

1.11 IMPROVING THE RELIABILITY OF THE PROGNOSIS OF ATMOSPHERIC DISPERSION USING DATA ASSIMILATION

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INTRODUCTION

In case of large-scale nuclear accidents real-time atmospheric dispersion models are an important tool to support decision-makers with spatial and temporal information on the dispersion forecast and the extent of the expected contamination. The accuracy of the real-time calculations of spatial and temporal distributions of the air concentration, deposition and corresponding radiation levels is limited due to uncertainties in the applied dispersion algorithms, limitations in knowledge and availability of atmospheric input data, and the release conditions during an accident.

To improve the reliability of the prognosis of the radiation exposure during an accident it is envisaged to use the on-line data of the National Radioactivity Monitoring Network. In a first step, the monitored radiation levels are related to the calculated radiation levels. Based on the plant status source-term estimates and a first estimate of the input parameters are deduced. For the next step both the results of air dispersion model calculations as well as the data of the monitoring network are compared using RIVM's Model Validation Tool (*Eleveld, H. and H. Slaper, 2002*). A sensitivity and uncertainty analysis (*Kok, Y.S., H. Eleveld and C.J.W. Twenhöfel, 2004*) identified the relevant input parameters of the air dispersion model. This is followed by a data assimilation technique based on RIVM's validation tool, which is applied to modify the input space for the air dispersion model providing the improved reliability of the prognosis when compared to intermediate (already analysed) results.

DATA ASSIMILATION TECHNIQUE

Data assimilation techniques are used to obtain an optimal deterministic atmospheric dispersion prognosis, e.g. *Robertson, L. and Langner J., (1998)* and *Rojas-Palma, C. et al. (2004)*. This technique is widely used in numerical weather forecasting. In short, for the atmospheric dispersion prognosis the transport of the calculated puffs on the grid is effected by the acquired dose rate measurements.

We followed a dissimilar scheme, optimising the input parameters of the atmospheric dispersion model by using the observed data, thereby minimising the uncertainty of the model prediction. The match between the model results and the observed data is delivered by the rank value of RIVM's Model Validation Tool, which is described in the next section. By fitting the input space using the rank value a better result can be expected for the atmospheric dispersion prognosis, see Figure 1.

The minimisation procedure, BCPOL, is taken from the IMSL Math Library version 3 (*Visual Numerics, 1997*) and is suited for minimisation of non-smooth functions with simple bounds using a direct search complex algorithm (*Gill, P.E. et al., 1981*). The idea is to fit the input data for time step t_0 to improve the prognosis for time steps $t_0 + N$. This minimisation procedure was especially chosen for its robustness.

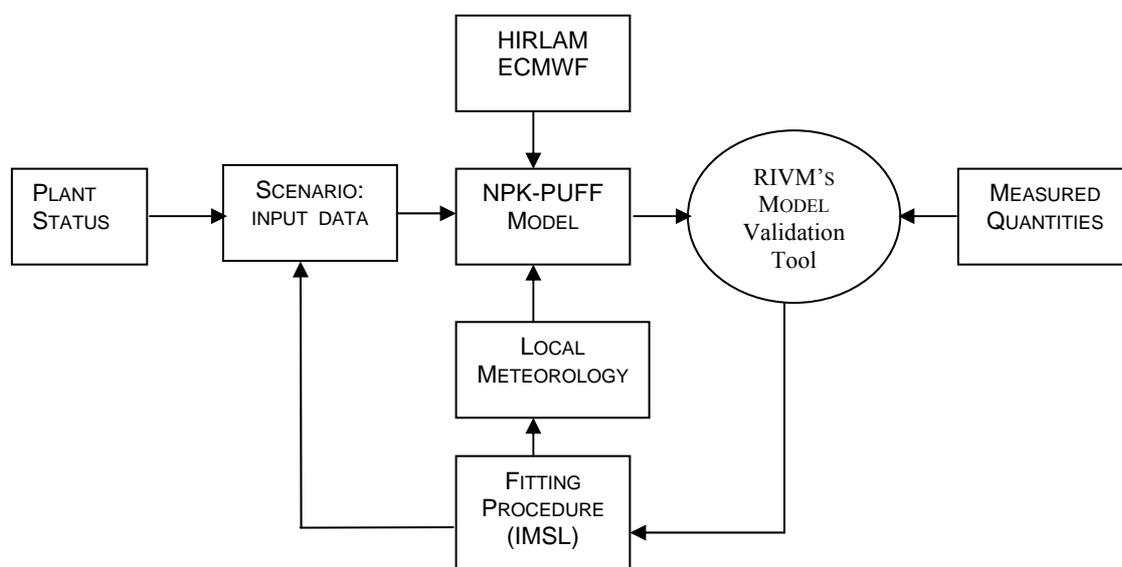


Figure 6. Flow chart of the data assimilation technique using RIVM's Model Validation Tool and a fitting procedure of IMSL to establish an improved prognosis of the dispersion modelling.

RIVM'S MODEL VALIDATION TOOL

The Model Validation Tool (Eleveld, H. and H. Slaper, 2002) is a tool to validate atmospheric dispersion model results against observed concentrations on a time and spatial scale. It includes a statistical methodology that brings a surplus value by the calculation of physical parameters such as the distance and error-angle between the observed centre of mass and modelled centre of mass. In case of a mismatch in terms of the so-called ranking parameter between model results and experimental data, the underlying statistical parameters and physical parameters will reveal the origins of the differences. Ten statistical parameters are used and an overall ranking parameter is based on the combination of all ten parameters. The ranking parameter ranges from perfect agreement (value 0) to extreme disagreement (value 100).

Besides the possibilities of scoring deterministic models against measurements using the Model Validation Tool, it is possible to intercompare probabilistic models, Bijwaard H. and H. Eleveld (2002).

RESULTS AND DISCUSSION

In the absence of elevated levels on our monitoring network the Kincaid data, as distributed by Olesen (1994), is used to demonstrate the working of the data assimilation technique revealing the most favourable input parameters for the air dispersion model. The NPK-PUFF atmospheric dispersion model, operational as a long-range dispersion model (Verver, G.H.L. and F.A.A.M. De Leeuw, 1992) and recently adapted for the meso-range and short-range scale (Eleveld, H. 2002), has been applied for this evaluation.

In Figure 2, the results are shown of the data assimilation technique using the effective emission height and the wind vector as adjustable parameters. Only these two parameters were chosen for practical reasons for this first attempt evaluating the working of the data assimilation technique. For both the effective emission heights and the wind vectors (at an altitude of 100 m) the adjustments were kept the same for all the hours at one iteration step. So, for the first iteration step, the effective emission height was kept at 400 m and the wind angle correction was kept at 0 degrees for all hours. Kincaid day 25 July 1980 was evaluated

as the input data and observed data for this day appeared to be inconsistent (Eleveld, H. and H. Slaper, 2002). One of the questions was if the minimisation routine was able to find a correct minimum for this particular situation. The original ranking performance showed extreme disagreement. Then, after some 25 iterations the ranking parameter value dropped to below 60, indicating a reasonable agreement. After 42 iterations, the minimisation procedure BCPOOL stopped as one of the criteria was satisfied.

The effective emission height was determined to be some 1070 m and the original input wind vectors were changed some 54 degrees. Validating the NPK-PUFF model in previous instance the effective emission height was calculated to some 700 m (Hantke T. and H. Eleveld, 2002). Depending on the atmospheric conditions it is of course possible that the effective emission height (or centre of mass of the puff) is in effect higher, due to an underestimated thermal plume rise of the initial stage (Beychok, M.R., 1994). Another possibility is that an incomplete set of parameters is optimised.

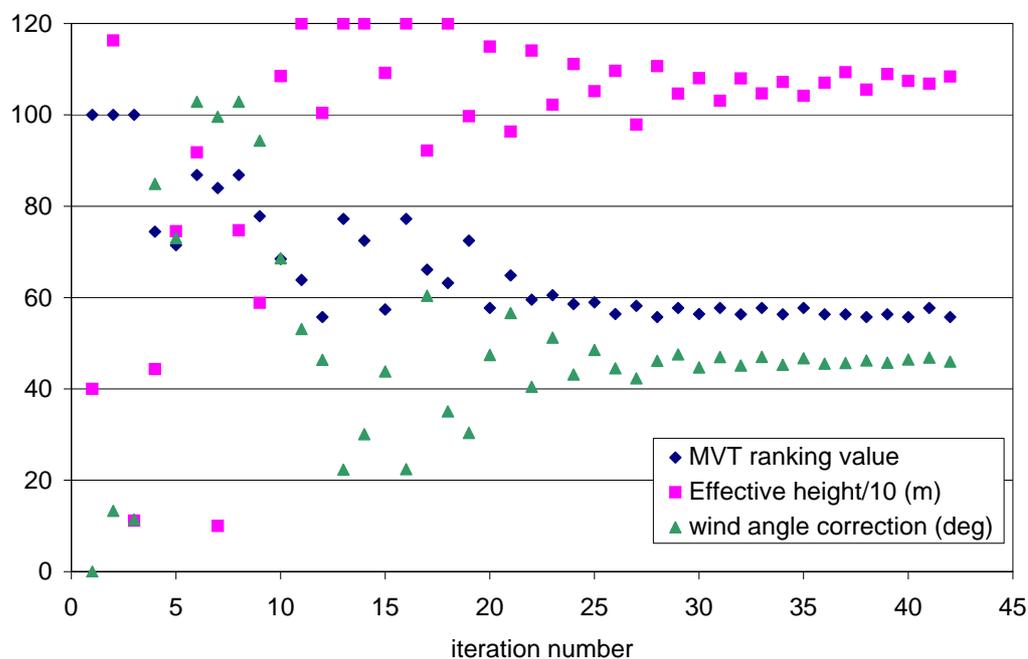


Figure 7. Results of the data assimilation technique for Kincaid day 1980-07-25, using the original input data at the start, the MVT tool and the fitting procedure. Only the effective emission height and the wind vector were adjusted.

In Figure 3, the results of the data assimilation are shown using a geographical information system. It is clear that the modelled results are significantly improved. Nevertheless, the calculated dispersion is rather compact compared to the observed concentrations. Therefore, the dispersion calculation may be improved some more if more input parameters (surface resistance, Lagrangian time scale, Monin-Obukhov Length, etc) were used in this data assimilation. At the other hand, it is of importance that the number of iterations must be limited in order to deliver an improved prognosis in time. By identifying the most important parameters optimisation with respect to computing time can be made. Kok, Y.S. et al. (2004), discuss an exploratory study in this direction.

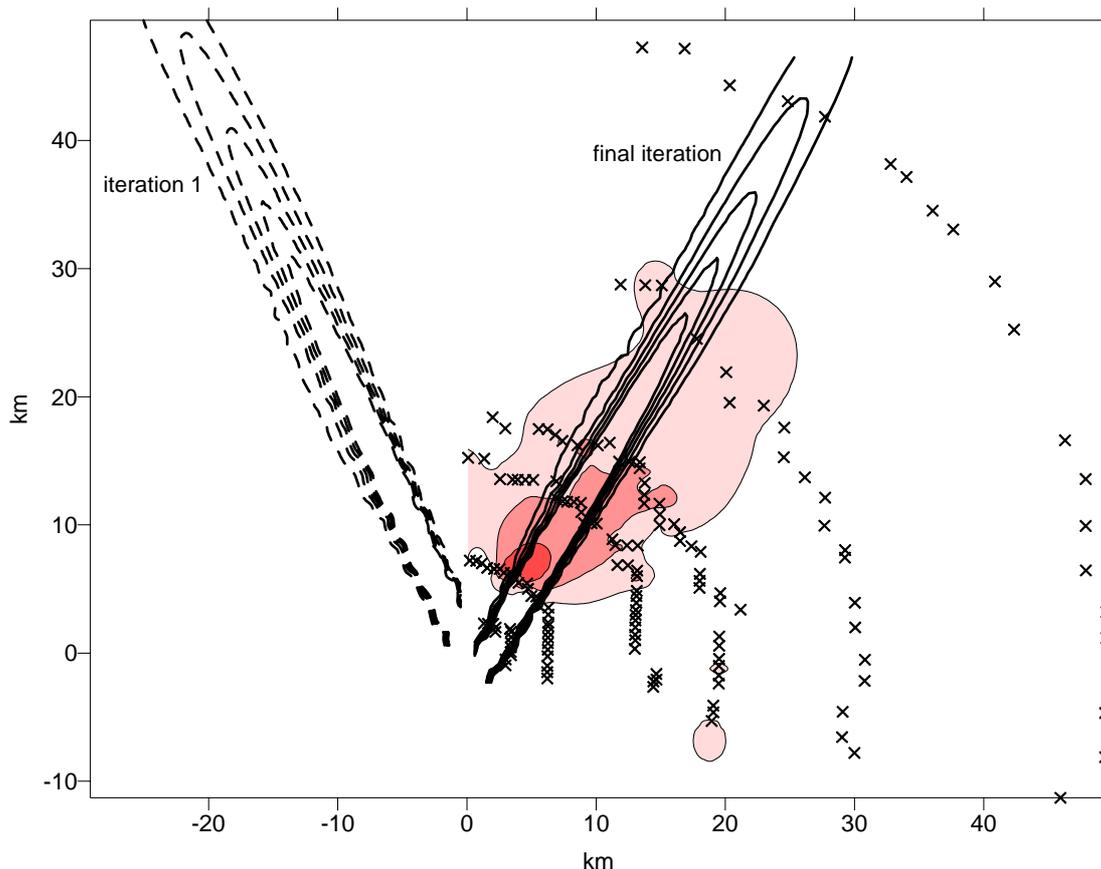


Figure 8. Graphical representation of the result from the fitting procedure for Kincaid day 1980-07-25, see also Figure 2. The crosses represent the receptor points, the filled contours show the interpolated observed concentrations, and the other contours are the modelled results of the first and last iteration.

CONCLUSIONS

In this paper preliminary results of our data assimilation technique are shown. The technique is based on RIVM's Model Validation Tool optimising the input space, including the local meteorological input. A day of the Kincaid data set (25 July 1980) was chosen in the absence of elevated levels of our monitoring network. The specific day was selected as it showed an inconsistency in the input data and monitoring data. Only two input parameters were used in this analysis, the effective emission height and the direction of the wind vector at an altitude of 100 m. In the successful optimisation process, the ranking parameter of the Model Validation Tool decreased from 100 (extreme disagreement) to 56, indicating a reasonable agreement, using the data assimilation technique.

In addition to the presented results, it is important that other input parameters and more data sets are evaluated to ensure a correct working of the presented data assimilation approach. Also, the improvement of the prediction for time t_0+N using (incomplete) data of time t_0 must still be demonstrated.

If this approach successfully reduces the uncertainties in the prognosis in a time efficient way, the objective is to include the method in our operational decision support system for nuclear emergency management.

REFERENCES

- Beychok, M. R., 1994: Fundamentals of stack gas dispersion, 3rd edition, Irvine, California, USA.
- Bijwaard, H. and H. Eleveld, 2002: Comparisons of atmospheric dispersion modelling according to old and new regulations in the Netherlands, 8th International Conference on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes, 148–152, Sofia, Bulgaria.
- Eleveld, H. and H. Slaper, 2002: Development and application of an extended methodology to validate short-range atmospheric dispersion models, *Quantitative Methods for Current Environmental Issues*. London (UK): Springer Verlag - London (UK), 147-165, eds. Anderson C. W., Barnet V., Chatwin P. C., El-Shaarawi A. H.
- Eleveld, H., 2002: Improvement of dispersion models by using RIVM's Model Validation Tool, 8th International Conference on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes, 29–33, Sofia, Bulgaria.
- Gill, P. E., W. Murray, and M. Wright (1981), Practical Optimization, Academic Press, New York.
- Hantke, T. and H. Eleveld, 2002: Validation of the Gaussian puff models TSTEP and REM-3 using the Kincaid dataset, *Int. J. Environment and Pollution*, **18**(3), 209- 222.
- Kok, Y. S., H. Eleveld, C. J. W. Twenhöfel, 2004: Sensitivity and uncertainty analyses of the atmospheric dispersion model NPK-PUFF, 9th International Conference on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes, 1-4 June 2004, Garmisch Partenkirchen, Germany.
- Olesen, H. R., 1994: Model Validation Kit for the workshop on Operational Short-Range Atmospheric Dispersion Models for Environmental Impact Assessments in Europe, NERI/Denmark, Reprint March 1996.
- Robertson, L. and Langner J., 1998: Source function estimate by means of variational data assimilation applied to the ETEX-I tracer experiment, *Atmospheric Environment* **32**(24), 4219-4225.
- Rojas-Palma, C., H. Madsen, F. Gering, R. Puch, C. Turcanu, P. Astrup, H. Müller, K. Richter, M. Zheleznyka, D. Treebushny, M. Kolomeev, D. Kamaev and H. Wynn, 2003: Data assimilation in the decision support system RODOS. *Radiation Protection Dosimetry*, **104**(1), 31-40.
- Verver, G. H. L. and F. A. A. M. De Leeuw, 1992: An operational puff dispersion model. *Atmospheric Environment*, **26A**, 3179-3193.
- Visual Numerics, 1997: IMSL Math Library, Fortran subroutines for mathematical applications, 3rd edition, Houston, Texas, USA.