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A predictive model for urban air pollution evaluation.

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Abstract ***- Several models which could be useful to estimate pollutant concentrations as a function of the emission distribution and the attendant meteorological conditions, have been investigated.***
Up to now a lot of them have been based upon physical principles.
In this work an alternative black box approach, in air pollution modelling, have been proposed. The main target of this approach is the prediction, on the basis of meteorological prevision, the air pollution concentration as a function of the expected number of vehicles.
The integration of this model in an emission control scheme, for the control of the motor vehicle flux, may represent a very useful approach to the urban air quality problem.

I. INTRODUCTION.

Air pollution in urban areas has become a very important phenomenon [1], [2]. Its characteristics have not changed significantly in the most recent decade, but the improvement in atmospheric process acknowledge, control technology, and legislative regulations for threshold emission have emphasised its effect on human life [1]. Many studies concerned with the relationship between observed concentrations of air pollutants and human receptors have been carried out. Substances, altering physical or chemical properties of the air, added in sufficient concentration to produce a measurable effect on man or vegetation are considered as pollutants [3].
Today, especially in urban areas, a large amount of pollutant compounds are released daily from human activities. In particular, the emission of carbon oxide compounds and many others compounds resulting from activities of currently dominant life forms, may be considered no less than a catastrophic form of localised and diffused atmospheric pollution.
Many studies, in fact, have emphasised that localised critical concentrations of pollutants can seriously affect air quality [1], [2]. Sometimes, dispersive processes, by reducing the concentrations of polluting substances to levels below the immediate biological response, may provide a more or less continuous low dosage to occupants of an extended area. This phenomenon can cause slow accumulation of polluting substances.
The effects of low dosage of pollutants and the possibilities of synergism among two or more substances simultaneously breathed at subacute concentrations for extended periods of time have been investigated.
The emissions of commerce, industry, and transportation are largely concentrated in urban areas and generate high local concentrations of fuel combustion products [3].
In particular Carbon Monoxide (CO) is considered a dangerous asphyxiant because it combines strongly with the hemoglobin of the blood and reduces the blood's ability to carry oxygen to cell tissues. It's, a colorless, odorless, and tasteless gas lighter than air [3], [4].
The automobile is by far the largest CO emission source.
Positive action, to control the pollution phenomenon, often occurs only after serious disaster and it is seldom anticipatory.
In order to develop alternate environmental strategies, simulation models are required. Moreover, they have to be validated with data collected by networks of stations including remote as well as impact locations [4], [5].
Up to now a many of the adopted models have been based upon physical principles [3], [6]. An important factor that has discouraged the application of these methods has been the poor knowledge about many of the basic meteorological processes involving pollutants in the lower layer of the troposphere.
In this work an alternative black box approach, in air pollution modelling, has been proposed. In fact black box identification methods appear more suitable for local model purposes because they can autotune parameters [7]. In particular the model for a strategic road in Catania, a medium sized town in southern Italy, has been identified.

II. THE INTEGRATION OF THE MODEL IN THE EMISSION CONTROL SCHEME.

The main target of this approach is the prediction, on the basis of meteorological prevision, the air pollution

concentration as a function of the expected number of vehicles.

The integration of this model in an emission control scheme, for the control of the motor vehicle flux, may represent a very useful approach to the urban air quality problem.

In Fig. 1 an example of the considered emission control scheme is reported.

The model *M* is by far the most significant element in the above presented control scheme [7], [8].

The number of motor vehicles have been considered as the system input variable while carbon monoxide concentration measured in a monitoring station, very close to the street, has been considered as the output variable.

A control unit *C* is present too. On the basis of the signal e value, generated by the comparison between the innocuous allowed CO level and the estimated level, the control unit *C* may act on the allowed number of vehicles.

III THE PROPOSED MODELS

In this section some models will be introduced. The proposed models will be different in stricture, input variables and parameters estimation techniques.

Hourly sampled data, collected from January '96 to October '96, have been used. Data have been recorded by one of the twenty stations performing the monitoring network of Catania. In particular the considered station is placed next to a highly trafficed road.

An important factor that has discouraged the authors in using a physical approach for model estimation has been the poor knowledge about many of the basic processes involving pollutants in the lower layer of the troposphere.

For example it is very hard to take into account the dependence of geostrophic wind, for which the pressure gradient force and Coriolis force balance each other, on the horizontal gradient temperature.

Moreover, the complex topography of cities, the roughness of urban surfaces and conductive flux of heat into and out of the denser surface materials of the city make a detailed description of the physical phenomenon involved in pollutant diffusion too difficult.

On the basis of these considerations a black box approach is proposed [7].

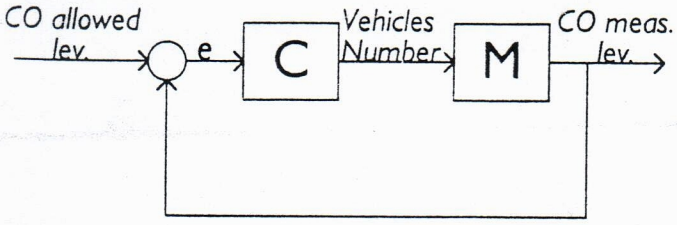

Fig. 1. The emission control scheme.

A. The linear model

The first model is based on the proportional scaling method. In this model the concentration of pollutant is assumed to be linearly related to the emission.

The analytical model structure is the following:

$$CO = f(N_a, N_m, N_l) \tag{1}$$

where :

the carbon monoxide concentration, *CO*, represents the model output,

N_a is the number of cars,

N_m is the number of motorcycles,

N_l is the number of lorries.

Since linear models are considered, the Mean Least Square (MLS) optimisation method has been used [7]. In section B. and C. the same identification technique will be used.

In Fig. 2 the comparison between the measured data and the estimated ones is reported.

A very poor estimation capability of the linear model has been achieved.

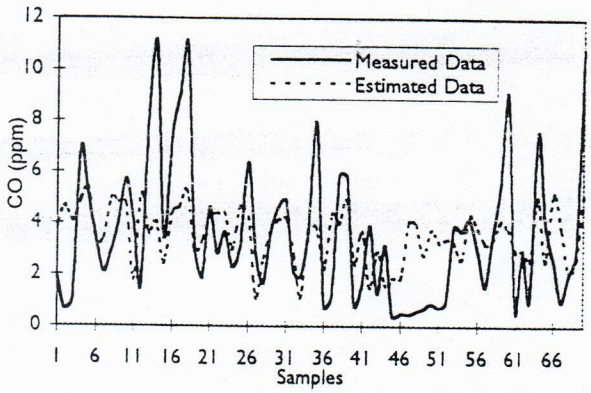

Fig. 2. The comparison between the measured data and the estimated ones with linear model.

B. The meteorological model

Better results have been obtained by using meteorological models, including wind direction, wind velocity and temperature as input.

It is well known that meteorological parameters such as wind speed, turbulence intensity, atmospheric pressure and temperature are governing factors [3], [6].

For example when pollution is released from a point source into a turbulent atmosphere, the pollution is carried forward by the wind and expands in all directions. The global spread of the pollutant depend on its atmospheric residence time [2].

The analytical model structure is the following:

$$CO(k) = f(N_a, N_m, N_l, T, \cos(\alpha / 2), V) \tag{2}$$

where :

T is the temperature value recorded next to the station,

V is the wind speed,
while the term $\cos(\alpha/2)$ can be justified by observing the position of the monitoring station in the considered road, reported in Fig. 3.

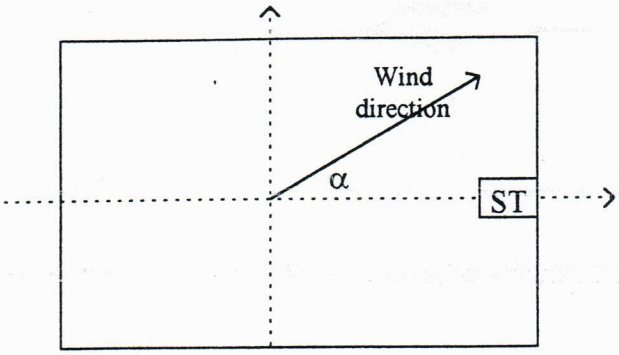

Fig. 3. The position of the monitoring station in the considered road

By using the above introduced term it is possible to quantify the fraction of the released pollutant recorded by the station *ST*.
In Fig. 4 the comparison between the measured data and the estimated data is shown.
By using this model an improvement in model estimation capability has been achieved.

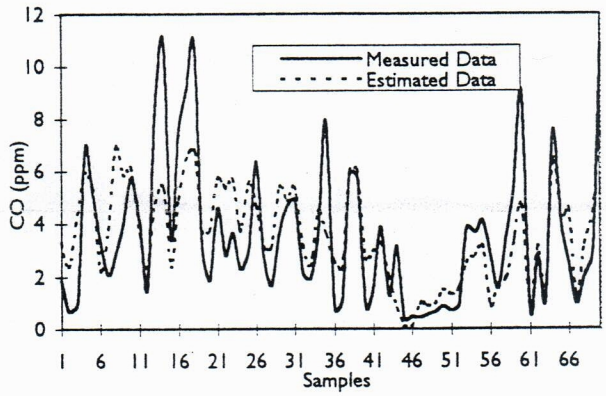

Fig. 4. The comparison between the measured data and the estimated data with meteorological model

C. The dynamic model

In this section non linear dynamic models have been investigated.
For evaluating the dynamic order to be introduced into the model the autocorrelation function has been used [9].
The results, obtained by using the above discussed data set, are reported in Fig. 5. A first order dynamic has been chosen.
The analytical model structure is the following:

$$CO(k) = f(N_a, N_m, N_l, T, DV, V, CO(k-1)) \qquad (3)$$

where $CO(K-1)$ represents the sample estimated at the previous step.
In Fig. 6 the comparison between the measured data and the estimated data is reported.
By using this model good results have been achieved.

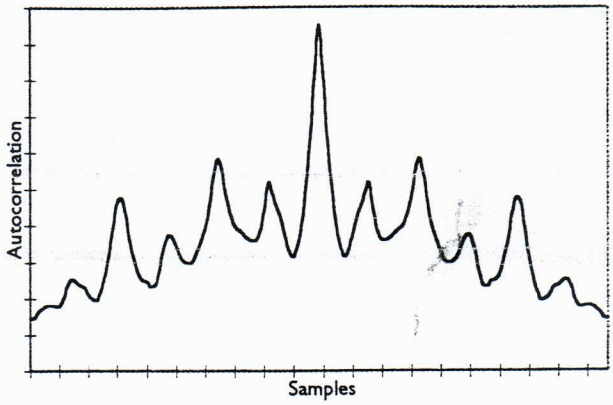

Fig. 5. The autocorrelation function.

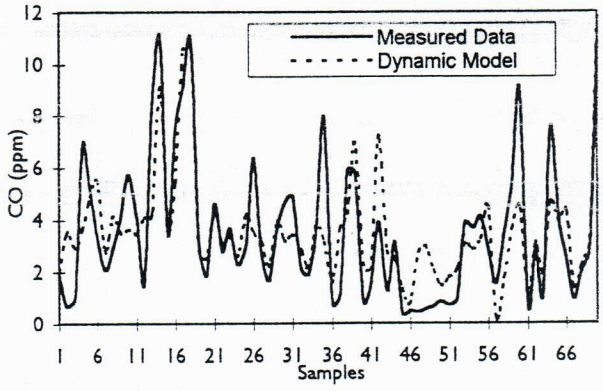

Fig. 6. The comparison between the measured data and the estimated data with dynamic model .

D. The neural model

Up to now LMS identification technique has been used.
Since neural model estimation seems a powerful modelling tool - if non linear relationships are sort after - this kind of approach will be proposed.

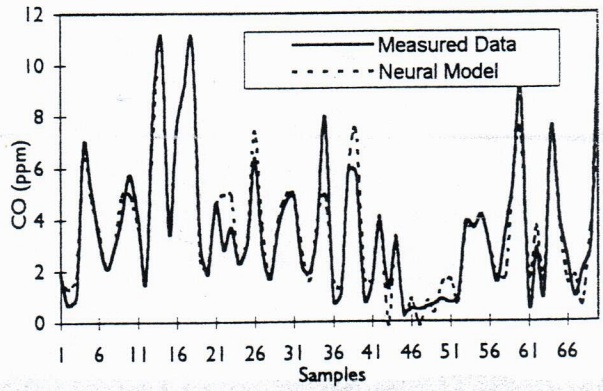

Fig. 7. The comparison between the measured data and the estimated data with neural model .

In particular Multi Layer Perceptrons (MLPs), programmed to use the classical back-propagation learning algorithm have been developed [10].
Also MLPs with *n* input neurons, corresponding to the input signals reported in Eqn. (3), and one output neuron, corresponding to the *CO* level reported in the same equation, have been considered.
MLPs with one hidden layer, and various numbers of hidden neurons, have been considered.
In Fig. 7. the comparison between the measured data and the estimates data is reported.
By using this model good results have been achieved.

IV. THE ADEQUACY OF THE PROPOSED MODELS

It is well known that one way to check the adequacy of a model is to check the properties of the residuals of the fitted model [8]. If they are random, it is persuasive evidence that the proposed model adequately fits the data and the residuals will be nothing more than the random measurement errors. The random errors typically are assumed to be normally distributed.
Under these considerations, let us suppose that the residuals appear normally distributed, the standard deviation σ will be used as the model error index [9]:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}\left[e_i - \bar{e}\right]^2}{N}} \qquad (4)$$

where:
$e_i = y_{is} - y_i$ are the residuals between the estimated trend, y_{is}, and the real one, y_i, respectively.
$\bar{e}$ is the mean value of the residuals.
The accuracy of the proposed models has been investigated by using the above mentioned index. The increment of σ with model complexity reduction has been observed.

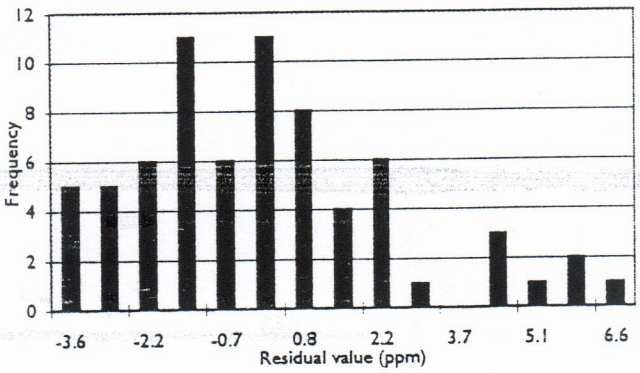

Fig. 8. the residuals density plot for the linear CO model

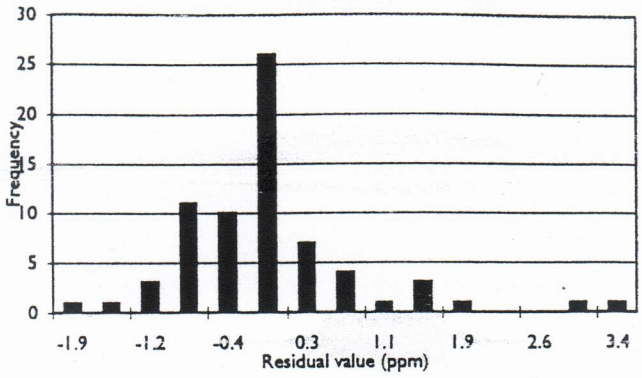

Fig. 9. The residuals density plot for the neural CO model

In Figs. 8 and 9, as an example, the residuals density plots for the linear and neural CO models are reported [8].

V. CONCLUSION

The possibility to model the dependence of CO level, recorded in urban areas, on traffic emission has been taken into account. Several linear and non linear models have been proposed. In particular by using meteorological input and Neural Networks identification methods good results have been achieved.
The estimated model allows for the urban traffic flux control.
The integration of the model in an emission control scheme has been taken into account too.

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