"Presented at the APCA Specialty Conference on "Quality Assurance in Air Pollution Measurement", New Orleans, Lousiana, March 1979.

IBM

IBM PALO ALTO SCIENTIFIC CENTER
G320-3381, April 1979

T-4 (2)

THE KALMAN FILTERING METHOD AND ITS APPLICATION TO AIR POLLUTION EPISODE FORECASTING

PAOLO ZANNETTI
PAUL SWITZER

IBM PALO ALTO SCIENTIFIC CENTER REPORT NO. G320- 3381

April 1979

THE KALMAN FILTERING METHOD AND ITS APPLICATION TO AIR POLLUTION EPISODE FORECASTING

Paolo Zannetti[+]

Paul Switzer[o]

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

[+]IBM Scientific Center, Venezia, Italy

[o]Stanford University, Stanford, California

Abstract

This paper presents an application of the Kalman filtering method to multi-station air pollution modeling in order to obtain a useful real-time predictor of concentration levels, especially during episode situations. Special attention has been paid to avoiding certain high dimensionality problems of the Kalman filter while still retaining some of the deterministic "physical" information of the transport and diffusion phenomena. Moreover, a method is proposed to forecast future state values using only a probabilistic knowledge of future state-transition matrices, which is the most common situation in air pollution real-time forecasting with probabilistic meteorological input. Specifically, the method is applied to SO_2 and meteorological data (Summer 1975) supplied by the RAMS network (Environmental Protection Agency's Regional Air Pollution Study) installed in the St. Louis Missouri area. The results of the proposed methodology are compared with those supplied by single-station predictors.

1. Introduction

Kalman filters are a class of linear minimum-error-variance sequential state estimation algorithms. They have been used in many applied fields and, in particular, in navigation space guidance and orbit determination[1] and in hydrology[2]. The linear discrete version of this methodology can be used for forecasting problems where the transition mechanism of a discrete system is described by the discrete "message model"

$$\underset{\sim}{x}(t+1) = \underset{\sim}{\Phi}(t+1,t)\underset{\sim}{x}(t) + \underset{\sim}{\Gamma}(t)\underset{\sim}{w}(t+1) \tag{1}$$

In this equation, $\underset{\sim}{\Phi}(t+1,t)$ is the state-transition matrix from t to t+1, $\underset{\sim}{x}(t)$ is the state vector at time t, $\underset{\sim}{w}(t+1)$ is a zero-mean white noise stochastic process with covariance matrix $\underset{\sim}{V}_{\underset{\sim}{w}}(t+1)$, and $\underset{\sim}{\Gamma}(t)$ is the noise transition matrix. The dimension of $\underset{\sim}{w}$ is not necessarily equal to that of $\underset{\sim}{x}$.

In the general theory, the state $\underset{\sim}{x}(t)$ is not observed directly. Instead, observations have the form of an "observation model"

$$\underset{\sim}{z}(t) = \underset{\sim}{H}(t)\underset{\sim}{x}(t) + \underset{\sim}{v}(t) \tag{2}$$

included in the system noise process $\underset{\sim}{w}(t)$.

A very important problem arises in the application of the Kalman filter to air pollution problems. In fact, it is necessary to avoid the high dimensionality of the resulting Kalman filter equations. For example, when $\underset{\sim}{\Phi}$ is the time-evolution transition matrix of the K-model, a simple spatial grid of 20×20×10 points produces Kalman filter matrices of dimension 4000×4000. Many proposals have been made for the simplification of this problem. In particular, either the Green function can be used[5] to reduce the equation of the K-model to a difference equation of relatively small dimension, or a discrete form of Chandrasekar-type equations can be applied[6] for the same goal. Alternatively, the region can be partitioned into subregions[3] and, if the subvectors of the subregions are not coupled (or weakly coupled), the filter algorithm can be applied separately to each of the subvectors, so reducing the size of the matrices which must be manipulated. Finally, a multiple linear regression model can be used[4] for $\underset{\sim}{\Phi}$, so reducing the dimension of the filter to the number of monitoring stations in the area, losing however the "physical" information of the diffusion phenomenon.

Our proposed method uses for the dimension of the filter the number of monitoring stations, but it incorpoithm (Kalman filter) for the estimation of the state of a linear time-varying dynamic system, driven by white noise of zero mean and known variance. Under the further assumptions that $\underset{\sim}{v}$, $\underset{\sim}{w}$ and $\underset{\sim}{x}$ are mutually uncorrelated, the relevant formulas are [$\underset{\sim}{x}(t_2|t_1)$ is the estimate at time t_1 of $\underset{\sim}{x}(t_2)$]:

predicted state $\underset{\sim}{x}(t+1|t) = \underset{\sim}{\Phi}(t+1,t)\underset{\sim}{x}(t|t);$ (3)

predicted error covariance matrix

$$\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t+1|t) = \underset{\sim}{\Phi}(t+1,t)\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t|t)\underset{\sim}{\Phi}^T(t+1,t) + \underset{\sim}{\Gamma}(t)\underset{\sim}{V}_{\underset{\sim}{w}}(t+1)\underset{\sim}{\Gamma}^T(t); \quad (4)$$

filter gain matrix

$$\underset{\sim}{K}(t+1) = \underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t+1|t)\underset{\sim}{H}^T(t+1)[\underset{\sim}{H}(t+1)\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t+1|t)\underset{\sim}{H}^T(t+1)+\underset{\sim}{V}_{\underset{\sim}{v}}(t+1)]^{-1}; \quad (5)$$

after processing the observation $\underset{\sim}{z}(t+1)$

$$\underset{\sim}{x}(t+1|t+1) = \underset{\sim}{x}(t+1|t) + \underset{\sim}{K}(t+1)[\underset{\sim}{z}(t+1)-\underset{\sim}{H}(t+1)\underset{\sim}{x}(t+1|t)]; \quad (6)$$

new error covariance matrix

$$\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t+1|t+1) = [\underset{\sim}{I}-\underset{\sim}{K}(t+1)\underset{\sim}{H}(t+1)]\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t+1|t); \quad (7)$$

where $\underset{\sim}{V}_{\underset{\sim}{\tilde{x}}}(t_2|t_1)$ is the covariance matrix of the error $\underset{\sim}{x}(t_2)-\underset{\sim}{x}(t_2|t_1)$.

In the Appendix a computer oriented scheme of equations (1-7) is developed. This method uses equation (3) recursively in order to obtain the forecast up to p time-steps ahead. This forecast requires, at each time t, the estimates $\underset{\sim}{\Phi}(t+k,t+k-1|t)$, k=1,2,...p of future state-transition matrices which may be highly time dependent. In air pollution, for example, the state-transition matrix

3. An application of the Kalman filter to SO_2 forecasting

The methodology of the previous section has been applied to hourly meteorological and SO_2 data. The period of analysis is Summer 1975 (2208 hourly time periods) and the data was supplied by three monitoring stations of the RAMS network (Environmental Protection Agency's Regional Air Pollution Study) installed in St. Louis, Missouri (Figure 1). The following time series have been used: three SO_2 time series, (Station 3, industrial area; Station 5, commercial area; Station 13, suburban area) wind speed (Station 3), wind direction (Station 3), temperature vertical gradient (Station 5), and hour of the day. All these, except SO_2, have been categorized as follows:

- wind speed, 3 classes (≤ 2m/s, >2m/s and ≤ 6m/s, >6m/s);
- wind direction, 8 classes

  (N-NE,NE-E,E-SE,SE-S,S-SW,SW-W,W-NW,NW-N);
- temperature vertical gradient, 3 classes based on the variable $s = \frac{\Delta T}{\Delta z} + \frac{1^{\circ}C}{100m}$ ($s<-0.005$ unstable, $s\ge -0.005$ and $s\le 0.005$ neutral, $s>0.005$ stable); and
- hour of the day, 5 classes (night, transition, low

$$q^{h+1}_{\alpha\alpha'} = \sum_{\alpha''=1}^{57} q^{h}_{\alpha\alpha''} q^{1}_{\alpha''\alpha'} \quad ,h=1,\ldots,k-1 \tag{9}$$

The transition matrix estimates, given the system state $\alpha(t)$ at time t, are then (p=8)

$$\underset{\sim}{\Phi}(t+k,t+k-1|t) = \sum_{\alpha'=1}^{57} \underset{\sim}{\Phi}_{\alpha'} q^{k}_{\alpha\alpha'} \quad ,k=1,\ldots,8 \tag{10}$$

The general program scheme, described in the Appendix, has been applied to our data in the following way. The state vector $\underset{\sim}{x}(t)$ has four components given by the three SO_2 hourly concentrations measured for the time t in ppm at the three selected stations, and a forth component which is identically 1 as required for the easier application of multiple regression methods. For each of the 57 meteorological-time-of-day categories α, we have in Table V a 4×4 state-transition matrix $\underset{\sim}{\Phi}_{\alpha}$ which is estimated by multiple regression methods. A simplified version of the general methodology (1-7) has been used in which, for computational purposes, the covariance $\hat{V}_{\underset{\sim}{\Gamma}\underset{\sim}{w}}$ of $\underset{\sim}{\Gamma}\underset{\sim}{w}$, expressed in ppm^2 and estimated from the data, has been completely ascribed to $\underset{\sim}{w}$ by setting

$$\underset{\sim}{V}_{\underset{\sim}{w}} = \underset{\sim}{\hat{V}}_{\underset{\sim}{\Gamma}\underset{\sim}{w}} = \begin{pmatrix} 2.436\ 10^{-5} & 6.495\ 10^{-6} & 2.656\ 10^{-6} \\ 6.495\ 10^{-6} & 5.160\ 10^{-5} & -2.626\ 10^{-6} \\ 2.656\ 10^{-6} & -2.626\ 10^{-6} & 2.561\ 10^{-4} \end{pmatrix}, \quad \underset{\sim}{\Gamma} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \tag{11}$$

This estimate, $\hat{V}_{\underset{\sim}{\Gamma}\underset{\sim}{w}}$, has been calculated using the error series $\underset{\sim}{x}(t+1)-\underset{\sim}{\Phi}_{\alpha(t+1)}\underset{\sim}{x}(t)$ during the analyzed period single-station fitting predictor defined in another paper[9].

This latter predictor has been defined in the following way. For any given combined class α (α=1,2,...,57) let $\underset{\sim}{T}_\alpha^0 \equiv \{t_1, t_2, \ldots\}$ be the collection of hourly periods during which that condition α obtained. Define μ_α^0 and σ_α^0 to be the mean and the standard deviation of the observed SO_2 hourly concentrations at time $\underset{\sim}{T}_\alpha^0$. Similarly define $\underset{\sim}{T}_\alpha^k \equiv \{t_1+k,\ t_2+k,\ \ldots\}$ and let μ_α^k, σ_α^k be the mean and standard deviation of the observed SO_2 hourly concentrations at times $\underset{\sim}{T}_\alpha^k$. Finally, define ρ_α^k to be the lag k autocorrelation between the SO_2 concentrations at times $\underset{\sim}{T}_\alpha^0$ and those at times $\underset{\sim}{T}_\alpha^k$. With these 5×n parameters (in our case 285) for each k, we apply the following k-hours-a-head predictor:

$$\frac{c(t+k|t) - \mu^k_{\alpha(t)}}{\sigma^k_{\alpha(t)}} = \rho^k_{\alpha(t)} \frac{c(t) - \mu^0_{\alpha(t)}}{\sigma^0_{\alpha(t)}} \tag{12}$$

that allows the concentration estimation $c(t+k|t)$ on the basis of the observed combined class $\alpha(t)$ and SO_2 concentration $c(t)$ at time t. In the case where $c(t)$ and $c(t+k)$ are modeled to have a joint normal distribution in each condition class, then this predictor is equivalent to the conditional mean of $c(t+k)$ given the data at time t. The predictor may also be regarded as an AR(1) model conditioned on the meteorological-time-of-day class.

improvement may be expected by better taking into account, in the definition of matrices $\underset{\sim}{\Phi}$, the physics of the diffusion phenomena.

Acknowledgements

We thank Dr. Piero Sguazzero and Dr. Danny Shieh of the IBM Scientific Centers of Venice, Italy and Palo Alto, California for useful discussions. This work has been developed in connection with 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 Stanford University.

5. M. Hino, "Prediction of atmospheric pollution by Kalman-filtering", Proc. Symp. on Modeling for Prediction and Control of Air Pollution (1974).

6. A. A. Desalu, L. A. Gould and F. C. Schweppe, "Dynamic estimation of air pollution", IEEE Trans. Automat. Contr., AC19(6): p 904 (1974).

7. A. P. Sage and J. L. Melsa, Estimation Theory with Applications to Communications and Control, McGraw-Hill, New York. 1971, p 529.

8. G. Finzi, G. Fronza, S. Rinaldi and A. Spirito, "Prediction and real-time control of SO_2 pollution from a power plant", Proceedings of the 71st Annual Meeting of the APCA, Houston, June 25-30, 1978.

9. P. Zannetti and P. Switzer, "Some problems on validation and testing of numerical air pollution models", to be presented at the 4th Symposium on Turbulence, Diffusion and Air Pollution, Reno, Nevada, January 15-18, 1979.

F. Saving

Forcing of the symmetry of VX for numerical stability, And saving of its main diagonal

G. Filter gain matrix

$$K = VX \cdot H_1^T \cdot [H_1 \cdot VX \cdot H_1^T + VV]^{-1}$$

H. Process the observation $Z = \underset{\sim}{z}(T+1)$

$$X = X_1 + K \cdot [Z - H_1 \cdot X_1]$$

I. A-posteriori error covariance matrix with a formula numerically more stable[1] than (7)

$$VX = [I - K \cdot H_1] \cdot VX \cdot [I - K \cdot H_1]^T + K \cdot VV \cdot K^T$$

J. Saving

Forcing of the symmetry of VX for numerical stability, and saving of its main diagonal

K. Loop

$T = T+1$, then end if $T > T_{MAX}$, otherwise go to step B.

For a more complete documentation on this subject, the APL version of the main program of the algorithm is included in this Appendix. This main program calls other APL functions whose role is easily understandable by their names.

		day-hour																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
month	june 75	1	1	1	1	1	2	2	3	4	5	5	5	5	5	5	4	3	3	2	2	2	1	1	1
	july 75	1	1	1	1	1	2	2	3	4	4	5	5	5	5	5	4	3	3	2	2	2	1	1	1
	august 75	1	1	1	1	1	2	2	3	4	4	5	5	5	5	4	4	3	3	2	2	1	1	1	1

Table I. Determination of the hour-of-day classes (insolation) based on the month and the hour of the day.

Comb. Class	Meteo Class	hour-type Class	Comb. Class	Meteo Class	hour-type Class	Comb. Class	Meteo Class	hour-type Class
1	1	All	20	7	5	39	13	4
2	2	1	21	8	1	40	13	5
3	2	2	22	8	2-3-4-5	41	14	1
4	2	3	23	9	1	42	14	2
5	2	4	24	9	2	43	14	3
6	2	5	25	9	3	44	14	4
7	3	All	26	9	4	45	14	5
8	4	All	27	9	5	46	15	1
9	5	1	28	10	All	47	15	2
10	5	2	29	11	1	48	15	3
11	5	3	30	11	2-3-4-5	49	15	4
12	5	4	31	12	1	50	15	5
13	5	5	32	12	2	51	16	All
14	6	1	33	12	3	52	17	1
15	6	2-3-4-5	34	12	4	53	17	2
16	7	1	35	12	5	54	17	3
17	7	2	36	13	1	55	17	4
18	7	3	37	13	2	56	17	5
19	7	4	38	13	3	57	18	All

Table III

Definition of the 57 combined classes on the basis of the 18 different meteorological classes and the 5 hour-of day classes.

Comb. Cl. α	$\underset{\sim}{\Phi}_{\alpha}$ Elements											
	(1,1)	(1,2)	(1,3)	(1,4)	(2,1)	(2,2)	(2,3)	(2,4)	(3,1)	(3,2)	(3,3)	(3,4)
1	.902	.018	-.005	.001	.650	.515	-.081	.008	.063	-.015	1.167	-.001
2	1.433	-.118	-.049	.003	.560	.713	-.075	.005	-.019	-.092	.762	.004
3	.795	.131	-.018	.001	1.272	.648	.068	-.002	.087	-.182	.677	.005
4	1.211	.301	-.040	-.003	.144	1.155	-.008	-.003	.835	-.314	.673	.025
5	.846	-.038	-.055	.004	-.401	1.037	.014	.004	.145	.136	.927	.011
6	.787	.007	.031	.002	.170	.807	-.072	.004	-.604	.293	.577	.006
7	.441	-.000	-.002	.001	-1.159	.946	-.054	.006	-.136	.142	.877	-.001
8	1.111	.027	.034	-.000	.830	.501	.605	-.001	-.349	.229	.584	.003
9	.601	.001	.001	.001	.111	.833	.015	.004	2.196	-.082	.733	-.002
10	1.169	-.009	-.014	-.000	-1.928	.978	.052	.011	2.175	-.013	.596	-.005
11	.878	-.039	-.032	.001	-.028	.511	-.022	.004	3.169	.216	.794	-.006
12	.657	-.010	.012	.001	.250	.612	.033	.005	1.341	-.113	.886	-.001
13	.761	-.056	.010	.002	.050	.291	.027	.015	.969	-.039	.910	-.006
14	.769	.001	.004	.001	.241	.603	-.033	.003	-.269	-.010	.798	.002
15	.594	.036	.006	.001	-.399	1.136	-.061	.001	-.111	-.089	.623	.006
16	.166	.000	.164	.001	-.170	.658	.106	.005	.195	.003	2.008	-.005
17	.361	-.006	.056	.001	.124	.804	-.562	.018	-1.043	.038	1.474	-.000
18	.285	.002	.090	.002	1.493	.714	-.047	-.002	-.369	.072	.931	.002
19	.896	-.042	-.045	.002	.015	.627	-.069	.004	.633	-.306	.683	.008
20	.879	.066	.070	-.002	.511	.748	-.013	.000	.547	.061	.774	-.002
21	.493	.052	-.002	.002	-.036	.316	-.002	.002	2.433	-.224	.793	-.003
22	.687	.083	.001	.001	.013	.278	-.009	.002	.987	-.029	.908	-.002
23	.339	.057	.019	.002	-.002	.382	.005	.001	-.139	.228	1.138	.002
24	1.187	-.191	.101	-.000	.416	.657	.008	-.001	-.298	-.520	1.078	.007
25	1.012	-.155	-.055	.004	-.009	.691	.013	.002	1.120	-.289	.510	.005
26	.873	.067	-.007	.001	-.025	.986	-.023	.001	-.146	-.019	.680	.013
27	.940	.002	-.059	.002	-.022	.749	-.070	.006	.046	.082	.838	.003
28	.283	.084	-.000	.001	-.057	.936	.044	-.001	.060	.021	.274	.004
29	.698	.106	.010	.002	.065	.682	.003	.001	.167	-.796	.831	.005
30	1.002	.260	-.010	-.001	.090	.640	-.004	.001	-.054	-.080	.466	.003
31	1.209	.242	.002	-.001	.019	.760	-.008	.001	-.773	.035	.669	.010
32	.828	-.018	-.006	.003	.161	.483	-.003	.002	.106	-.377	1.104	.001
33	1.322	-.499	.051	.002	.915	-.056	.042	-.001	.925	-.598	.842	.000
34	.949	-.070	.039	.002	.135	.603	-.008	.002	-.081	-.025	.757	.011
35	.701	-.049	-.042	.006	.061	.617	.015	.001	-.151	.382	.865	.004
36	.744	-.135	-.018	.003	-.007	.749	-.037	.002	-.817	-1.033	.364	.020
37	1.002	-.543	.065	.003	.005	.214	.027	.002	-.178	-.190	.274	.007
38	.585	.022	.142	.001	.158	.355	-.037	.002	.247	-.010	.923	-.001
39	.630	.011	.043	.001	.110	.487	.053	.001	-.655	-.109	.361	.009
40	.632	-.012	-.041	.003	-.242	1.024	-.062	.003	.024	-.094	.417	.004
41	.628	.261	.088	.000	-.043	1.114	.194	-.001	.023	.096	1.088	-.001
42	.617	.162	.060	.001	-.022	.478	.006	.002	-.139	.174	.366	.004
43	.446	.604	.329	-.002	.144	.232	.008	.001	-.017	.014	.889	.000
44	.307	.062	.252	.003	.036	1.009	.202	-.001	-.046	.148	.307	.006
45	.844	.203	-.151	.002	-.074	.792	-.088	.003	.039	.576	1.087	-.002
46	1.016	-.381	.133	.000	.039	.653	.063	.001	.027	.051	.366	.002
47	.336	-.165	.004	.005	-.002	.026	-.005	.003	-.029	-.034	.133	.003
48	.840	.657	.216	-.002	.001	.790	.567	-.000	-.042	-.008	.569	.002
49	1.945	.575	.019	-.005	.038	.643	.007	.000	.184	.403	.116	.000
50	.701	-.139	.039	.003	.011	.869	-.017	.000	.130	.028	.179	.002
51	.744	.198	-.012	-.001	-.251	.939	-.004	.002	-.013	.002	1.319	-.001
52	.402	-.002	.006	.002	-.715	1.343	-.008	.003	.093	-.040	.175	.003
53	.420	-.014	-.013	.003	-.405	.758	-.052	.006	-.079	.149	.387	.002
54	1.170	.572	-.143	-.003	.357	1.032	-.091	-.001	-.507	.393	.856	.003
55	.503	.180	-.037	.003	.156	.550	.090	.002	.056	.122	.899	.001
56	.772	.041	-.011	.001	-.111	.670	.122	.002	.167	.447	.861	-.002
57	.315	-.040	-.007	.003	-.002	.811	-.011	.001	.029	-.826	.264	.009

Table V. $\underset{\sim}{\Phi}_{\alpha}$ transition matrices for each combined class α. The fourth row of each matrix is identically 0 0 0 1.

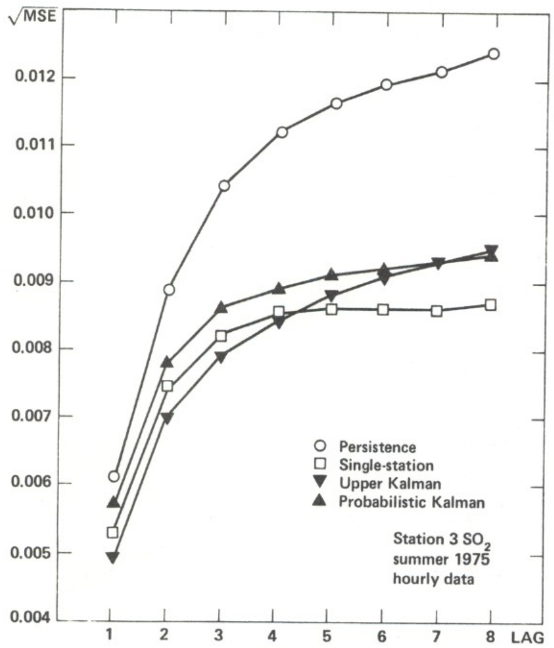

Fig. 2a

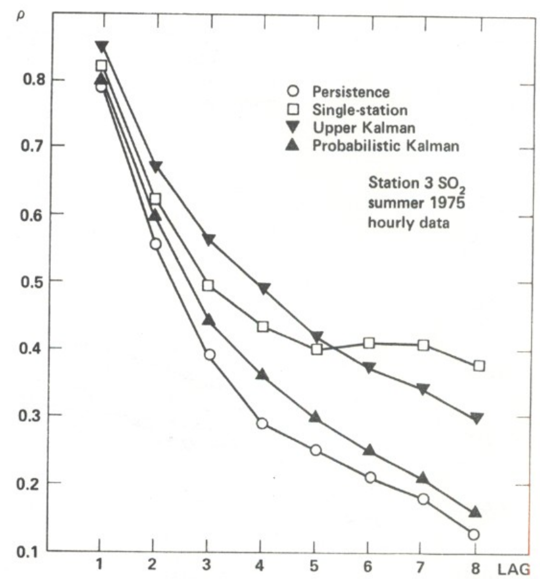

Fig. 2b

Figure 2 Root mean square error (a) and correlation coefficient (b) between measured and forecasted data, for different forecasting lags, of the following models: concentration persistence (O), single-station predictor (□), Kalman filter upper bound (▼) and probabilistic bound (▲). Data of Station 3.

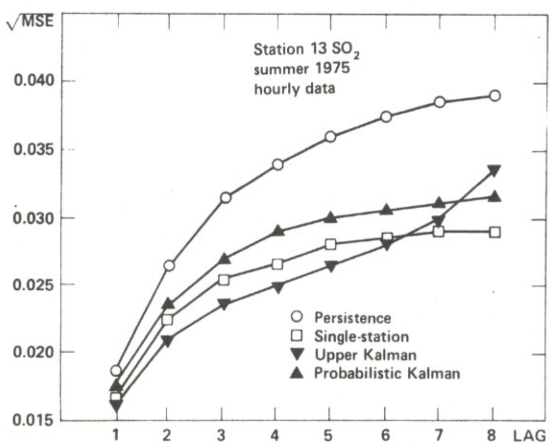

Fig. 4a

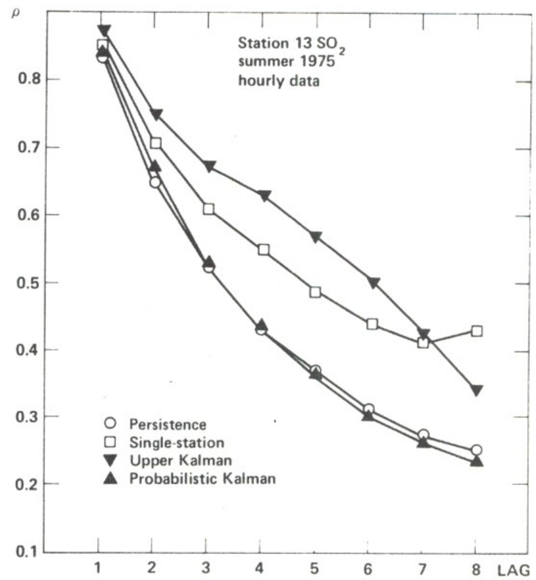

Fig. 4a

Figure 4 Same as Figure 2 for Station 13.

SCIENTIFIC CENTER REPORT INDEXING INFORMATION

1. AUTHOR(S): P. Zannetti and P. Switzer

2. TITLE: The Kalman Filtering Method and its Application to Air Pollution Episode Forecasting

3. ORIGINATING DEPARTMENT: Palo Alto Scientific Center

4. REPORT NUMBER: G320-3381

5a. NUMBER OF PAGES: 27

5b. NUMBER OF REFERENCES: 9

6a. DATE COMPLETED: January 1979

6b. DATE OF INITIAL PRINTING: April 1979

6c. DATE OF LAST PRINTING:

9. SUBJECT INDEX TERMS: 16 Mathematics

7. ABSTRACT:

This paper presents an application of the Kalman filtering method to multi-station air pollution modeling in order to obtain a useful real-time predictor of concentration levels, especially during episode situations. Special attention has been paid to avoiding certain high dimensionality problems of the Kalman filter while still retaining some of the deterministic "physical" information of the transport and diffusion phenomena. Moreover, a method is proposed to forecast future state values using only a probabilistic knowledge of future state-transition matrices, which is the most common situation in air pollution real-time forecasting with probabilistic meteorological input. Specifically, the method is applied to SO_2 and meteorological data (Summer 1975) supplied by the RAMS network (Environmental Protection Agency's Regional Air Pollution Study) installed in the St. Louis Missouri area. The results of the proposed methodology are compared with those supplied by single-station predictors.

8. REMARKS: This paper is a more extended version of the article (same title) accepted for presentation at the APCA Speciality Conference "Quality assurance in air pollution measurement", March 11-14, 1979, Grand Hotel, New Orleans, LA.

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.

W. G. TUEL, JR., Optimum Reorganization Points for Linearly Growing Files, ACM Transactions on Database Systems, Vol. 3, No. I, March, I978, 32-40.

E. SPEDICATO, J. GREENSTADT, On Some Classes of Variationally Derived Quasi-Newton Methods for Systems of Nonlinear Algebraic Equations, Numer. Math., Vol. 29, I978, 363-380.

A. K. HUI, B. H. ARMSTRONG, A. A. WRAY, (G320-3357), Rapid Computation of the Voigt and Complex Error Functions, J. Quant, Spectrosc. Radiat. Transfer Vol. 29, pp 509 - 516 Pergaman Press 1978.

W. G. TUEL, C. J. BERRY, Data Bases for Geographic Facility Design and Analysis Conference on Computing in Civil Engineering, pp 449 - 464, ASCE/Atlanta, GA/June 26 - 29, 1978.

J. GAZDAG, Extrapolation of Seismic Waveforms by Fourier Methods in IBM Journal of Research and Development, Vol. 22, No. 5, September 1978 (481 - 486)