Real time risk assessment for atmospheric dispersion of accidentally released air pollutants from nuclear power plants

W. K. Graber and F. Gassmann
Paul Scherrer Institute, CH-5232 Villigen-PSI, Switzerland

Abstract

Wind field patterns in an area of 30 by 30 km² over the Swiss Plateau between the Alps and the Jura were measured with 22 temporary meteorological stations and 2 SODARs during four months in 1997. Hourly averages from this high resolution network were combined with meteorological information from routine stations and from a high resolution weather prediction model. A cluster analysis for this data-set lead to 12 different wind field classes with a high separation quality. It is demonstrated, that an on-line acquisition of meteorological data from routine stations only (after removing the temporary stations) can be used to diagnose the recent wind field class with a probability of 96 % to hit the correct wind field class. This diagnosis reveals wind fields with a very high spatial resolution in a very short time. Consequently, it is useful as a contribution to a decision support system for safety management after accidental releases of nuclear or chemical air pollutants. Further, a method is outlined to use the weather prediction model to forecast the wind field class. An average probability of 79 % to hit the correct wind field classes for a forecast time of up to 24 hours is evaluated.

1 Introduction

An emergency decision support system for accidental release of radioactivity or chemicals into the atmosphere requires a detailed knowledge of the local and regional meteorological conditions. Especially, knowledge of the wind field in
complex terrain is essential for developing a clear picture of the atmospheric dispersion after an accidental release. To make an emergency decision support system operative, we hypothesis that wind fields in a region with complex orography can be attributed to a small number of wind field classes which can be defined by a few routine stations.

For emergency applications, the functional reliability of a system as well as the simplicity of its use and the clarity and accuracy of immediate results are of prevalent importance. The following approach is based on a classification of the regional wind fields. Wind field classes based on extensive measurements in the region to be protected are considered to be much more convincing than complicated and difficult calculations with, e.g., a mesoscale model. Further, a limited number of classes could serve as a basis for emergency planning and preparation quite analogous to the strategic defense options of a country often condensed to a few cases that can be activated with a minimum of explanations. For our meteorological problem, the only information to decide which wind field class is active in a given moment comes from routine meteorological measurements via an on-line connection.

2 Experimental set-up and classification

The site of the wind field study is located in the area of the Aare valley shown in Fig. 1. The Aare river flows from south-east towards the middle of Fig. 1., then turns west and after 16 km to north. 22 ground stations were placed in an area of about 30 by 30 km² in the area of the Aare valley according to Fig. 1. In addition to the ground stations, two SODARs (SOund Detection And Ranging) were placed in the region to obtain information of the vertical structure of the wind field up to 300 m above ground.

The measurements of the ground stations were averaged to one hour means over all 2952 hours of the intensive field campaign lasting from July 1 to October 31, 1997. The wind profiles from the two SODARs were averaged to yield wind vectors for 3 layers in 100 m, 200 m and 300 m above ground. Thus, both SODARs contribute together 6 data points to the data-set. Additionally, the wind, temperature and relative humidity information from 20 routine stations supplement the meteorological information in the investigated area. To bridge the gap from the regional meteorological situation to the continental scale, the output of a high resolution numerical weather prediction model was included in the data-set. The model used is a non-hydrostatic mesoscale model routinely operated by the Swiss Meteorological Institute (MeteoScweiz) as described by Schubiger and de Morsier [1], 1992.

The SM operates on an area from 37 to 55 degree northern latitude and from 5 degree western to 20 degree eastern longitude. The data included in the present study comprise 25 points of the SM within the area under consideration. The grid
of the SM is indicated in Fig. 1. The height of the grid points chosen from the SM are all approximately 300 m above ground. The spatial resolution of the SM is 14.5 km, the temporal resolution is 1 hour. Including the meteorological information from the SM, the overall data-set comprises 72 points with wind, temperature and relative humidity data. Consequently, this data-set reflects the general weather situation in combination with a very high density of spatial information about the terrain induced local flow pattern based on experimental data.

Figure 1: Wind stations used during the intensive field campaign. Rivers and lakes are marked with white dots. Horizontal and vertical axis denote the Swiss Kilometer net. The orography is shadowed and contours are plotted for 400, 600, 800 and 1500 mASL. The grid of the weather prediction model SM ("Swiss Model") is indicated with black lines, the squares mark the wind stations.
The classification of the wind fields is based on the cluster analysis described by Kaufmann and Weber [2] (1996). In a first step, the hourly mean values of the wind speed are normalized to 1 ms\(^{-1}\) averaged over all stations. After this procedure, wind fields with the same flow pattern but different wind speeds are very similar. The normalization prevents the formation of high speed wind field classes with no differences in flow patterns but only in wind speed.

In the next step the cluster analysis is performed with the complete linkage procedure. The classification is based on a measure for the difference between two wind fields of any two hours. The following distance of wind fields of hour \(t\) to hour \(\tau\) is defined:

\[
d_{\tau t} = \frac{1}{N} \sum_{j=1}^{N} \left( (u'_{ij} - u'_{\tau j})^2 + (v'_{ij} - v'_{\tau j})^2 \right)
\]

where \(u'_{ij}\) and \(v'_{ij}\) are the west and south components of the normalized wind vector of station \(j\) at time \(t\), the station index \(j\) runs over all stations with valid data for both hours.

The cluster analysis is realized for 12 classes with a FORTRAN program including the procedure for the complete linkage clustering from IMSL (IMSL: mathematical and statistical library of FORTRAN routines, Houston, Texas). All 12 classes of the final classification are described in detail in Graber and Tinguely [3] (1999).

### 3 Modeling wind fields and dispersion scenarios

The Lawrence Livermore National Laboratories, California, kindly made available a program package comprising the model MEDIC for interpolation, the model MATHEW for divergence corrections and the model ADPIC for dispersion calculations (Taylor et al. [4], 1994).

In a first step after classification, for every class, the mean winds of all 72 data points are interpolated with MEDIC to a regular grid. In the present case, the horizontal resolution is 500 m and the grid consists of 100 by 100 points. The area ranges from 565 to 615 km east and from 175 to 225 km north specified in the Swiss Kilometer grid. 48 vertical levels are introduced, each with 50 m height. The interpolation for one grid point includes all data points in a weighted average. The weights are given by one over the square of the distance between grid and data point. The model also takes care of vertical wind profiles measured with the two SODARs.

The model MATHEW evaluates divergence in the interpolated wind field and introduces corrections to eliminate divergence or convergence. The corrections
are made in slight adaptations of the horizontal wind field on every layer and by introducing vertical wind speeds. This step is essential if the wind field is used for a dispersion calculation. The result of the wind field calculations for one out of 12 wind field classes is shown in Fig. 2: The example shows the wind field class 6 on the 9th level, corresponding to a height of 700 mASL. The rotating wind field in the middle of Fig. 2 is clearly visible.

Figure 2: Wind field in 700 mASL for class 6 plotted over the topography corresponding to Figure 1. The mean wind speed is 1, according to normalization.

The wind fields for all 12 classes were calculated and can be taken from the corresponding file in case of an on-line diagnosis of the wind situation. Since the model runs are computer time consuming, this is a substantial improvement with respect to the acquisition speed in the framework of a decision support system. Based on the wind field modeling described above, a dispersion with the model ADPIC can be calculated afterwards for visualizing the flow pattern of a hypothetical release at a given emission source.
Diagnosis of wind field classes with routine stations

Twenty of the data points used in the classification are provided by routine stations from the Swiss Meteorological Institute. These data are continuously available on-line and are updated every 10 min. The data from the SM are also available permanently in intervals of 1 hour and with a 30 hours forecast period. 22 data points and profile data from the two SODARs come from temporary stations and are no routine data, they were available only for the four months of the intensive field campaign.

For an accurate diagnosis of the recent wind field class, wind data of the temporary stations are reconstructed with multivariate regression. For each wind component $u$ and $v$ of the temporary stations, the routine and SM data during the field campaign are used as independent variables. As an example, the result is shown for one data point in Fig. 3, where the two wind components are displayed. The reconstruction shows a very high correlation

![Figure 3: Correlation of west ($u$) and south ($v$) wind component between measured data and data reconstructed from routinely available data points by multivariate regression, for a selected station.](image)

For the diagnosis, the recent wind measurements, the SM data and the reconstructed wind data for the temporary data points are compared with all 12 average wind values of the 12 classes. Again, the distance between the recent wind data and these averages are used for this evaluation. The corresponding definition of the distance for this diagnosis is identical to that in equation (1). The
sum runs over all N=72 data points, including the reconstructed data for temporary points. For the recent hourly wind data 12 distances result and the diagnosis for the recent wind field class is given by that class which has the smallest distance to the recent hourly data. The mean probability for diagnosing the "real" hourly wind field over all 12 classes is 96%. This percentage reflects the high quality of the reconstruction procedure and the reliability of the classification scheme.

5 Method to forecast wind field classes

The SM runs routinely every day and is successfully used to reconstruct wind at the temporary station points. Therefore, the prognostic capability of the model can be used in the framework of the on-line wind field class determination.

In this chapter the expected probability of hitting the correct wind field class over a forecast time of 24 hours is evaluated. In analogy to the multivariate regression for the temporary station data shown in the previous chapter, a forecasted wind field class can be found by reconstructing all data points from the SM data. Fig. 4 shows the multivariate regression over all 2952 hourly wind values of the field campaign, for a selected station, the correlation coefficients are around 0.8 for both wind components. The average of the correlation coefficient for the reconstruction by multivariate regression over all stations was found to be 0.77.

![Figure 4: Correlation of west and south wind components between measured and reconstructed data by multivariate regression from data of the weather prediction model SM, for a selected station.](image)

As in case of the diagnosis, the forecasted wind field class is derived from the reconstructed wind values by evaluating the minimal distances to all 12 classes. The overall average probability of hitting the correct wind field class as tested with the data from the field campaign over the 24 hours is 79%. The result
scatters between 68 and 86%, but shows no significant dependence on the forecast time. In general, the described method for wind flow forecast in complex topography is quite promising.

6 Discussion and Conclusions

The classification into 12 wind field classes delivers a useful set of wind fields which serves as a decision support system for safety management after accidental releases of pollutants into the atmosphere. The wind field classification scheme described above combines the very high spatial resolution of a temporary field campaign with the continental wide information from weather stations integrated in a numerical weather prediction model.

Based on the on-line acquisition of wind data from routine stations in combination with the use of the weather prediction model "SM" a reliable diagnosis of wind field classes can be performed in a very short time. The method of reconstructing wind data at locations where only temporary measurements are available has proven successful in this procedure: The probability of hitting the correct class was evaluated to 96%. The method for reconstructing station wind data is also useful to forecast the wind field classes: The probability of hitting the right wind field class within a 24 hour period is 79%. This forecasting facility will be implemented into the on-line procedure of the wind field diagnosis framework in the near future. A detailed description of the study is found in Graber and Gassmann [5] (2000).

References


Section Eleven:

Case studies