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A NEURAL NETWORK MODEL FOR FORECASTING HOURLY PM_{10} LEVELS IN URBAN AREA

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The study of atmospheric pollution at local scale is one of the most important topics in environmental sciences. Nowadays air quality monitoring networks in urban, sub-urban and rural areas are very diffuse and a large amount of data is available. The quality and the quantity of the data are significantly increased, and, contemporaneously, innovative data analysis methodologies have been developed. Multivariate analysis, fuzzy logic, neural network have been introduced in modelling and forecasting procedures in order to elaborate operational techniques for level characterization of atmospheric pollutants at different spatial and temporal scales [1-4]. Particularly procedures based on artificial neural network (ANN) have been applied with success to forecast levels of PM, CO and O_3 [5-8]. These techniques show a capability to make regressive approximation of non-linear functions in high-dimensional space and they are more flexible in comparison to traditional statistical techniques. In this study we present an application of ANN to forecast hourly levels of PM_{10} in urban area starting from data measured in N-previous days. We would underline that the final goal is not the identification of the optimal simulative model for reproducing the atmospheric pollutant patterns but the development of an operational procedure able to give a simple characterization of the investigated phenomena in order to make easier and effective the data diffusion by local authorities. The database includes PM_{10} hourly concentrations measured from March 2001 to February 2002 in three stations of the air quality monitoring network of Potenza town (southern Italy). In these series the percentage of data missing is lower than 1%. Moreover data on atmospheric pressure, relative

humidity and wind velocity are available. The ANN model is a feed-forward multi-layer perceptron (MLP) with an only hidden layer. The conjugate gradient learning algorithm is used. The learning capability of the model and the average goodness of the prediction are evaluated by Mean Absolute Percentage Error (MAPE) and by the number of concentration values that the model is not able to predict. In a preliminary phase (N=1), we test the model performances changing both some model parameters (training set dimension, number of epochs, number of hidden neurons) and data input structure (data coming from a single station, mix of data coming from different stations). In a successive phase, we analyze the results obtained introducing meteorological parameters in data input. At the end we discuss the model performance for forecasting PM_{10} hourly data with N=2 and N=3 (48 and 72 hourly data measured in the previous days). The results indicate that, in the study area, a simple model of ANN is able to forecast PM_{10} hourly levels with a good approximation (error on the validation set is about 22%). The quality of data, in terms of data missing, plays a significant role and represents the main limit of these forecasting techniques at local scale. In order to improve the model performance increasing the number of input variables, the results suggest not only to take into account meteorological parameters but also to better characterize the dynamic features of emission source pattern.

1 References

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