

A simple feed forward neural network for the PM10 forecasting: comparison with a radial basis function network

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Abstract: The problem of air pollution is a frequently recurring situation and its management has social and economic considerable effects.

Given the interaction of the numerous factors involved in the raising of the atmospheric pollution rates, it should be considered that the relation between the intensity of emission produced by the polluting source and the resulting pollution isn't immediate.

The aim of this study is to realize and to compare two support decision system (neural networks and multivariate regression model), that, correlating the air quality data with the meteorological information, are able to predict the critical pollution events.

The development of a back propagation neural network is presented to predict the daily PM10 concentration one, two and three days before.

Keywords: PM10, forecast, neural network, multivariate regression model.

1. Introduction

The air we breathe every day can be contaminated by polluting substances emitted by industries, vehicles or other sources. These polluting substances can have bad effects both on human health and on the environment.

One of the most dangerous pollutant is PM10, that is particulate matter having an average aerodynamic diameter smaller than 10 micron.

Health effects range from minor effects, such as nose and throat irritation, to more serious effects such as aggravation of existing respiratory and cardiovascular disease, increased hospital admissions and premature death. (Dockery 1989; Dockery 1993; Gamble 1998; IARC 1987; Oberdorster 2001; Slaughter 2005)

Air pollution control is necessary to prevent the situation from its worsening in the long run. On the other hand, short-term forecasting of air quality is needed in order to take preventive and evasive action during episodes of airborne pollution.

A classical forecasting method is based on multivariate statistical analysis, but now the Artificial Neural Network (ANN) is becoming an effective and popular mean alternatively to conventional methods.

2. Application of feed forward neural networks on automatic PM10 data

The network type used in this paper is the feed forward back propagation. In this case the connections belonging to the first hidden layer are oriented from the input neurons towards the intermediate ones from which the connections towards the output neurons originate.

The measurements got by San Nicola monitoring station of the Municipality of Bari constitute the primary data source of PM10 input data; they have been obtained by OPSIS sampler model SM 200-series. The forecasting of the major weather parameters (temperature, wind speed, pressure, relative humidity, rain) available from the website www.wunderground.com and the forecasting of the Saharan dust, obtained by the “Centro Nacional de Supercomputaci3n” web site, satellite images and back trajectories analysis are used for the weather input data.

2.1 Training and optimization of the network

The network was trained with validated data of PM10 coming from San Nicola monitoring station from January 2005 to March 2006 and with meteorological data.

Before being processed, all the data were scaled from 0 to 1.

The software Matlab, in particular the tool box Neural Networks, developed by the Mathwork was used to constitute the network.

The training data were divided in:

- Training set, used to optimize the parameters of the network
- Validation set, whose data aren't included in the training phase directly, but only indirectly to control constantly the forecasting ability of the network during this phase
- Test set, used only to control the forecasting ability of the model when the training phase finishes.

The optimization was performed by means of a Simplex method (Nelder 1965) using the learning rate, the maximum weight increasing, the number of neurons and epochs as parameters, leaving unchanged the learning and the training functions, because they showed a much smaller influence on the Relative Root Mean Square Error (RRMSE) compared with the other parameters.

$$RRMSE = \sqrt{\frac{1}{n} \left(\sum \left(\frac{Y_{calc} - Y_{meas}}{Y_{meas}} \right)^2 \right)}$$

where Ycalc is the PM10 forecasted concentration, Ymeas is the PM10 measured, n is the number of samples considered.

3. Results and discussion

After the training, the network was ready to predict the PM10 concentrations in the considered area.

In Figures 1.a and 1.b the results obtained on a test set in the period from March 2006 to January 2007 are shown. The output is the daily mean PM10 concentration for S. Nicola monitoring station. The PM10 data of the 2 days before the forecasting on a time period beginning from 12 a.m up to 12 a.m were used as input together with the above-mentioned atmospheric parameters.

In Figure 1c the foreseen values obtained, using as input only the forecasting meteorological without any information about the previous day PM10 concentrations are shown.

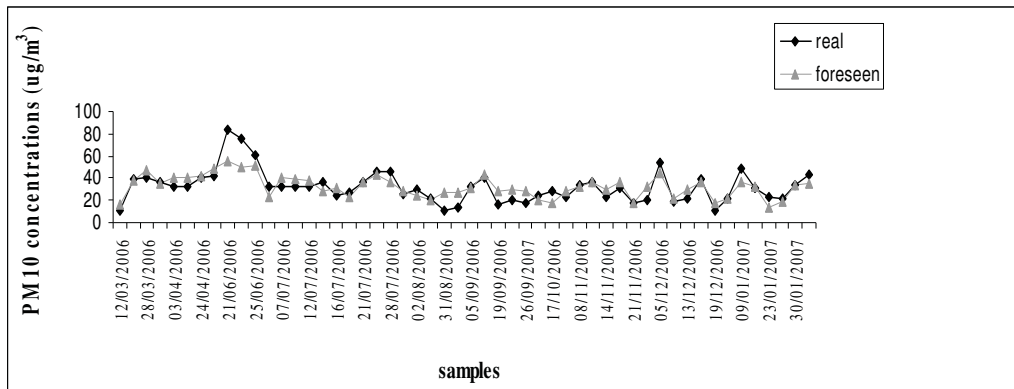


Figure 1.a: 1-day forecasting using as input the PM10 data, the atmospheric pressure, the temperature and the wind speed.

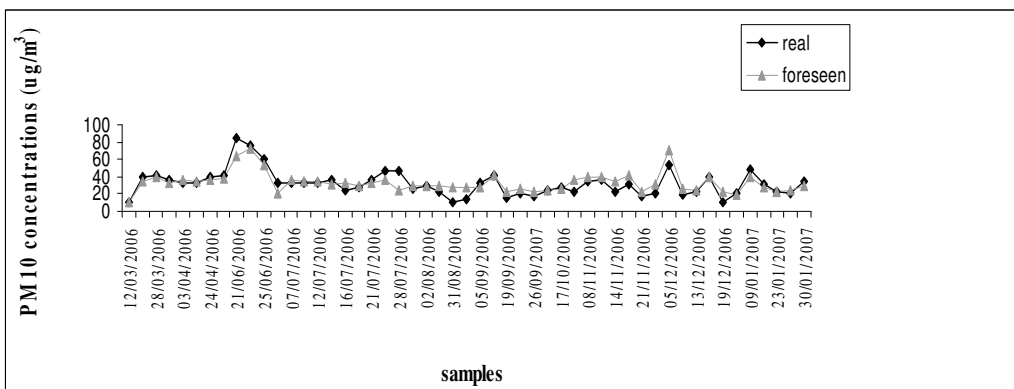


Figure 1.b: 1-day forecasting using as input the PM10 data, the atmospheric pressure, the temperature and the wind speed, the Saharan dust and the rain data.

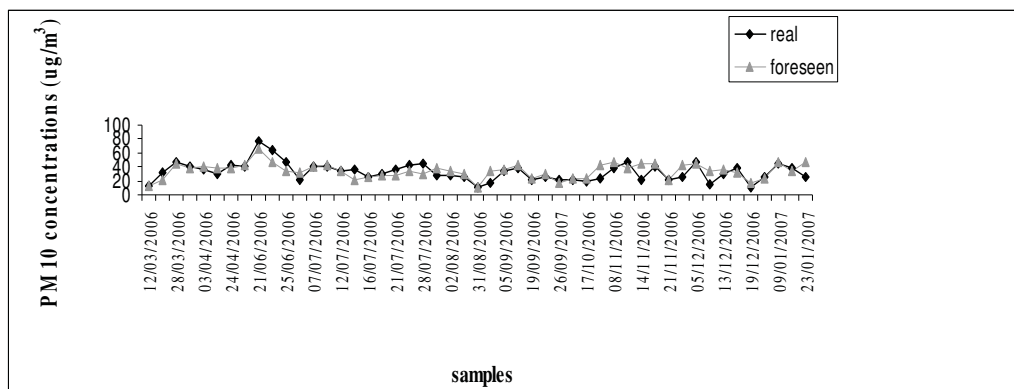


Figure 1.c: 1-day forecasting using as input the atmospheric pressure, the temperature and the wind speed, the Saharan dust and the rain data.

In a second phase, the neural network was used in order to forecast the PM10 concentrations two and three days before. In this case the network was used in iterative mode using as input parameters the meteorological forecasting of the considered day and the PM 10 data of the two previous iteration, starting with the real daily concentrations of the two previous days.

3.1 Comparison between the ANN and a radial basis function network for 1-day forecasting

The Radial Basis Function (RBF) (Broomhead 1988, Rumelhart 1986) was developed from an exact multivariate function interpolation (Powell 1987) and has attracted a lot of interest since its conception.

The orthogonal least squares learning algorithm (Chen et al., 1989) was used to choose Gaussian kernel function centres and the weights of the network.

The input processed data were the same used for the MLP network development.

In Figure 2 the results showing the comparison between the MLP and the RBF models are shown for 1-day forecasting on a test set in the period of time from July 2006 to February 2007.

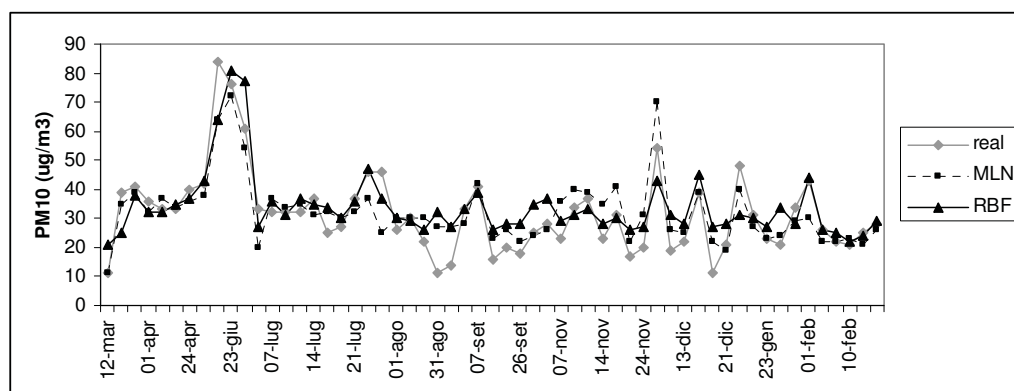


Figure 2: Comparison between the PM10 real values, the MLP and the RBF values

4. Conclusions

The results showed that the neural network constitute a good alternative in comparison with the traditional methods generally used, as the linear multivariate regression methods.

The feed forward neural networks give more accurate results compared to the radial basis function networks, even though the RRMSE difference is lower than 10 % both in the 1-day and 2 – days forecasting.

ANN can accurately model the relationships between PM10 concentrations and meteorological parameters and, increasing the number of input variables, improves the prediction performance of the model in terms of RRMSE.

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