NEURAL NETWORKS TO PREDICT OZONE POLLUTION IN INDUSTRIAL AREAS

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ABSTRACT

In this paper a novel approach, based on a neural network structure, is introduced in order to face with the problem of pollutant estimation in an industrial area. In particular a short-term prediction (six hours ahead) of the O_3 pollutant mean value has been performed. The results obtained show the capability of such structures to model complex chemical reactions heavily dependent on the meteorological conditions and on the typical geographical characteristics.

1 MODELS OF AIR POLLUTION

The complexity of atmospheric phenomena implied serious difficulties in defining "air quality" in its various and real aspects: on the contrary, a low on this subject has to provide simple criteria which could be directly adopted. Under such point of view and after the acquisition of criteria from the World Health Organization and from the European Community, Italy has promulgated a series of lows in 1983 which fix maximum values for the pollutant mean value concentrations and also state the standards for air quality. In particular for the O_3 pollutant, the maximum mean value allowed for a hour that has not to be reached more than one time in a month has been fixed to $200\mu g/m^3$.

The mechanism of formation-recombination of the O_3 pollutant is governed by complex chemical reactions which take place in the atmosphere, in presence of solar radiation. In geographical places characterized by the presence of industrial plants, other pollutants, such as hydrocarbons and azote-oxides, alter the classical ozone-cycle, giving often rise to high concentrations of O_3, which contribute to the formation of the so-called "photochemical smog"[1]. Of course such complex phenomenon is furtherly complicated by factors heavily dependent on the particular geographical place, such as all the meteo quantities.

Recently the possibility of creating monitoring networks for recording pollutant concentrations in the atmosphere has revealed a powerful strategy in order to acquire a considerable knowledge about the dynamics of such phenomena as regards their diffusion and their consequences on human health. Moreover the possibility derived to think about predictive models to control air quality, but such a task, for the drawbacks previously outlined, represents a very hard problem, if faced with the classical modelling of dynamical chemical reactions. Therefore a black-box identification strategy has appeared suitable. In literature several models have been introduced in order to perform black-box estimate of other pollutant levels, such as SO_2 , in industrial areas [2]. In particular hour concentration predictions have been performed. The model employed belong to the class of ARIMA models (Auto Regressive Integrated Moving Average), [3], whose parameters are derived considering, besides the pollutant concentration, meteorological data of the place taken into consideration. Moreover a second order stochastic structure has been employed [2]. The results obtained were with no doubt encouraging, but the high non linearities which characterize such phenomena suggest the use of neural networks as modelling architectures.

2 AIR POLLUTION MODELLING VIA NEURAL NETWORKS

In this paper Multi Layer Perceptrons (MLPs) are taken into consideration in order to build predictive models for O_3 air pollution in an industrial

petrochemical area at the aim to control air quality. It has to be remarked that till nowadays data drawn from measures are used to monitorize air quality. Therefore procedures to avoid high pollution situations start only when such situations have already taken place. From such considerations it derives that using available data to build predictive models could avoid many dangerous situations to happen. In order to build such predictive models the use of neural networks is fully justified since such architectures have been established to be universal interpolators, both from the theoretical point of view of continuous functions approximation [4] and for their application to non linear system identification [5]. The industrial area taken into consideration is placed in Sicily (Italy), near the city of Siracusa, in the triangle "Priolo-Melilli-Augusta". This area has twelve centers of data recording, placed in key positions, in order to suitably monitorize the dynamics of pollutants. It has therefore been adopted the strategy of building a neural network able to estimate the pollutant concentration next to each center. Following such a way a network can be built for pollutant estimation over the whole area.

2.1 Results for the O_3 estimation

The authors have already been involved in the estimation of SO_2 pollutant; they implemented a neural structure obtaining good results [6]. Though the physical phenomena that involve the dynamics of Ozone are quite different from those ones relatives to the other pollutants, the experience acquired has guided towards the use of a neural MLP based structure for the Ozone estimation.

As regards the data taken into consideration, since the O_3 dynamics is strictly related to the dynamics of the meteo quantities as well as to the dynamics of other pollutants with which O_3 is likely to combine and recombine, among all the recording stations existing in the industrial area, the station has been considered which could offer the richest number of meteo and pollutant information, together with, of course, the measures of O_3.

Therefore the following quantities have been taken into account for the pollutant prediction:

temperature (T), relative humidity (RH), wind speed (WS), wind direction (WD), solar radiation (RAD), NOx (Nitrogen oxides), NMHC (Not Methanic HydroCarbons).

The hypothesis is of course that the meteo predictions are available, in such a way as to make simpler the network learning. Moreover the model has been learned to estimate the mean values of pollutant concentration. Such values are in fact considered by low to define air quality.

The aim is to perform the pollutant prediction, and therefore to build-up a model of the phenomenon starting directly from data: the situation at hand obliges to perform a "black-box identification strategy" [2], i.e. a methodology in which nothing is a-priori known about the model order, the number of parameter required for the modelling task, and so on.

In order to draw some information about the model structure, the auto-correlation function for the O_3 pollutant time series has been considered. The delayed samples mostly correlated with the current one should be considered to draw some information about the model order.

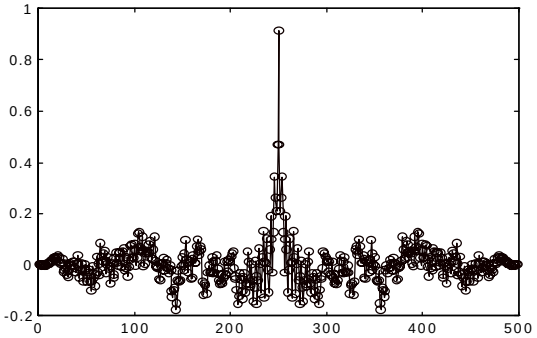

Fig.1: Typical Autocorr. Function for O_3

From the analysis of the auto-correlation function and after a few trials the model order has been fixed to 3.

The input pattern structure has therefore been fixed to:

[T(k-3)··T(k), RH(k-3)··RH(k), WS(k-3)··WS(k), WD(k-3)··WD(k), RAD(K-3)··RAD(k), NMHC(k-3) ··NMHC(k-1), NOx(k-3)··NOx(k-1), O_3(k-3)··O_3(k-1)]

The target is represented by: [O_3(k)].

The structure of the neural network has therefore been found to be:

29 input units; 10 hidden units; 1 output one.

The quantities present in the pattern refer, as previously mentioned, to the mean values of the measures taken in a 6-hours time interval, referring to data recorded at 30 minute time steps.

The data used to perform the whole work were drawn from the summer period of one year data provided by the C.I.P.A. (Industrial Consortium for Environmental Protection): the choice of the summer period derived from the fact that in this period the major pollution problems take place.
During the processing of such data several problems have been encountered, mainly due to the lack of lots of measures. Some measures were absent at regular time periods, for the auto-calibration of the stations, but lots of other "practical" problems led to the lack of a considerable quantity of data. Since the mean O_3 concentration was to be predicted, it was decided to perform 6-hours mean value prediction: due to the lack of data, the information was assumed to be valid only if the 6-hours window would contain at least 4 valid data. Otherwise the whole pattern was discarded. Such a "data filtering" heavily reduced the number of patterns available for the network learning and testing phase. In particular a set of 250 patterns has been considered to perform the learning phase, while 94 patterns belonging to the following time window have been used to test the performance of the trained neural network.
The results which refer to the 6-hours mean values of O_3 are reported in the following figures.
In particular, Fig.2 reports a comparison between the measured and the estimated O_3 mean value concentration at the end of the learning phase.

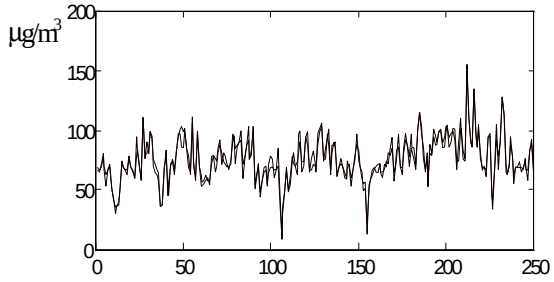

Fig.2: Estimated and measured samples of O_3 at the end of the learning phase

The error distribution, depicted in Fig.3 clearly shows that the largest majority of the error is placed between $\pm 5 \mu g / m^3$.

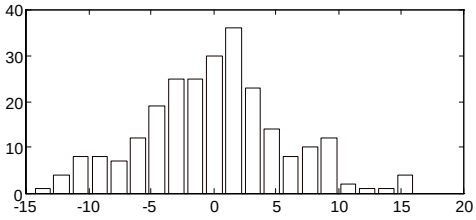

Fig.3: Error ditribution for the learning patterns

At he end of the learning phase the following 94 samples have been presented to the neural network input for the testing phase. The results are reported in the Fig.4.

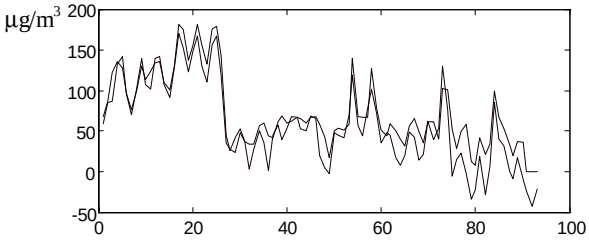

Fig.4: Estimated and measured normalised samples of O_3 during the testing phase

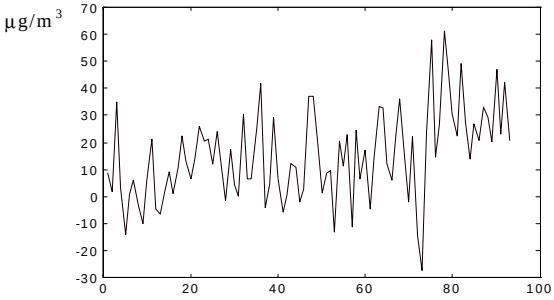

Fig.5: Error trend for the whole testing phase

From the analysis of Figs.4 and 5 it derives that the prediction error degrades as the number of prediction steps increases. The fact may depend of the time varying nature of the system under consideration. Therefore it has been thought to build a predictive model which could be able to adapt itself to the time-varying conditions of the system. Such a fact it likely to be solved with the adopted neural structure, because neural networks can be designed to learn on line, i.e. to adapt their weights once received the new I/O data from the system. Following such consideration, from the analysis of Fig.5, it has been decided to consider as acceptable the predicted samples up to the 40th (see Fig.5), and to re-train the neural network considering as learning patterns the set obtained by

discanding the first 40 learning patterns and including the most recent ones (those ones correctly predicted). The risults of the new testing phase are reported in Fig.6 and Fig.7.

It has to be outlined that, while the first learning phase can be time consuming, owing to the fact that the model has to be "learned" starting from weights randomly selected, the successive phases are quite fast, because only a light tuning in the parameters is required. In the example under consideration the former learning phase needed about 10000 iterations in order to obtain the reported results, while the latter one only about 200. Such a strategy is suitable to be adopted for an on-line prediction. Moreover one model lead to a suitable prediction rate for 40 samples of 6-hours mean value concentration, i.e. for about 10 days.

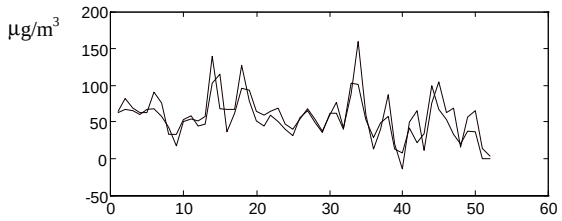

Fig.6: Estimated and measured samples of O_3 during the testing phase

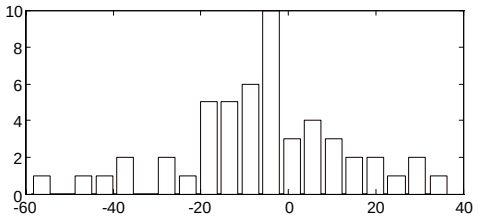

Fig.7: Error distribution during the learning phase

As it can be derived from the analysis of the figures, the estimation of the O_3 mean value concentration can be considered suitable, especially of one considers the lack of a considerable quantity of measures. Currently a considerable afford is being performed to improve the neural network performance and therefore to provide better performance.

3 CONCLUSIONS

In the paper a neural network approach has been employed in order to predict the O_3 pollutant mean value concentration in an industrial petrochemical area. The model obtained performs the estimation of the pollutant concentration starting from the measure of some meteorological quantities as well as of some past samples of the O_3 concentration. The results obtained show the suitability of the proposed approach. In particular the model built refers to the estimation of O_3 next to a particular station of data recording. Taking into consideration that the area possesses a network of data collecting, it will be possible to build a network of devices devoted to the estimate of the pollutant concentration in key points positioned into the whole area. Moreover the paradigms of neural processing allow that the model is built-up drawing all the necessary information directly from measures, and therefore is able to represent the dynamics of complex chemical reactions together with all the peculiarities of the geographical place the measure refer to, which heavily influences the reaction dynamics. It has also to be outlined that the model has been drawn notwithstanding a great lack of measures, due to several causes, such as instrument auto-calibration, problems in data recording, and so on. Taking into account considerations, the model obtained acquires more relevance.

Acknowledgments

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