*Presented at the 71st APCA Annual Meeting, Houston, June 1978*

IBM

IBM PALO ALTO SCIENTIFIC CENTER
G320-3371, May 1978

~~F-7~~
P-14

# SHORT-TERM REAL-TIME CONTROL OF AIR POLLUTION EPISODES IN VENICE

P. ZANNETTI

## 1977 IBM PALO ALTO SCIENTIFIC CENTER REPORTS

320-3353 January 1977
Compiled by R. A. BLAINE, Nuclear Reactor Programs for the IBM System/370: Revision I (440 p.)

320-3354 February 1977
S. M. ROBERTS, J. S. SHIPMAN, A New Derivation of the Scott Formulation of Invariant Imbedding (13 p.)

320-3355 February 1977
J. GREENSTADT, The Application of Cell Discretization to Reactor Problems (25 p.)

320-3356 March 1977
S. M. ROBERTS, A Note on the Parallel and Sequential Solution of Stiff Differential Equations (14 p.)

320-3357 March 1977
A. K. HUI, B. H. ARMSTRONG and A. A. WRAY Rapid Computation of the Voigt and Complex Error Functions (19 p.)

320-3358 May 1977
H. H. WANG, The Application of the Symmetric SOR and the Symmetric SIP Methods for the Numerical Solution of the Neutron Diffusion Equation (30 p.)

320-3359 June 1977
S. M. ROBERTS & J. S. SHIPMAN, On the Formulation of Invariant Imbedding Problems (33 p.)

320-3360 July 1977
B. H. ARMSTRONG, Transport of Thermal Phonons in Dielectric Solids, I. (86 p.)

320-3361 September 1977
J. GAZDAG, Wave Equation Migration with the Phase Shift Method (27 p.)

320-3362 September 1977
S. M. ROBERTS, J. S. SHIPMAN, Generalization of the Kagiwada-Kalaba Method of Invariant Imbedding (25 p.)

320-3363 October 1977
B. H. ARMSTRONG, Transport of Thermal Phonons in Dielectric Solids, II. Acoustic Absorbtion (72 p.)

320-3364 November 1977
B. H. ARMSTRONG, Background Internal Friction of Solids (37 p.)

320-3365 December 1977
J. V. DAVE, Effect of Aerosols on the Estimation of Total Ozone in an Atmospheric Column from the Measurements of its Ultraviolet Radiance (48 p.)

## 1978 IBM PALO ALTO SCIENTIFIC CENTER REPORTS

320-3366 March 1978
J. V. DAVE, Extensive Datasets of the Diffuse Radiation in Realistic Atmospheric Models with Aerosols and Common Absorbing Gases (39 p.)

320-3367 March 1978
A. H. KARP, Efficient Computation of Spectral Line Shapes (19 p.)

320-3368 April 1978
S. M. ROBERTS, J. S. SHIPMAN, The Fundamental Matrix and Two Point Boundary Value Problems (17 p.)

320-3369 May 1978
J. V. DAVE, Performance of a Tilted Solar Cell Under Various Atmospheric Conditions (36 p.)

320-3370 May 1978
J. V. DAVE, Isotropic Distribution Approximation in Solar Energy Estimations (19 p.)

320-3371 May 1978
P. ZANNETTI, Short-Term Real-Time Control of Air Pollution Episodes in Venice (24 p.)

320-3475, June 1977
Compiled by G. MURRAY, Abstracts of Palo Alto Scientific Center Reports (126 p.)

320-2575 November 1975
Compiled by J. JAUBERT, Abstracts of Houston Scientific Center Reports (119 p.)

The availability of reports is correct as of the printing date of this report.

\+ Appeared in an outside publication. Not available in Scientific Center report form. Please refer to the list of outside publications on the inside back cover for availability of reprints.

. Copies of report are no longer available from the Scientific Center.

## Abstract

This paper reviews the available methodologies for short-term forecasting of air pollution episodes. The study is oriented to define and test suitable algorithms which perform real-time air quality control in an industrialized-urban area. In particular, after a definition of the problem (control of the episodes) with respect to the general air quality problem (analysis, control and planning of the atmospheric environment), the paper shows some applications of the proposed methodologies to the city of Venice, whose artistic patrimony is seriously damaged by air pollution due to both domestic and industrial local emissions. By analyzing meteorological and air quality data collected by two monitoring networks installed in the Venetian area, it has been possible to test the different algorithms and validate the most suitable of them. Results show the different performances of the models and suggest a real-time alert methodology, to be used by local Industrial Committee, in order to temporarily reduce their pollutants emissions in the area.

a) only the most sophisticated models (K-models) show good results[3] in episode real-time control;

b) K-models are generally tested and calibrated during a limited period of time, related to the availability of a good set of meteorological and emission data, whose knowledge requires a big effort sometimes impossible in real-time;

c) K-models require a big computer and large amounts of computer time; and

d) deterministic models cannot handle unknown variation of input parameters (e.g. emissions) which is often the main reason for computational errors.

In conclusion, even a good K-model can hardly work during periods different from those in which it has been calibrated and tested. However, its application remains very important when a deterministic understanding of the complex real world is necessary (e.g., planning or *a-posteriori* episode evaluation).

As a consequence of previous remarks, stochastic or mixed predictors can be better used for episode control. This approach has the important feature of taking into account all the available past data (emission, meteorology and concentration) for the forecasting of the concentration at any future time. In this way the predictor can use the additional information of the actual concentration data measured at times close to the forecasting time. Such information is often more relevant than that obtained by the always insufficient physical understanding of transport and diffusion phenomena.

The following paragraphs will develop these points both with a more complete description of the available mathematical models for episode prediction, and by showing the results obtained in the Venice area with the proposed approaches.

## II. MATHEMATICAL MODELS FOR EPISODE PREDICTION

According to previous categorization work[2] in this field and by considering the remarks developed in the previous paragraph, the following numerical models can be applied to air pollution episode real-time forecasting:

a) Gaussian model[4,5] : $(E+M)_t \to (M_d) \to [\hat{C}]_t$;

b) K-model[3,6] : $(E+M)_t + [\hat{C}]_{t-1} \to (M_d) \to [\hat{C}]_t$;

c) Autoregressive model[7,8,9]: $\{C\}_{t-i} \to (M_s) \to \{\hat{C}\}_{t+j}$;

d) Multiple regression model[10,11,12] : $\{E+M+C\}_{t-i} \to (M_s) \to \{\hat{C}\}_{t+j}$;

and

e) Mixed model[13] : $\{E+M+C+[\hat{C}]\}_{t-i} \to (M_d+M_s) \to \{[\hat{C}]\}_{t+j}$;

where:

$E$ : emission data;

$M$ : meteorological data;

$C$ : concentration measured data;

$\hat{C}$ : concentration predicted data;

$M_d$ : deterministic model;

$M_s$ : stochastic model;

$(.)_t$ : variable at time t;

$[.]_t$ : position dependent variable in all the domain at time t;

$\{.\}_{t-i}$: time-dependent variable at time t-i with $i=1,2,\ldots,i_{max}$;

and

$\{.\}_{t+j}$: time-dependent variable at time t+j with $j=0,1,2,\ldots,j_{max}$

(Local Industrial Committee) consists of 21 stations measuring ground level $SO_2$ and four meteorological stations in the industrial area (thirty-minute averages). In this paper, after a short description of previous results obtained by analyzing the whole data base, a subset of the data has been used to test the proposed statistical models. In fact, one year of 30-minute average data at Stations 3,4,5,8,10,11 (EZI), located all around the industrial area, and one year of hourly data at Station 10 (ISS), located in the urban center of Marghera, have been used. In particular, many stochastic predictors have been applied to data collected at Station 3, located in the northern boundary of the industrial area, which shows the highest pollution measures in the region.

Important characteristics of the area have been pointed out in previous work[17]. The total $SO_2$ emission due to industrial activity has been estimated at about 160,000 metric tons per year for the period 1973-74; in the same period the emission due to domestic heating and other urban activities was about 10,000 tons per year. Monthly averaged $SO_2$ values are between 10 and 50 ppb (summer) and between 60 and 120 ppb (winter); the substantial increase in pollution levels during winter is due both to the presence of local domestic emissions and to a meteorological situation which is favorable to high pollution levels. The diurnal variation of $SO_2$ concentration was analyzed by computing seasonally averaged $SO_2$ concentration as a function of time of day at every monitoring station. In the winter, the combined effect of domestic heating and of polluted winds blowing from the industrial area causes a peak of concentration in all the stations between 9 and 11 a.m.. Moreover, all the stations, except those located in the historical center of Venice, show another peak at night. In the summer, the influence of the diurnal cycle of wind direction frequency (sea-breeze effect) is predominant and completely explains the patterns of the diurnal cycle at every station. The pollution level in the city of Venice is considerable lower than on the mainland. Nevertheless, particular meteorological conditions occurring in winter, as well as the influence of both urban and industrial sources, produce a limited number of episodes (concentration higher than 200 ppb) in which pollution levels are reached comparable to those in the industrial area. These situations most frequently occur in conjunction with very light westerly winds, i.e., winds blowing from the industrial area towards Venice.

### III.3 Data Fitting

Box-Jenkins[15] ARIMA autoregressive integrated moving average) models and seasonal ARIMA models have been applied to both 30-minute $SO_2$ measurements and to 4-hour, daily, and weekly average $SO_2$ values during the period of analysis. The application of several models of this type has led to the following general conclusion: AR(1) model (first order autoregressive process) shows good forecasting performance and, in any case, an efficiency comparable with that of more complex ARIMA models. The stationary AR(1) process can be expressed as

$$x_t-\mu = \phi(x_{t-1}-\mu) + \varepsilon_t \tag{1}$$

where

$x_t$ is the average $SO_2$ concentration in the t-th time step (ppb);

$\mu = E\{x_t\}$ is the average concentration (ppb) (E is the expectation);

$\varepsilon_t$ is white noise (ppb);

$\phi$ is the model parameter estimated by $\gamma_{xx}(1)/\gamma_{xx}(0)$;

and

$\gamma_{xx}(\ell)= E\{(x_t-\mu)(x_{t+\ell}-\mu)\}$ is the autocovariance function ($ppb^2$).

30-minute average. The forecasting of the next 30-minute $SO_2$ average on the basis of previously observed pollution levels has given the satisfactory results summarized in Table I (columns 1 to 6) in which the AR(1) model forecasting performance (column 6) is compared with that of the persistence model (next 30-minute average is predicted to be the previous 30-minute average, column 5). These comparisons show the general improvement obtained with AR(1) predictor.

4-hour, daily and weekly average. The most polluted station in the area (Station 3) has been used as a pilot station for an accurate analysis of average $SO_2$ pollution levels. Table II (columns 1 to 6) shows the efficient application of the AR(1) predictor, with the exception of the weekly average which presents a non-correlated behavior ($\phi$=0.02).

Cyclostationary predictor models. The presence of a daily cycle in the $SO_2$ measured data, has suggested applying cyclostationary (CS) processes.[18] Precisely, the AR(1)CS process has been considered, namely the model described by

$$\tilde{x}_{i+1}(k) = \phi_i \tilde{x}_i(k) + \varepsilon_i(k) \qquad (2)$$

where:

$\tilde{x}_i(k) = [x_i(k)-\mu_i]/\sigma_i$ is the cyclo-standardized concentration;

$x_i(k)$ is the concentration at the i-th time step of the k-th day (ppb);

$\mu_i=E\{x_i(k)\}$ is the average concentration at the i-th time step of the day (ppb);

$\sigma_i=[E\{(x_i(k)-\mu_i)^2\}]^{\frac{1}{2}}$ is the standard deviation at the i-th time step of the day (ppb);

$N$ is the number of time steps in which the day is divided;

$\phi_i$ is the model parameter to be used at the i-th time step of each day; it is estimated by $\gamma^i_{xx}(1)/\gamma^i_{xx}(0)$;

$\gamma^i_{xx}(\ell)=E\{(x_i(k)-\mu_i)(x_{i+\ell}(k)-\mu_{i+\ell})\}$ where $x_{i+\ell}(k)=x_{i+\ell-N}(k+1)$ and $\mu_{i+\ell}=\mu_{i+\ell-N}$ in the case when $i+\ell>N$ ($ppb^2$);

and

$\varepsilon_i(k)$ is white noise (ppb).

With respect to the variance of the white noise, the cyclostationary model exhibits a substantial improvement if compared with the AR(1) (Table I and Table II, last column). In particular, it should be noted that the cyclostationary models take into account the daily cycle better than the best representative of the seasonal ARIMA models.

### III.4 Real Time Forecasting

Adaptive models. All the above described predictors show a general decrease of forecasting accuracy when used during periods different from those in which their parameters were calibrated. This is a typical behavior of statistical models. In order to remove this shortcoming, an application has been carried out of adaptive AR(1) and AR(1)CS models, whose parameters are estimated on a learning period of given fixed length immediately preceding the forecasting time. In this way the learning period moves along the $SO_2$ times series. The adaptive models can be used to represent the entire process, without distinguishing from season to season, using their adaptive ability. The application of such a method allows the use of the predictors without distinguishing between "data fitting" (i.e., forecasting in the same period used for parameter estimation) and "real time forecasting". Nevertheless, they provide results comparable with those shown in Table I and Table II, as can be seen in Figure 3 where adaptive AR(1) and AR(1)CS are even better than the predictors in the fitting cases.

Multiple linear regression models. In order to improve the performance of the $SO_2$ forecast, account has been taken of the meteorological input by using two simple regression models including $SO_2$ average data and the following meteorological parameters: temperature, wind speed and percentage of polluting wind direction occurrence. Precisely, daily and 4-hour average $SO_2$ values at Station 3 (EZI), and the corresponding meteorological measurements, have been used by the following models:

model I : $C_t = aT_t + bP_t + cS_t + d + e_t$ ; and (3)

model II : $C_t = a'T_t + b'(P_t/S_t) + c' + e'_t$ ; (4)

where:

$C_t$ is the average $SO_2$ concentration (ppb);

$T_t$ is the average temperature (°C);

$P_t$ is the percentage of polluting winds (from S and SE for Station 3(EZI));

$S_t$ is the average wind speed (m/s);

a,b,c,d,a',b',c' are the parameters of the models; and

$e_t, e'_t$ are the errors of the models (ppb).

By least squares estimation of the parameters it is possible to obtain the series $\{e_t\}_t$ , $\{e'_t\}_t$ which can be described with an AR(1) model in order to decrease the variance of the white noise. By this separation between the "meteorological" and the "stochastic" contribution a predictor has been obtained which can be used as a first alert tool in forecasting pollution episodes. Computation of model parameters shows the validity of the approach according to the physics of transport and diffusion of pollutants (b and b'>0, and c<0). Table III shows the forecasting improvement obtained especially by applying model I. Figure 4 shows the winter measured and forecast (model I) daily $SO_2$ average values. These models have been applied using the measured meteorological parameters which, in general, are unknown in advance. Moreover, the same period has been used for the evaluation of the regression parameters and the forecasting computation. In this way models I and II show, in Table III and in Figure 4, their best "theoretical" performance, although an efficient use of this methodology needs an estimation of the meteorological trend and the usage of a dynamic adaptive estimation of the regression parameters. However, the above results show the potential efficiency and the adaptive ability of this approach.

## IV. CONCLUSIONS

The preceding results have shown the validity of the proposed methodologies in short-term real-time forecasting of air pollution episodes. In particular, in order to install a working alert system for episode control in the Venice area, it is necessary:

a) to have a real-time storage of the monitoring station data;

b) to improve the forecasting of the time evolution of meteorological factors;

c) to define an intervention procedure for an optimized emission reduction strategy.

In this way it will be possible to operate with the proposed models in order to avoid, in the study area, the violation of air pollution standards.

## ACKNOWLEDGEMENTS

The author is indebted to Ente Zona Industriale di Porto now Marghera and Istituto Superiore di Sanita' for the meteorological and $SO_2$ data supplied. A sincere appreciation is expressed to Dr. S. Boscolo and Mr. M. Fantini of the Venice IBM Scientific Center for their help in the data base arrangement. Appreciation is also extended to Prof. P. Switzer (Department of Statistics, Stanford University), Dr. B.H. Armstrong and Dr. L.J. Shieh (Palo Alto IBM Scientific Center) for their reading of the manuscript. This work has been developed in connection with the STAAP project (Statistical Techniques Applied to Air Pollution): a collaboration between the Palo Alto and Venice IBM Scientific Centers and the Department of Statistics of the Stanford University.

## REFERENCES


1. E. Runca, P. Zannetti and P. Melli, "Air Quality Management: proposal for a computer oriented approach", Presented at the International Symposium "Simulation '77", Montreux, June 22-24, 1977.

2. Y. Horie, "Evaluation of episode control schemes through air quality data analysis", *J. Air. Poll. Control Assoc.* **25**(11): 1148 (1975).

3. C. C. Shir and L. J. Shieh, "A generalized urban air pollution model and its application to the study of $SO_2$ distributions in the St. Louis Metropolitan area", *J. Appl. Meteor.* **13**(2): 185 (1974).

4. L. J. Shieh, P. K. Halpern, B. A. Clemens, H. H. Wang and F. F. Abraham, "Air quality diffusion model: application to New York City", *IBM J. Res. Develop.* **16**: 162 (1972).

5. L. V. Gibson, Jr. and L. K. Peters, "A short-term air quality model for sulfur dioxide in Louisville, Kentucky", *J. Air Poll. Control Assoc.* **27**(3): 218 (1977).

6. G. L. Marziano, A. Sutera, L. Gianolio and M. Ciprian, "Application of a three dimensional diffusion model to the study of $SO_2$ distribution in the Venice area and its verification", Presented at the Seminar "Air Pollution Modelling", IBM Scientific Center, Venice, Nov. 27-28, 1975.

7. G. M. McCollister and K. R. Wilson, "Linear stochastic models for forecasting daily maxima and hourly concentrations of air pollutants", *Atmos. Environ.* **9**: 417 (1975).

8. D. P. Chock, T. R. Terrell and S. B. Levitt, "Time-series analysis of Riverside, California air quality data", *Atmos. Environ.* **9**, 978 (1975).

9. P. Zannetti, G. Finzi, G. Fronza and S. Rinaldi, "Time series analysis of Venice air quality data", Presented at Symposium on Environmental Systems Planning, Design and Control, August 1-5, 1977, Kyoto Japan.

10. G. C. Tiao M. S. Phadke and G. E. P. Box, "Some empirical models for the Los Angeles photochemical smog data", *J. Air Poll. Control Assoc.* **26**(5): 485 (1976).

11. P. Zannetti, "Modelling and forecasting $SO_2$ air pollution levels: a statistical approach", Presented at the International Conference "Applied Numerical Modelling" Southampton, July 11-15, 1977.

12. Y. Sawaragi, T. Soeda, T. Yoshimura, S. Ohe, Y. Chujo and H. Ishihara, "The prediction of air pollution levels by nonphysical models based on Kalman filtering method", *J. Dynamic Systems, Measurement, and Control* **98**(12): 375 (1976).

13. S. G. Bankoff and E. L. Hanzevack, "The adaptive-filtering transport model for prediction and control of pollutant concentration in an urban airshed", *Atmos. Environ.* **9**: 793 (1975).

14. E. Runca, P. Melli and P. Zannetti, "Computation of long-term average $SO_2$ concentration in the Venetian area", *Appl. Math. Modelling* **1**: 9 (1976).

15. G. E. P. Box and G. M. Jenkins, *Time series analysis forecasting and control*, Holden-Day, San Francisco, 1970.

16. L. J. Shieh and C. C. Shir, "Analysis of input parameters and results of urban air pollution computation", Presented at the 3rd Symposium on Atmospheric Turbulence, Diffusion and Air Quality, Raleigh, N.C., October 26-29, 1976.

17. P. Zannetti, P. Melli and E. Runca, "Meteorological factors affecting $SO_2$ pollution levels in Venice", *Atmos. Environ.* **11**: 605 (1977).

18. L. Franks, *Signal theory*, Prentice Hall, Englewood Cliffs, New Jersey, 1971.

Table I. For each station and for two seasons are shown the average $SO_2$ value, the variance of the data, the AR(1) model parameter, the noise variance of: persistence model, AR(1) model, and cyclostationary AR(1) model.

| | Station number (EZI) | $\mu$ (ppb) | Variance of the data ($ppb^2$) | AR(1) $\phi$ | $\sigma_\varepsilon^2$ variance of white noise ($ppb^2$) | | |
|---|---|---|---|---|---|---|---|
| | | | | | Persistence model | AR(1) | AR(1)CS |
| Winter 74-75 | 03 | 97 | 6241 | 0.83 | 2104 | 1927 | 1693 |
| | 04 | 87 | 7609 | 0.78 | 3313 | 2954 | 2772 |
| | 05 | 52 | 3613 | 0.89 | 808 | 763 | 711 |
| | 08 | 86 | 6866 | 0.83 | 2346 | 2146 | 1932 |
| | 10 | 22 | 1913 | 0.89 | 417 | 394 | 354 |
| | 11 | 74 | 4391 | 0.81 | 1638 | 1486 | 1358 |
| Summer 75 | 03 | 97 | 22686 | 0.86 | 6234 | 5806 | 5251 |
| | 04 | 14 | 439 | 0.74 | 232 | 201 | 176 |
| | 05 | -- | ----- | ---- | ---- | ---- | ---- |
| | 08 | 14 | 514 | 0.72 | 291 | 250 | 226 |
| | 10 | 40 | 2962 | 0.70 | 1763 | 1501 | 1284 |
| | 11 | 27 | 1426 | 0.75 | 723 | 631 | 563 |

Table II. 4-hour, daily and weekly average $SO_2$ values measured at Station 3 (EZI) during the period November 1974-October 1975. The table shows the variance of the data, the AR(1) model parameter, the noise variance of: persistence model, AR(1) model, and cyclostationary AR(1) model.

| Averaging time | $\mu$ (ppb) | Variance of the data ($ppb^2$) | AR(1) $\phi$ | $\sigma_\varepsilon^2$ variance of the white noise ($ppb^2$) | | |
|---|---|---|---|---|---|---|
| | | | | Persistence model | AR(1) | AR(1)CS |
| 4-hour | 94 | 13362 | 0.55 | 12124 | 9375 | 8237 |
| daily | 94 | 6115 | 0.53 | 5768 | 4413 | ---- |
| weekly | 94 | 2634 | 0.02 | 5256 | 2683 | ---- |

Table III. Analysis of 4-hour and daily average $SO_2$ values. Comparison of the variances of the white noise of the persistence model, AR(1) model, model I and model II (Station 3, EZI).

| | Season | $\mu$ (ppb) | Variance of the data ($ppb^2$) | $\sigma_\varepsilon^2$ variance of the white noise ($ppb^2$) | | | |
|---|---|---|---|---|---|---|---|
| | | | | Persistence model | AR(1) | model I +AR(1) | model II +AR(1) |
| 4-hour | winter 74-75 | 97 | 4111 | 2799 | 2325 | 2168 | 2344 |
| 4-hour | summer 75 | 97 | 16284 | 17348 | 12736 | 7647 | 11129 |
| daily | winter 74-75 | 97 | 2487 | 1929 | 1546 | 1017 | 1235 |
| daily | summer 75 | 97 | 5144 | 7947 | 4939 | 2430 | 2762 |

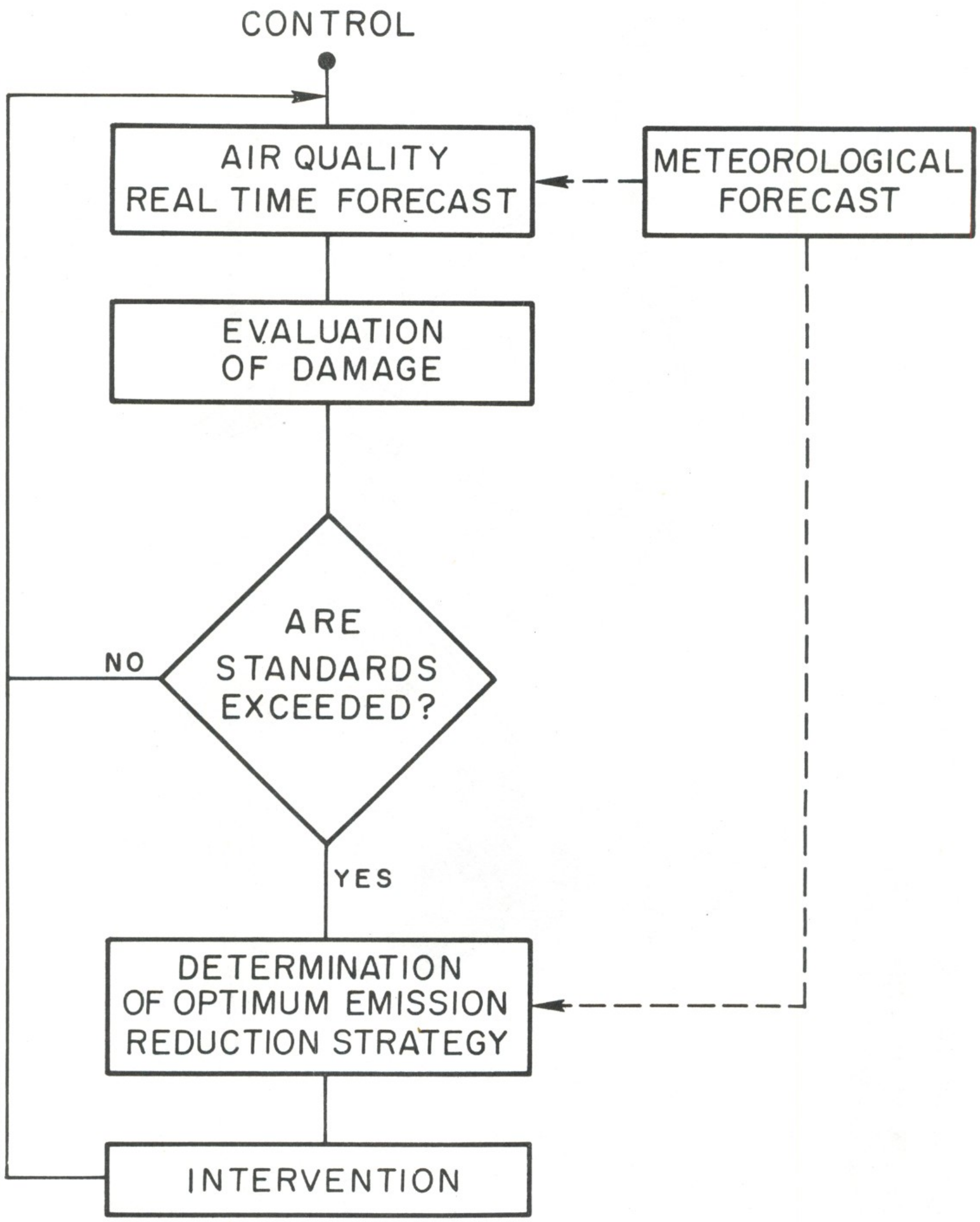



Figure 1. Control of air pollution episodes.

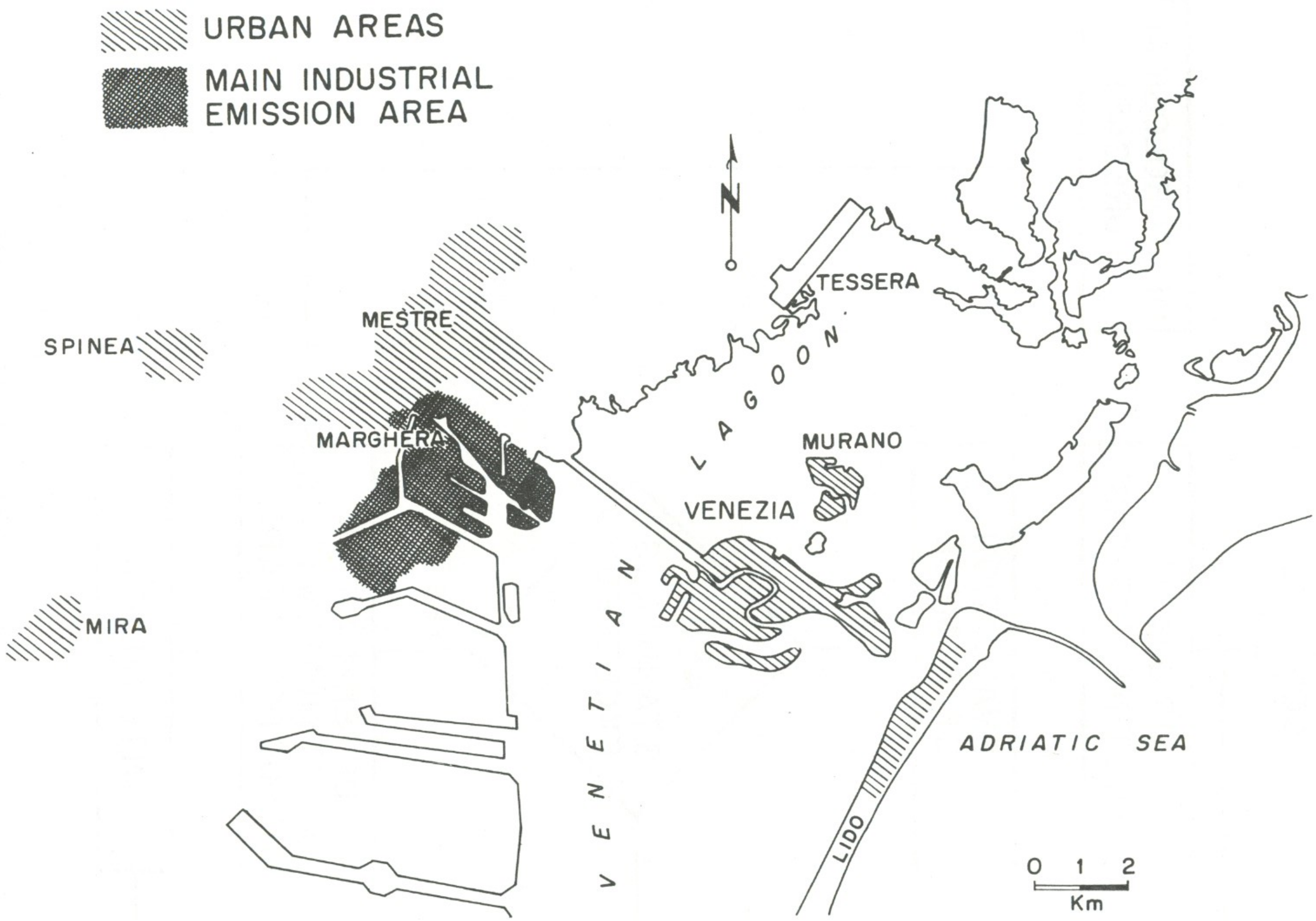
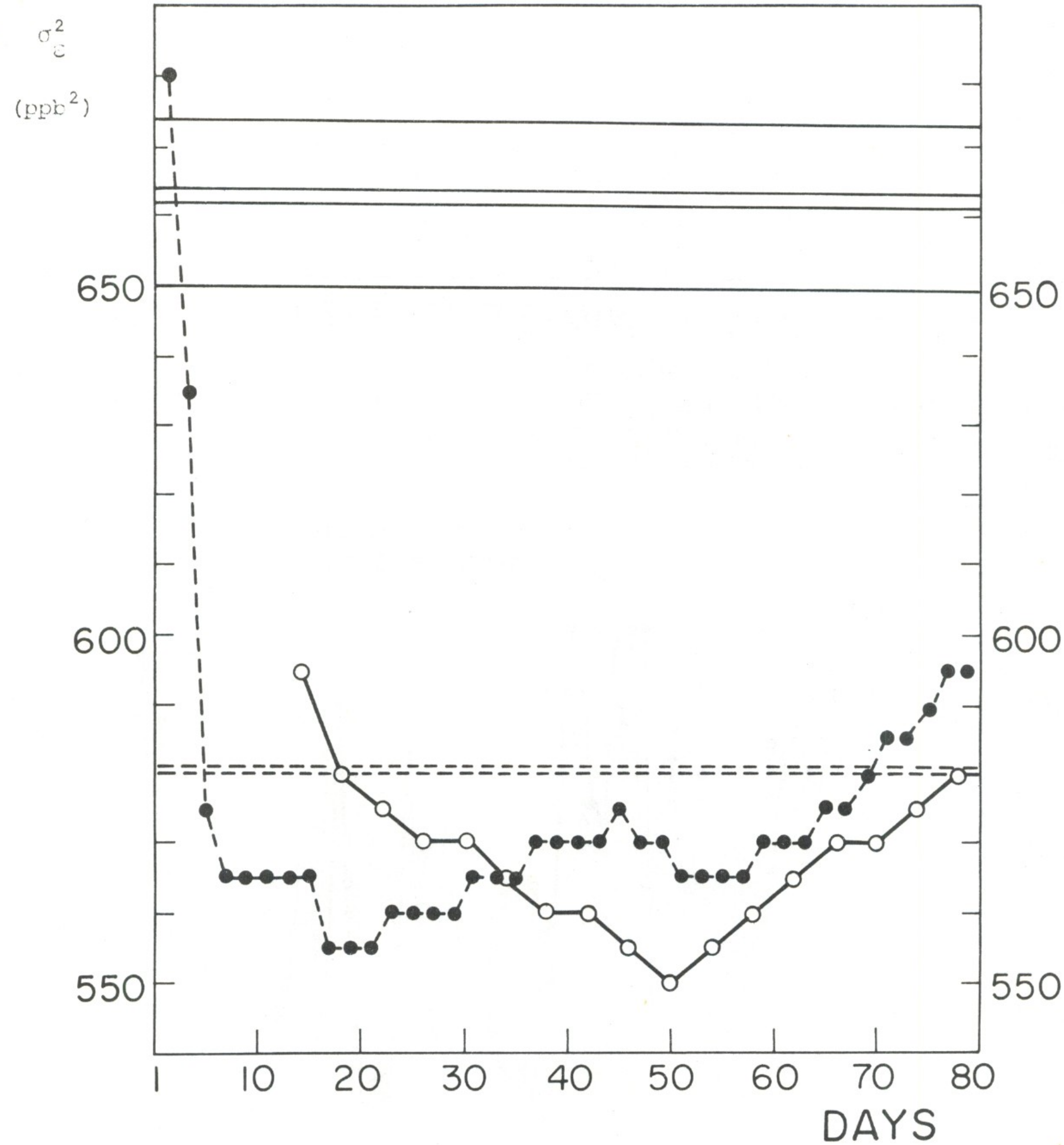



Figure 2. The Venetian Lagoon area.




<u>Figure 3.</u> Values of $\sigma_\varepsilon^2$ for AR(1) (dots) and AR(1)CS (circles) adaptive models applied to data recorded at Station 10 (ISS) during 1974 (one year analysis). The values are plotted versus the learning period. Horizontal lines show comparable $\sigma_\varepsilon^2$ values of non-adaptive models for the fitting (dashed lines) and forecasting (solid lines) cases (forecasting obtained by using the parameters estimated during the same season one year before).

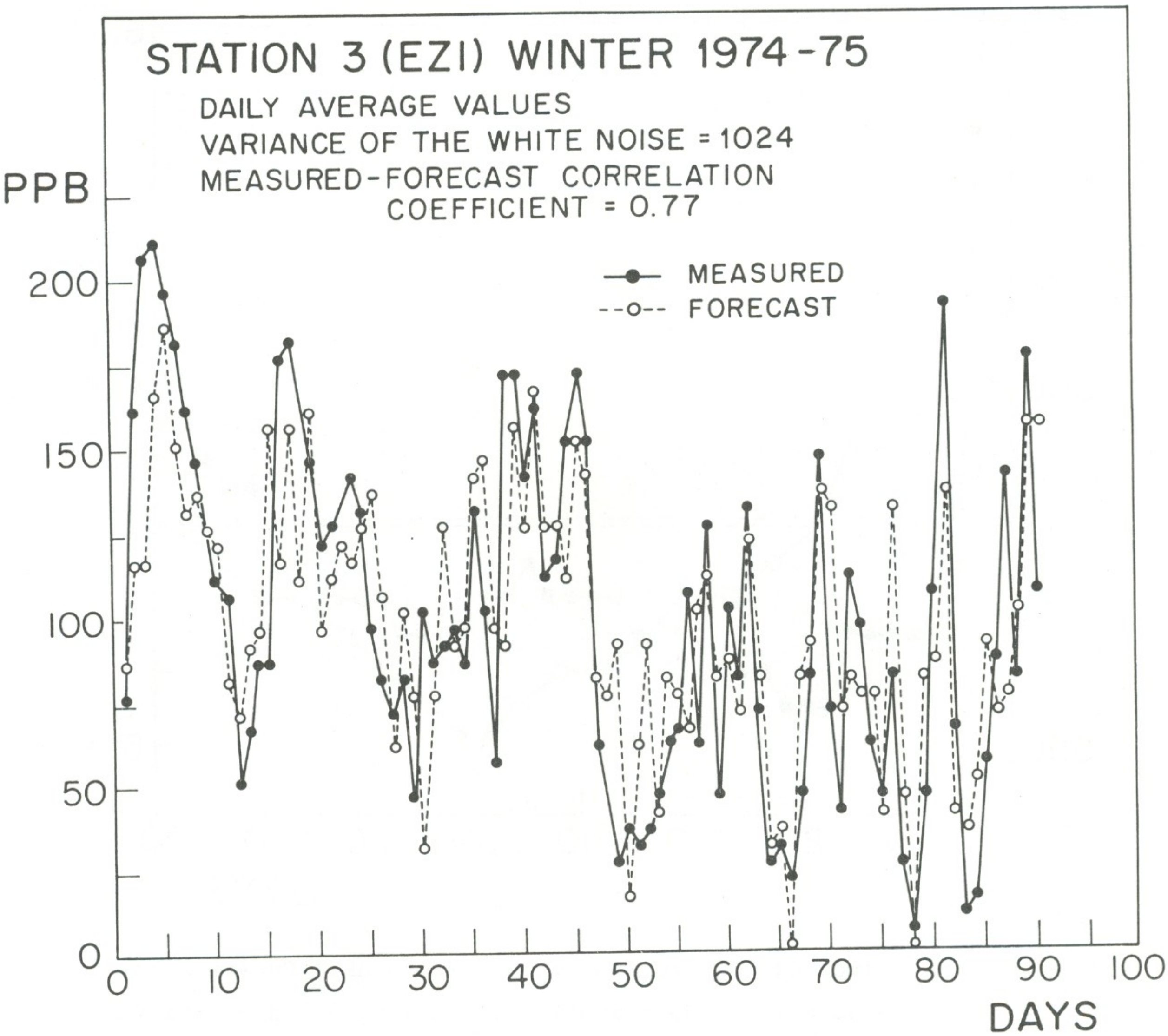



Figure 4. Measured and forecasted (model I+AR(1)) daily $SO_2$ average values during the winter 1974-75 (correlation coefficient of the persistence model = 0.60).

## 1977 PALO ALTO SCIENTIFIC CENTER OUTSIDE PUBLICATIONS

J. CANOSA & J. GAZDAG (320-3321), The Korteweg-de Vries-Burgers Equation, Journal of Computational Physics, Vol. 23, No. 4, April 1977, 393-403.

J. V. DAVE (320-3349), Validity of the Isotropic-Distribution Approximation in Solar Energy Estimations, Solar Energy, Vol. 19, 1977, 331-333.

P. M. HIRSCH, Interactive Graphics for Load Flow, 1977 Power Industry Computer Applications Conference, - PICA-77, Tenth PICA Conference, May 24-27, 1977, The Institute of Electrical and Electronics Engineers, Inc., 1977, 159-164.

J. A. JORDAN, JR. & F. M. SCHLAEPFER, An Interactive Computing Environment for Power System Planning, 1977 Power Industry Computer Applications Conference - PICA-77, Tenth PICA Conference, May 24-27, 1977, The Institute of Electrical and Electronics Engineers Inc., 1977, 166-174.

L. J. SHIEH, P. HALPERN, H. W. SHIMMIN, Diffusion Simulations of Process Stack Emissions Using Grid and Gaussian Models, Preprint Volume: Joint Conference on Applications on Air Pollution Meteorology, Salt Lake City, UT., November 29 - December 2, 1977. Published by American Meteorological Society, Boston, MA., 1977, 249-252.

W. G. TUEL, JR., The Role of Information Processing in Power System Engineering, In: Proceedings of the Lawrence Symposium on Systems and Decision Sciences, October 3-4, 1977 , Lawrence Hall of Science, Berkeley, CA., Western Periodicals Company, 1977, 24-28.

## 1978 PALO ALTO SCIENTIFIC CENTER OUTSIDE PUBLICATIONS

P. HALPERN, K. L. COULSON, Solar Radiative Heating in the Presence of Aerosols, IBM J. Res. Develop., Vol 22, No. 2, March 1978, 122-133.

IBM
Palo Alto Scientific Center, 1530 Page Mill Road, Palo Alto, California 94304