Optimizing monitoring networks for the detection of contaminant dispersion

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Abstract. To prepare for the unlikely event of a nuclear emergency, atmospheric dispersion models are used to forecast release concentrations and radionuclide deposition rates. By combining model predictions with spatial analyses of real-time gamma-dose rate measurements at permanent ($n = 153$) and mobile device stations ($n = 8$), more informed intervention decisions can be considered. The main objective of this research was to determine where to optimally locate mobile measuring devices in order to minimize costs associated with faulty decisions. Incorrect decisions may be the result of uncertainty in predicting the spread of a potential radioactive plume. Spatial simulated annealing was used to optimally position mobile devices by minimizing a weighted sum of expected false positive and false negative areas (i.e., false classification into safe and unsafe zones). Results indicated that the optimal placement of mobile devices tended to be in areas at, or just inside, the edge of an advancing radioactive plume.

1 INTRODUCTION

Long range transport and dispersion models are generally used as emergency preparedness tools to help forecast potential dispersion pathways for large emissions of harmful polutants (Galmarini et al. 2004). In the Netherlands, the NPK-PUFF model (Verver et al. 1990) simulates emissions from a radioactive source in hourly releases (or puffs). NPK-PUFF trajectories are estimated using meteorological forecasts such as wind fields (Eleveld et al. 2007), and this model is part of a GIS-based decision support system used by the Dutch National Institute for Public Health and the Environment (RIVM). Similar atmospheric dispersion models are used by other countries around the world.

In case of an emergency at a nuclear power plant, the actual release of radioactive nuclides can usually be delayed by a few hours. During this de-

lay, the RIVM can add extra measuring points to the permanent monitoring network using mobile devices. Two vans are available to transport several mobile devices to emergency areas (Smetsers 2005). As it is preferred that mobile measuring devices are placed before an anticipated accident, the location of these devices must be determined using model predictions.

However, models cannot provide complete and accurate information about future events. In this study, we distinguish between two sources of uncertainty in the NPK-PUFF model: input uncertainty and model uncertainty. Input uncertainty is associated with uncertainty in the values of model input parameters, e.g., meteorological uncertainty in wind speed and direction. Model uncertainty is associated with discrepancies between the computational model and real processes (Karssenberg and de Jong 2005).

In a study closely related to the current investigation, Jiang (2007) optimized the allocation of mobile measurement devices using a geostatistical approach. Radioactivity was modelled as the sum of a deterministic trend and a zero-mean spatially correlated stochastic residual. Jiang (2007) suggested several ways to improve the methodology to optimize mobile measuring devices. Pursuant to his findings, our main research objectives were to: define more realistic probability distribution functions (pdfs) of uncertain input variables; to propagate these errors through the NPK-PUFF model (Heuvelink 1998); to incorporate measurements of the static network (i.e., the 153 stations in the Netherlands) in order to avoid redundancy in the placement of mobile devices; and to take population density into account in the cost function used to assess optimal sampling designs. We used stochastic simulations to generate a range of potential plumes. The difference between the best NPK-PUFF model prediction and simulated plumes were measured using mobile and static devices and these meausrements were used to improve the NPK-PUFF prediction by interpolating the simulated residuals and adding them back to the prediction.

2 METHODS

The Borssele nuclear power plant, in the southwest of the Netherlands (Figure 1), was selected as the site for a simulated nuclear accident. NPK-PUFF was used to simulate a radioactive release of 1e+17 Bq ^{131}I (iodine). We focused on the hypothetical spread of radioactive contamination six hours after a release. Simulated wind direction was from the southwest, which is typical for the Netherlands, and wind speed was initially set at four m/s, resulting in a plume heading towards Rotterdam. The study area was defined by the maximum distance radioactive nuclides can be transpor-

ted within six hours. Figure 1 shows the 100×100 km study area with an overlay of the simulated plume, six hours after the pseudo accident.

In order to explore the effects of uncertainty in NPK-PUFF input parameters, temporal variation in four meteorological variables was estimated and modelled using conditional sequential Gaussian simulation (CGS, Deutsch and Journel 1998, Pebesma 2004). Figure 2 depicts examples of variability in the progression of wind speed, simulated over a six-hour time period using CGS. With CGS, alternative realizations of a variable can be created by means of a variogram model, which summarizes the semivariance of a variable as a function of distance in space or time (Isaaks and Srivastava 1989).

Unfortunately we were unable to consider spatial uncertainty because NPK-PUFF manual input files do not allow meteorological input parameters to vary spatially. Moreover, the input parameters used by NPK-PUFF are based on the High Resolution Limited Area Climate Model (HIRLAM). HIRLAM makes climate predictions at a resolution of 55 by 55 kilometers in six-hour time steps, and this resolution is spatially too coarse to adequately model spatial variability. Hence temporal variability in the meteorological input parameters was estimated using a climatological dataset provided by the Royal Dutch Meteorological Institute (KNMI). This meteorological dataset contained the six-hour HIRLAM predictions as well as the actual measured values for input variables (wind speed, wind direction, mixing layer height, and atmospheric stability) over a one year period. In addition, the dataset included hourly estimates of the observed and modeled input variables. As climate conditions vary seasonally and diurnally, a spring-day scenario was selected and only temporal variability in daytime data for the period between March and May, 2006 were summarized.

Differences between predicted and observed values were used to estimate pdfs of prediction uncertainty in the HIRLAM model estimates. These pdfs were then used to condition the temporal variograms at the six-hour time step, such that uncertainty was zero at time zero when climatic conditions were known; but at the six-hour prediction interval, uncertainty corresponded with HIRLAM prediction uncertainty (Figure 2). Thus uncertainty in meteorological variables increased through time, but was constrained by the HIRLAM prediction uncertainty at six hours.

Subsequent to our assessment of input uncertainties, model uncertainty was represented by an additive stochastic residual function. Based on the assumption that model uncertainty should be unbiased, model error was represented by a zero-mean, spatially correlated residual using a spherical variogram. The variogram range and nugget parameters were the mean va-

lues of a set of possible variogram functions designed to represent a range of model error (low to high). Model errors (stochastic residuals) were simulated using Gaussian simulation and then added to the output of NPK-PUFF simulated plumes (i.e. each of several possible model runs with a range of input parameters) for an overall estimate of uncertainty.

The optimal location of mobile measuring devices was then determined using spatial simulated annealing (SSA, Van Groenigen and Stein 1998). Simulated annealing is an algorithm developed to solve non-linear optimization problems. The optimization criterion selected for this research was the cost of making incorrect decisions due to prediction uncertainty. The cost function used permitted a non-linear weighting of *false positive* (predicted concentrations greater than intervention thresholds when the actual value was below) and *false negative values* (Figure 3). This allowed us to adjust the relative importance of population risk (e.g. failure to evacuate an unsafe area) and economic risk, or the risk of causing unnecessary panic (e.g. evacuation of a safe area). False negatives were weighted more highly than false positives and more densely populated areas received additional weightings because false negative errors in these areas affect the health and lives of people. A flowchart of the methodology is shown in Figure 4. Sampling design was optimized by iteratively searching for the best possible placement of all mobile devices, ensuring the greatest improvement in the reference dose map. The reference dose map was the chief NPK-PUFF prediction made in the absence of information collected by static and mobile measuring devices. In order to obtain measurements of the devices, simulated realities were created and sampled (Figure 4).
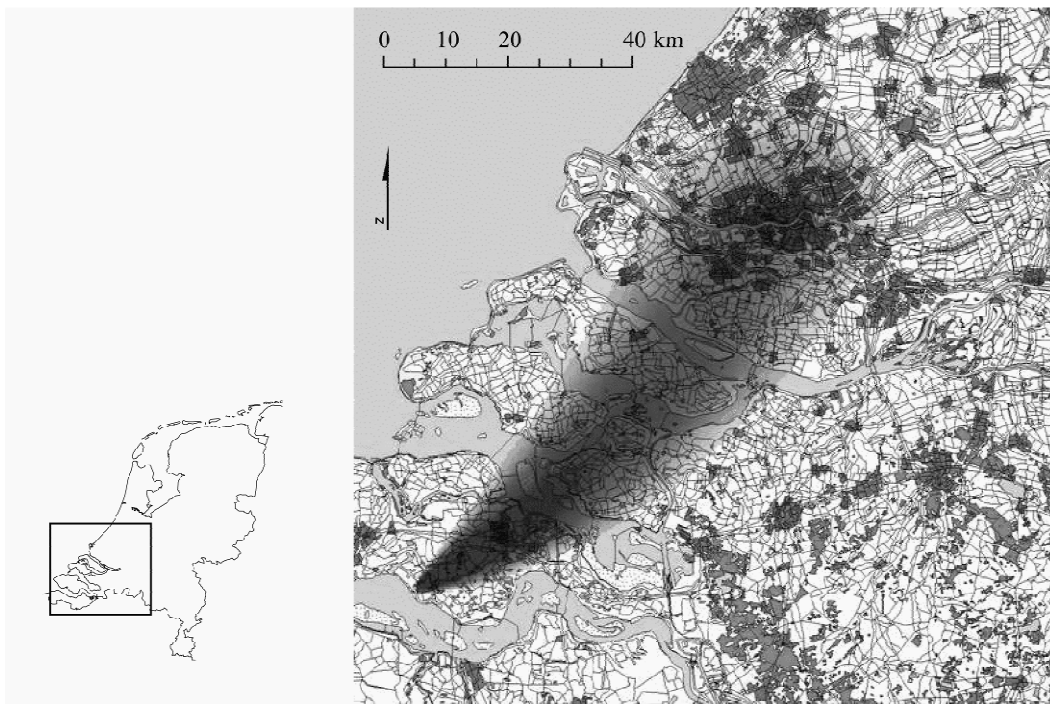
Figure 1: Study area in the Netherlands, depicting built-up areas and a schematic representation of a radioactive plume out of Borssele nuclear power plant. Darker grey indicates increased radioactivity.
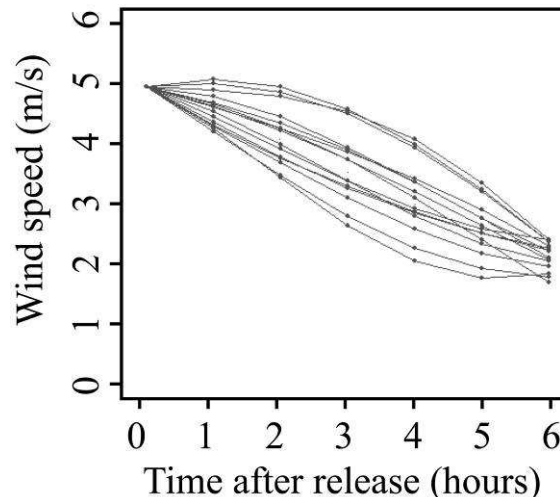

Figure 2: Schematic diagram of uncertainty in the development of wind-speed representing temporal variation and uncertainty in the six-hour HIR-LAM prediction.
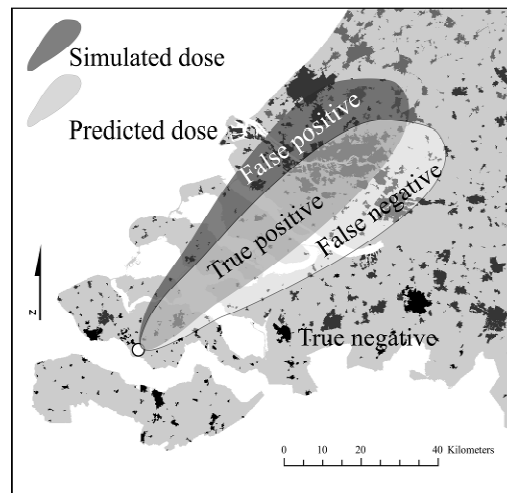

Figure 3: Example of areas with false positive and false negative costs given a predicted plume and uncertain meteorological parameters.
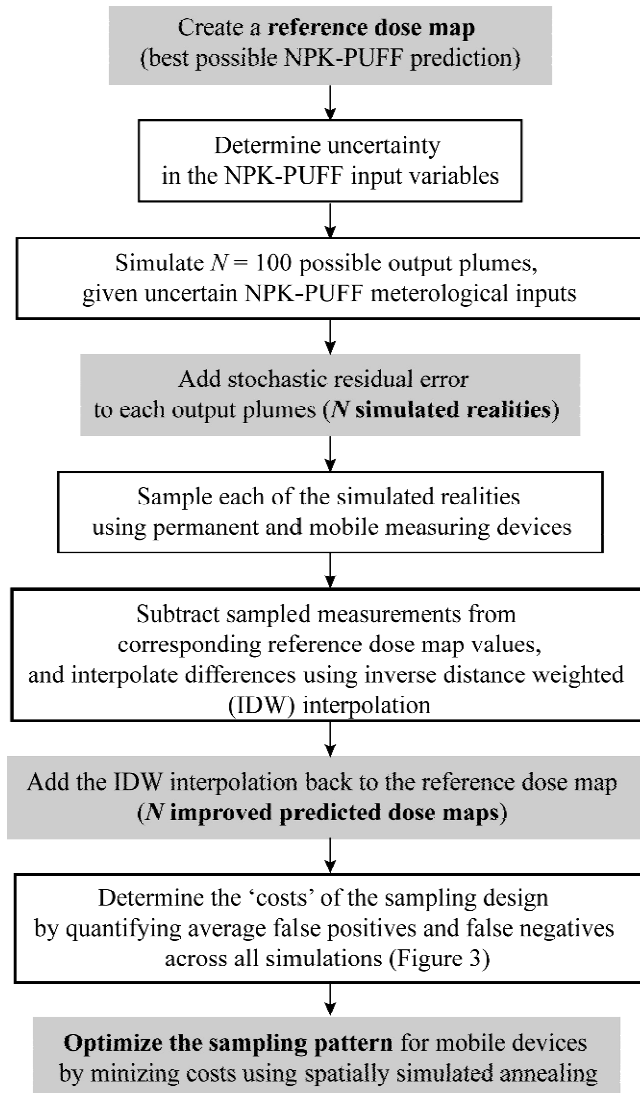
Figure 4: Flowchart of the steps to create a range of uncertain plumes and to determine the optimal placement of mobile measuring devices.

3 RESULTS AND DISCUSSION

Development of the total costs for a simulated annealing run with 1500 iterations (Figure 5) showed that the optimization algorithm occasionally accepted sampling designs with higher costs, thus avoiding local optima (Van Groenigen and Stein 1998). The probability of accepting worsening designs decreased with the number of iterations, which is characteristic of the simulated annealing approach. This method is known to find near optimal solutions to minimizing a given criterion (Van Groenigen and Stein 1998).

We found that the optimal placement of mobile devices in the event of a nuclear emergency at Borssele tended to be at the edge of the hypothetical radioactive plume (Figure 6). Due to uncertainty in the NPK-PUFF atmos-

pheric dispersion model, areas both within the plume and just beyond it had high prediction uncertainties; this was predominantly affected by wind speed and wind direction. When false negatives were weighted five times more highly than false positives, mobile devices were optimized closer to the outward edge of the expanding plume (Figure 6). Moreover, if densely populated areas were weighted more heavily, mobile devices were optimized closer to urban areas in line with the radioactive plume (Figure 7).
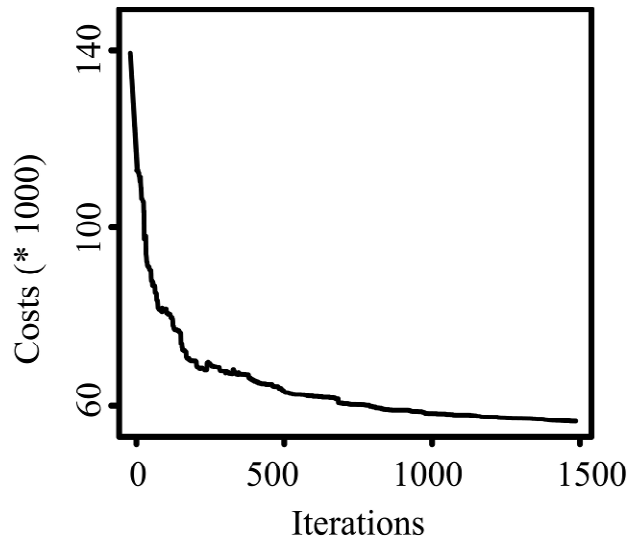

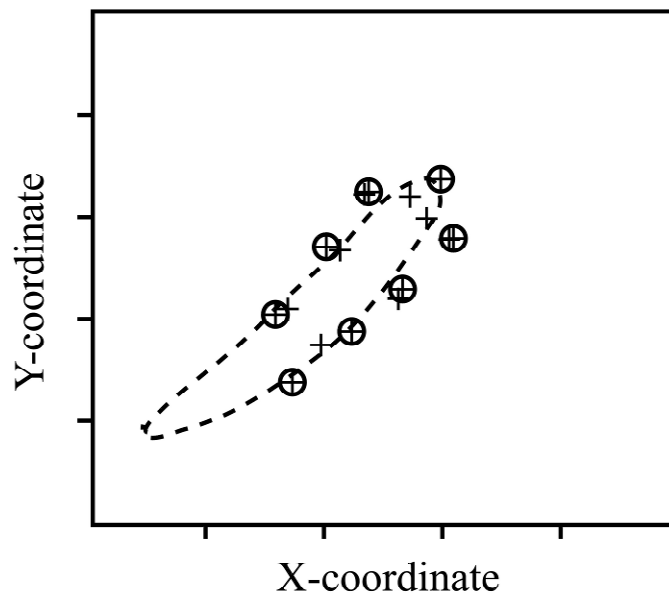Figure 5: Reduction in total costs with an increasing number of iterations using simulated annealing.

Figure 6: Placement of eight mobile devices given a false negative weight of five (*crosses with circles*) or a false negative weight of one (*crosses*).
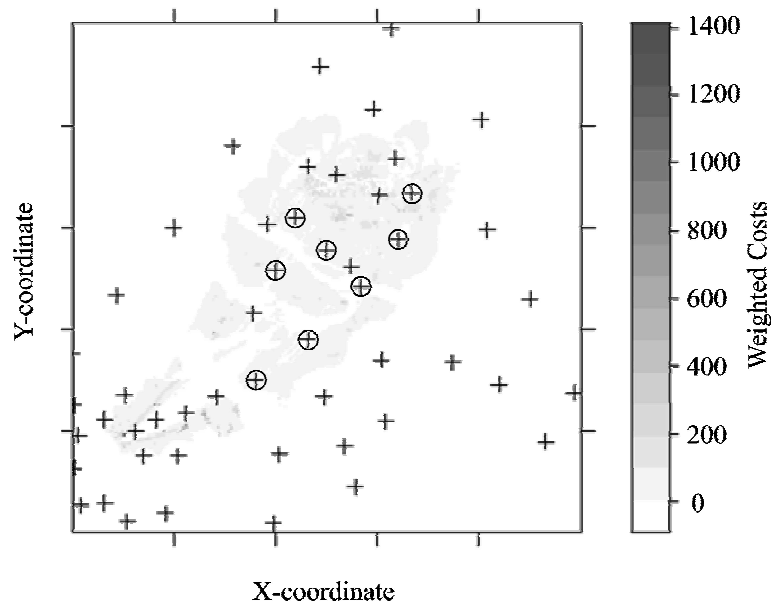
Figure 7: Mean cost estimates across all simulated realities; darker *grey* areas represent higher costs in densely populated areas where false negative predictions were weighted more highly than false positives. The permanent monitoring stations are depicted by *crosses* and mobile devices are depicted by *crosses with circles*.

A brief discussion of the most important limitations to this study is necessary here. Many simplifications were made to summarize uncertainty in the input variable pdfs, the most important of which was leaving out uncertainty in the spatial distribution of meteorological parameters. This was a serious drawback as, for example, wind speed and wind direction will vary considerably over the whole study area. Another important limitation is associated with the inverse distance weighting (IDW) interpolation used to improve NPK-PUFF model predictions. IDW was selected because it is a fast interpolation method, which is an important consideration given the large computational demands of the optimization algorithm. However, in some cases, the predicted map was not improved by the interpolation (*results not shown*). With IDW, the addition of a device in an area near the plume improved predictions in the immediate neighbourhood, but predictions further away sometimes worsened. An explanation for this result is that radioactive dose rates varied extremely over very short distances within the predicted plume. Thus, it was problematic to use distant measurements to improve predictions and IDW gives at least some weight to all points used in the interpolation. We compensated for this problem to some extent by restricting the interpolation range to 20 km, and by using an IDW power of three.

Two major recommendations to improve this work are therefore to further explore spatial uncertainty in the meteorological input variables, and to improve the interpolation method used to update the predicted plume. Interpolation methods such as kriging may not be ideal, given the uncertain nature of radioactive plume dispersion. It is unlikely that kriging would be able to solve the problems encountered with IDW interpolation because kriging requires that the underlying spatial relationships be known unerringly (i.e., the location and trend of the plume must be known). In spite of these problems, the methodology presented here provided promising and interesting results to optimize the locations of mobile measurement devices.

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5 ACKNOWLEDGEMENTS