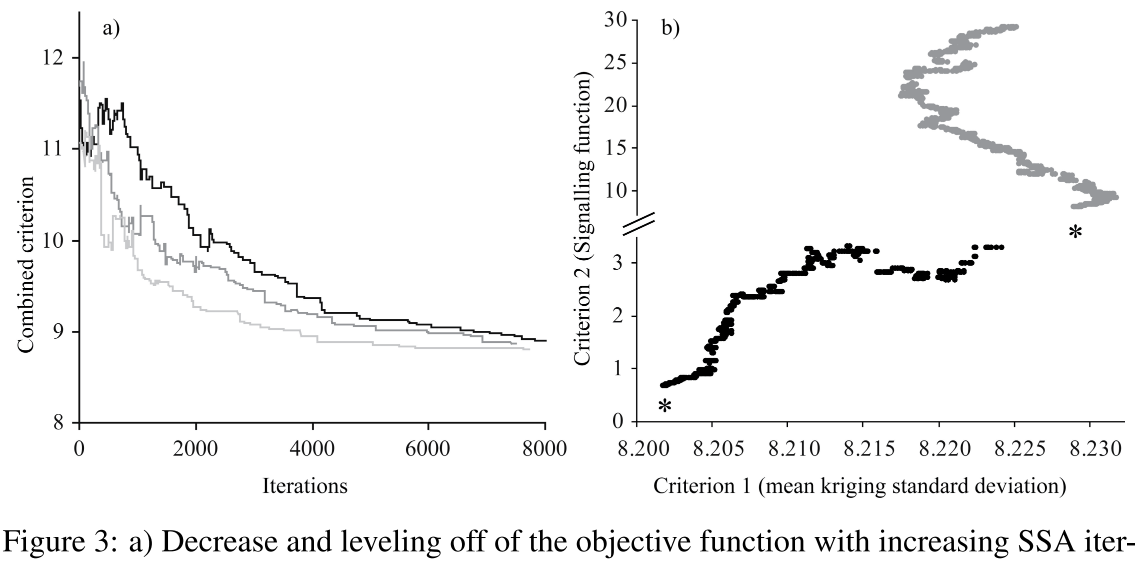

Figure 3: a) Decrease and leveling off of the objective function with increasing SSA iterations for three different replicates of small NPP accident scenarios. b)Trade-off between the two optimization criteria for a GEN radioactive emission scenario (*grey*) and an NNP accident scenario (*black*). Asterisk represents the end-point (optimum) of the simulation.

4 ACKNOWLEDGMENTS

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