4th Imeko TC19 Symposium on Environmental Instrumentation and Measurements
Protecting Environment, Climate Changes and Pollution Control
June 3-4, 2013, Lecce, Italy

ASPECTS ABOUT AIR POLLUTION PREDICTION ON URBAN ENVIRONMENT

M. Cacciola[1], D. Pellicanò[1], G. Megali[1], A. Lay-Ekuakille[2], M. Versaci[1], F.C. Morabito[1]

[1] UniversityMediterranea of Reggio Calabria, DICEAM
Via Graziella Feo di Vito, I-89100 Reggio Calabria, Italy, email matteo.cacciola@unirc.it

[2] University of Salento, DII
Via per Monteroni, I-73100 Lecce, Italy, email aime.lay.ekuakille@unisalento.it

Abstract: This paper focuses on the processing of experimentally measured pollution data. Since estimating air pollutant can have significant economic impact already on a short term basis as well as relevant consequences on public health on a medium-long term scale, various interdisciplinary researches are under way on this subject.

In this work, we pursue two goals: the former is to derive a representative model of the multivariate relationships that should be able to reproduce local interactions; the latter is to predict, when possible, the short term evolution of pollutants in order to prevent the onset of above threshold levels of pollutants that can be dangerous to humans.

As a by-product of the research, we could derive some directives to be supplied to local authorities, in order to properly organize car traffic in advance starting from the estimated parameters.

Keywords: Air pollution, Forecasting, Neural Networks, Neuro-Fuzzy Systems, Fuzzy Ellipsoidal Systems.

1. INTRODUCTION

Environmental data are very complex to model due to the correlation among several variables of different type which yield an intricate mesh of relationships. It normally happens to have multivariate dependency with non-linear behaviour. In addition, these variables do not meet the very common Gaussianity assumption.

Due to some reasons, it is quite impossible to take decisions based on black box models, particularly as for unpopular actions, like stopping vehicular traffic in a town. It is thus essential to derive a set of rules which can support the decisions. In other words, the prediction of an episode of pollution may benefit of the knowledge on the typical meteorological by means of specific stations [1], seasonal and traffic conditions of a particular area. The prediction of an episode of pollution is therefore of fundamental importance to safe the health of citizens. The soft computing methodologies are naturally suitable to help in forecasting the local behaviour of complex systems starting from the available measurements. We focused our attention on the prediction of hydrocarbons in the air because they are very dangerous for the public health as well as other particular pollutants [2].

We refer to surveys on Villa San Giovanni area. The structure of the available environmental data shows that both spatial and time dependence are of interest; in addition, the data are very complex because of non-linearity, non-stationarity, measurement noise, missing data and the need of periodically test the instrumentation of the monitoring station. There is, thus, a need to use smart signal processing of the observed data, possibly incorporating a priori knowledge on the model [3]. The present paper reports a study of estimation and short time prediction of atmospheric pollutants carried out by Fuzzy Inference Systems (FISs) and Neural Networks (NNs) approaches, exploited in the past for prediction of problems about environmental domains [4-6].

2. THEORETICAL OVERVIEWS ABOUT POLLUTION FORECASTING

2.1 Neural approach with Fuzzy knowledge

The problem of estimating the polluting level can be formulated as the search of a suitable mapping between the set of available measurements and the selected set of pollutant parameters. Typically, we know the present level of each pollutant variable and we have access to the previous hourly measurements of the variable. We should thus forecast the temporal evolution of the pollutant concentration by means of a time scheme of NNs. For our Hydrocarbons' Concentration (HC) prediction problem, the atmospheric parameters, the traffic data and the CO concentration can conveniently be used. This can be done in principle by designing a hybrid network scheme in which the available a priori knowledge could be included in the form of syntactic rules.

Currently, the available knowledge cannot be implemented in terms of crisp rules because of the uncertainty underlying the complex model (for example, the different dependency between pollutant variables in various wind direction conditions). The most suitable approach seems adaptive network schemes based on fuzzy inference, which allows us to incorporate knowledge in terms of fuzzy rules [7]. FISs appear to be very good tools as they hold the nonlinear universal approximation property, and they are able to handle experimental data as well as a priori knowledge on the unknown solution, which is expressed by inferential linguistic rules in the form IF-THEN whose antecedents and consequents utilize fuzzy sets instead of crisp numbers. In the multidimensional input space, we need to determine the number of clusters and their initial values for initialising iterative optimisation-based clustering algorithms such as fuzzy C-means. The cluster estimation method serves as a basis of a robust algorithm for identifying fuzzy models [8]. The estimation performance can easily be improved by using an algorithm of automatic extraction of FIS from numerical data [9].

2.2. Pollution forecasting by means of ellipsoidal fuzzy system

A fuzzy rule can have the shape of an ellipsoid in the input-output state space of a system. In this section of the work, we carry out a bank of fuzzy rules to predict atmospheric pollutants by means ellipsoidal patches and fuzzy curves.

Each Fuzzy rule is an ellipsoidal patch on the input-output space. Fuzzy Ellipsoidal systems consider each rule as an ellipsoid [10-12]. The ellipsoid is the locus of all z that satisfy:

$$a^2 = (z - c)^T A(z - c) = (z - c)^T P\Lambda P^T(z - c) \qquad (1)$$

where: A is the inverse of covariance matrix; Λ is a diagonal matrix of eigenvalues $\{\lambda_1; \ldots; \lambda_q\}$of A; P is an orthogonal matrix whose columns are the unit eigenvectors $\{e_1; \ldots; e_2\}$of A. P rotates the coordinate system to the eigenvectors to orient the ellipsoid. The Euclidean half-lengths of the ellipsoid of the axes equal to$a/\sqrt{\lambda_1}$, …, $a/\sqrt{\lambda_q}$. The k-th hyper-rectangle has 2q vertices at $a_k/\sqrt{\lambda_{k,1}}$, …,$a_k/\sqrt{\lambda_{k,q}}$in the rotated coordinate plane. The unit eigenvectors define direction cosines for each axis of the ellipse. The projection of the k-th hyper-rectangle onto the i-th axis is centered at $c_{k,i}$on the i-*th* axis and has length:

$$\rho_{k,i} = 2\, a_k \sum_{j=1}^{4} \frac{|\cos \gamma_{k.ij}|}{\sqrt{\lambda_{k,j}}} \qquad (2)$$

For a 2-D ellipsoid the rotation matrix is:

$$P = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \qquad (3)$$

Then the hyper-rectangle projections are:

$$P_{k,1} = 2\, a_k \left(\frac{|\cos\theta|}{\sqrt{\lambda_{k,1}}} + \frac{|\sin\theta|}{\sqrt{\lambda_{k,1}}} \right); \qquad (4)$$
$$\rho_{k,2} = 2\, a_k \left(\frac{|\sin\theta|}{\sqrt{\lambda_{k,2}}} + \frac{|\cos\theta|}{\sqrt{\lambda_{k,2}}} \right)$$

The main advantage of ellipsoidal fuzzy systems regards the possibility to cover input-output space by means ellipsoids differently oriented in the space, reducing the number of discovered samples.

2.3 Pollution forecasting by means of NNs and Cao's method

The classical NNs predictors use the "sliding window" technique. We consider a "window" of n points of the time series as input of a network, and we train the net using a single value as target. This method is called "the sliding window" because the input values slide over the full training set [13]. It is important to take into account two issues: the frequency used to sample the data, and the size of the window. The NNs designed for CO and HC prediction in this work are Multi-Layer Perceptrons (MLPs) consisting of only two layers of multiple neurons, the input and the hidden layer, and a single neuron in the output layer. The hidden layer neurons are activated by the hyperbolic tangent transfer function, while the output neuron has a linear activation function. Regarding the training step, the exploited algorithm is the resilient back-propagation type. To design an optimal pollutant time series predictor, we exploit the information obtained by the dynamic system theory to fix the principal parameters of the NN-based predictor in order to improve the performance of the "sliding window" technique. In this case, a very useful role is played by the analysis of the time series in the space state, through the Average Mutual Information function (AMI) [14] and the False Nearest Neighbours method (FNN) [15].

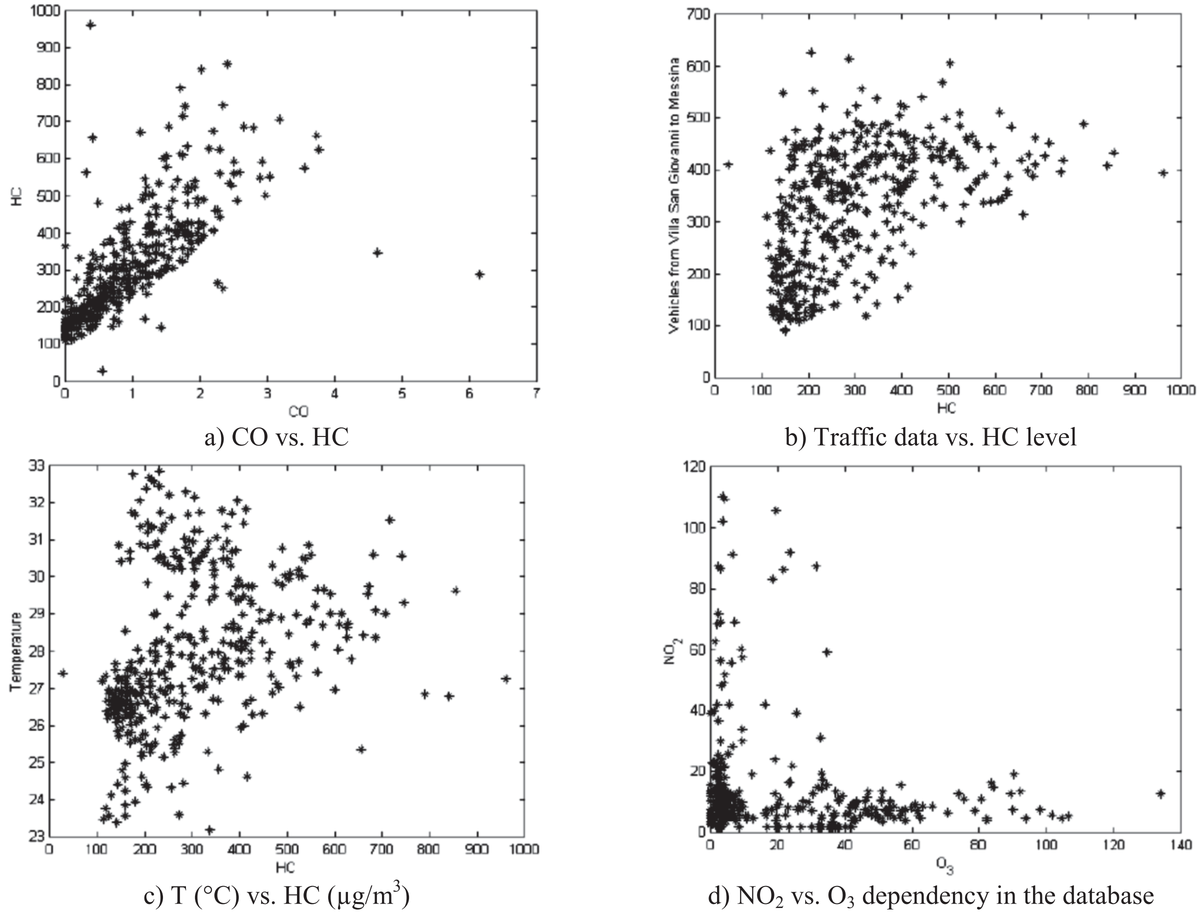
In this way, it is possible to reconstruct the space state of a pollutant time series and to establish, in this way, the fundamental parameters of a predictor network. But the FNN method depends not only on how many data points are available, but also on subjective parameters whose different values may lead to different results [13]. Certainly, Cao's method overcomes the shortcomings of the FNN approach and it is particularly efficient to determine the minimum embedding dimension of a scalar time series, like those of pollutants [16]. Thus, we used the first minimum of the AMI function to determine the sampling time interval and the information given by Cao's method to fix the size of the "sliding window". For simplicity, our attention has been concentrated on HC. The time series of the pollutant is firstly split into training and testing sets.

3. THE ENVIRONMENTAL DATABASE

Air pollution arises from the adverse effects on the environment of a variety of substances contaminants emitted into the atmosphere by natural and man-made processes. The temporal evolution of each pollutant depends on external variables in a complex way, and the kind of dependency can be rather different also in seemingly near locations. This fact implies the need of designing and/or optimizing the location of measuring station(s) in order to derive significant conclusions about the air quality. The above introduced problem is too complex to be solved by using analytical models. In this work, we use an environmental database that refers to the area of the Strait of Messina. The monitoring stations have been located downtown Villa San Giovanni, just along the road interested by traffic to Sicily. They were moved in different measuring points, anyway along the above mentioned road: time period

Table 1: Statistical quantities computed on the database

	Max	Min	Mean	Standard deviation	Skewness	Kurtosis
SO_2	109.407	0	7.4884	9.1087	4.3404	36.3145
CO	10.546	0	1.0067	0.913	2.6315	21.2147
O_3	135.692	0	20.9619	24.041	1.3117	4.4806
NO	279.181	0	15.5604	25.7522	4.809	36.6351
NO_2	168.718	1.722	18.2401	22.0091	2.8278	12.1922
HC	960.256	0	308.3483	159.6636	0.9048	4.039
PTS	396	0	59.7724	32.9931	3.538	30.3285
PM10	497.558	0	51.2416	61.462	3.4567	18.6915
Wind speed (m/s)	6.197	0.061	1.406	0.9008	1.3581	5.5984
Wind direction (degree)	354.945	91.86	221.2189	75.0959	0.1032	1.1855
Temperature (°C)	37.949	23.16	28.1623	2.1188	0.670	3.8443
Pressure (mbar)	1015.8	1004	1010.9	2.1322	-0.6687	3.4464



a) CO vs. HC
b) Traffic data vs. HC level
c) T (°C) vs. HC ($\mu g/m^3$)
d) NO_2 vs. O_3 dependency in the database

Fig. 1. Scatter plots showing the correlation between two typical pollution variables.

devoted to collect data in each location was four weeks approximately. The time series took into account refer to the period from July, 31 2012 to August, 17 2012. This period has been selected because the intense vehicular traffic. The database has the following structure [17]: data are organized in a matrix of 408 rows and 14 columns.14 variables can be found: the time observation, 8 pollutants concentrations (SO_2, CO, O_3, NO, NO_2, HC (hydrocarbons), PTS (total suspended solid particulate), PM10, i.e. <10 μm diameter particulate), some atmospheric parameters (wind speed, wind direction, temperature, atmospheric pressure) and traffic data (number of vehicles per hour in the two opposite crossing direction).Each variable is hourly sampled. Our attention is addressed to CO and in particular to HC concentrations because, in the time period under study, it exceeded the threshold of attention more than 61% and the threshold of alarm of 10%. Table 1 contains statistical parameters of both pollutants (CO is measured in mg/m^3, HC in $\mu g/m^3$).

3.1 Qualitative analysis

In order to well understand the behaviour of the collected quantities, we carried out statistical analyses by means of control cards (Shewhard's card, Cusum's card), which are based on the check of the measurements consistence between past and present [16]. By using correlation matrix, we can fit the correlation between a distribution of a pollutant and another one. The relevant linear correlations between pairs of variables are rare. Fig. 1(a) shows the typical correlation between CO and HC.

However, our attention is addressed to HC because, in the time period under study, it was 61% beyond the threshold of attention, while the threshold of alarm is set at around 10%.By observing the histograms of the pollutants, we can assume that their distribution can be assimilated to log-normal distribution. As for the HC, higher frequencies can be found, in correspondence with very high pollution levels when compared to the estimated model. The study of database gave prominence characteristics of regularity for atmospheric parameters: in our case, it seems that the conditions of high level of pollution occurs when the vehicular traffic is high and the wind velocity is medium, while the temperature falls into the range 26-32 °C. Thus, the thermal inversion has a strong influence on atmospheric pollution phenomena, because from this inversion depends the wind flows. However, since the availability of this information could be rare in other situations, we decided to exploit the correlation values between the hourly concentrations of O_3 and NO_2. When atmospheric stability occurs, NO_2 and O_3 are joined by a removal of the former to detriment of the latter. On the contrary, this kind of link becomes less intense when the atmospheric stability occurs because other processes take part, thus modifying the perfect joint of formation/removal. Fig. 1(d), reporting the correlation values between the hourly concentrations of O_3 and NO_2, shows that there are two different possible mechanisms governing the NO_2 and O_3 formation/removal process, depending on the meteorological condition and on the location of the sensors [18]. This kind of information is used in our fuzzy neural approach.

4. EXPERIMENTAL APPROACHES

4.1 Best results with Fuzzy Neural approach

We implemented a Sugeno-type first-order model [15] as the fuzzy knowledge base for the hybrid FIS-NN approach. It largely improves the classic NN-based approach by directly introducing fuzzy learning within the neuronal layers [9,10]. A network FIS scheme finally aims to facilitate the computation of the gradient vector for computing the parameter corrections. Once the gradient vector is obtained, a number of optimisation routines can be applied to reduce the error. The inputs of the procedure are, thus, interpreted as fuzzy variables. Each fuzzy value, representing a fuzzy variable, is characterised by a Fuzzy Membership Function (FMF). In turn, each FMF is expressing a membership measure to each of the linguistic properties. FMF are usually scaled between zero and unity, and they overlap. To improve the flexibility of our model, we used Gaussian FMFs throughout this work. The importance of the input in affecting the estimation of the output is determined on the basis of a figure of merit defined as the range of the fuzzy curve, which allows us to rank the input variable in order of importance and, thus, to properly reduce the complexity of the final system.

A typical fuzzy curve [7] describes the "weighted" relationship between two variables of the database under study: the fuzzy rules of main interest to describe the relationship are typically located where the system changes its behaviour. In particular, we place the fuzzy rules on zero derivative points, having double antecedents whose connective is "and". In this way, the transformation occurs into a space where the application of fuzzy patches becomes most easy. In a typical fuzzy surface [7], each sharp blob represents a fuzzy rule. To derive fuzzy rules with double antecedent from fuzzy surfaces reduces the risk of combinatorial explosion of the rules' number. The rules extracted by fuzzy surfaces include the rules extracted by fuzzy curves. As rather expected, the best inputs for predicting HC are the CO and the number of vehicles. Indeed, the traffic is mainly responsible of the pollution. The wind velocity is taken into account because it has an impact on the diffusion of the pollution variable. The so obtained fuzzy knowledge has been subsequently applied as the training rules in a MLP neural network. Table 2 reports the best results achieved in the prediction of the HC variable by using the relevant inputs selected with the fuzzy curves (i.e., the technique of the automatic extraction of the bank of FIS's rules from the available database). Some other input combinations have been investigated: several cases gave higher errors, mostly in the case of either insufficient number of inputs or inadequate "quality" of the inputs.

5.2 Best results with ellipsoidal Fuzzy System

We implemented a code allowing to automatically extract a bank of ellipsoidal fuzzy rules, in which the centre of each rule is determined by using a fuzzy c-means clustering algorithm [8, 16]. The number of ellipsoidal patches is chosen by the number of cluster centres that maximize the objective function associate to the fuzzy c-

Table 2: Prediction of HC Levels: GENFIS plus ANFIS approach

# In-study case	Pollutant	Inputs	Output	#Rules	Error
1	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-1h); Number of Vehicles(t-1h)	HC (one hour later)	10	0.0133
2	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-1h); Number of Vehicles(t-1h)	HC (one hour later)	27	Not relevant
3	HC	{HC(t-1h),...,HC(t-5h); {CO(t-1h),…,CO(t-5h)}; Temperature; NO_2(t-1h); NO(t-1h); TSP(t-1h)	HC (one hour later)	64	Not relevant
4	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-5h); HC(t-24h)	HC (one hour later)	57	0.0171
5	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-5h); HC(t-24h) Number of Vehicles(t-24h)	HC (four hours later)	54	Not relevant

means algorithm. Once the number of centres have been fixed, and, thus, the fuzzy clusters have been determined, the whole set of patterns is subdivided into a number of subsets corresponding to the number of clusters. For each subset we applied the Kosko's [15] theory reported in Section 2.2 in order to generate the ellipsoids. Fig. 2 visualise an example of fuzzy partition of the input-output space by means of ellipsoidal patches.

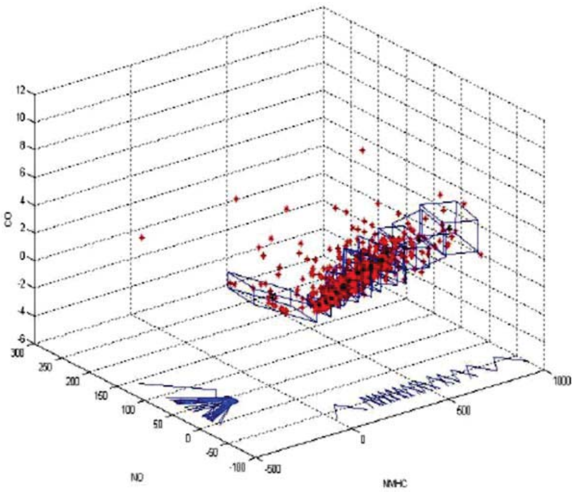


Fig. 2. Ellipsoidal fuzzy rules: membership functions for HC (x-axis), NO (y-axis) and CO (z-axis) are reported.

In order to simplify the image, we only represent the hyper-rectangles corresponding to the ellipsoids. We can also observe the presence of data that are not contained in the hyper-rectangles: the distribution of the ellipsoids does not completely cover the samples. In this case, the concept of fuzzy curves and surfaces can help us to reduce the impact of this problem (see Fig. 3). If we have a limited number of data, the ellipsoidal patches cannot be designed effectively. Thus, we should extract a bank of fuzzy rules by using fuzzy curves. Table 3 summarizes the best results achieved with this method.

5.3 Best results with NNs and Cao's method

According to the theoretical description, we proceeded with the analysis of the considered time series in the space state. The AMI function for HC data retrieves the first minimum at 4th hour, so this value is the new sampling time interval for the time series.

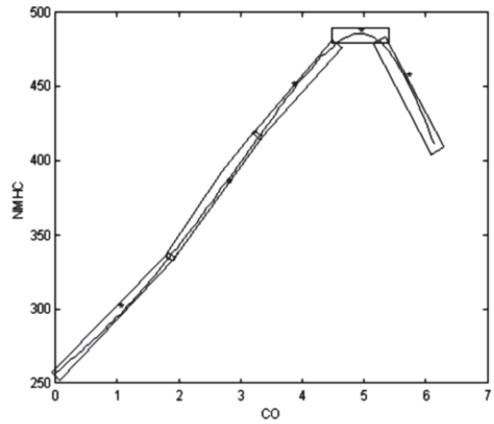


Fig. 3. A bank of fuzzy ellipsoidal rules extracted by means of fuzzy curves: each rectangle represents the envelop of the ellipsoid.

The minimum embedding dimension occurs in correspondence of dimension 8. This quantity represents the optimal size for the "sliding window", and then the number of inputs for the neural network. The number of hidden units is fixed appropriately in order to avoid an "over fitting" of the network.

After training procedure, the testing set is exploited to evaluate the quality of the prediction. These groups form as the training and testing sets, as also the target values in order that, during the learning phase, the network reproduce at the output the input values, "filtering" out noise and outliers. The number of hidden neurons of the pre-processing network are fixed and related to the considered pollutant. After training, the outputs generated when the testing set is presented at the inputs of the network are paste together to form the new "cleaned" time series. Obviously, we must pay attention to establish the number of hidden units of the pre-processing network in order to not destroy the information contained in the original time series. This can be done observing the autocorrelation function. Since the average daily concentration during the inspection period for both the pollutants is the same of that first the pre-processing, we are

Table 3: One-hour-ahead prediction of the HC levels: Ellipsoidal FIS's is used. Five previous samples of the HC variable have been used

# In-study case	Pollutant	Inputs	Output	#Rules	Error
1	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-1h); Number of Vehicles(t-1h)	HC (one hour later)	9	11.5
2	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-1h); Number of Vehicles(t-1h)	HC (one hour later)	14	11.0
3	HC	{HC(t-1h),...,HC(t-5h); {CO(t-1h),…,CO(t-5h)}; Temperature; NO_2(t-1h); NO(t-1h); TSP(t-1h)	HC (one hour later)	15	29.1
4	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-5h); HC(t-24h)	HC (one hour later)	13	62.4
5	HC	{HC(t-1h),...,HC(t-5h)}; CO(t-5h); HC(t-24h) Number of Vehicles(t-24h)	HC (four hours later)	22	59.9

Table 4: Performances of the proposed NN plus Cao's method, in terms of correlation coefficient (R-value) between the outputs and targets (%).

Pollutant	Hours of prediction									
	1	2	3	4	5	6	7	8	9	10
CO	95.7	93.6	93	92	91	93	91.2	90.3	88.5	89
HC	97.6	96.7	96.1	95.6	94.5	94.2	91.8	91.1	91.4	90.1

sure to preserve the relevant information of original data. The NN for CO time series prediction presents 5 input neurons in the first layer and 12 units in the hidden layer. The network for HC data has 6 input neurons and 8 hidden neurons. The testing sets of both pollutants are again used to evaluate the quality of prediction. The obtained results show that the designed neural systems are able to predict the CO and HC concentrations from one to ten hours in advance with an accuracy of more than 90%, as reported in Table 4.

6. CONCLUSIONS

In this work, we have designed predictor systems based on the use of hybrid fuzzy neural systems, of fuzzy ellipsoidal systems and on NNs for forecasting concentrations in the air. The experimental study is derived from the database which was made available through the in-situ measures in Villa San Giovanni, a southern Italy small city. In particular, the reported results refers to the concentration of HC measured and predicted locally along the road of transit of vehicles that go to and come from Sicily. In the case of using NNs and in order to improve the classical method of the "sliding window" to implement neural predictors, we have exploited Cao's method and AMI function to fix not only the best sampling time interval for our data, but also the size of the window. We have also used an image compression technique based on NNs to "clean" data from outliers and noise. The results obtained are very encouraging and shown that NNs plus Cao's method is surely a good approach to forecast time series. The forecasting of the pollutant levels by means of the fuzzy neural systems produces the best results because the learning procedure generates an optimal bank of fuzzy rules through automatic extraction from the database and tunes the model parameters by a gradient descent procedure.

7. REFERENCES

[1] P. Vergallo, A. Lay-Ekuakille, "Spectral Analysis of Wind Profiler Signal for Environment Monitoring" , Proc. IEEE I2MTC , May 13-16, 2012, Graz, Austria.

[2] A. Lay-Ekuakille, A. Trotta, "Predicting VOC Concentration Measurements: Cognitive Approach for Sensor Networks", IEEE Sensors Journal, vol.11, issue 11, pp.3923-3030, 2011

[3] L. Piper, A. Lay-Ekuakille, P. Vergallo, V. Pelillo, "A Novel Pseudo-Stationary Modeling of Pollutant Measurement Prediction from Industrial Emissions", in Proc. XX IMEKO World Congress Metrology for Green Growth, 2012.

[4] F.C. Morabito, M. Versaci, "Fuzzy neural identification and forecasting techniques to process experimental urban air pollution data", Neural Networks, vol. 16, no. 3-4, pp. 493-506, 2003.

[5] D. Marino, B. Ricca, "Neural Networks for Econometric and Environmental Models for Territory Management", in Proceedings of the XVII Italian Congress on Regional Sciences, 1999.

[6] D. Marino, F.C. Morabito, "A Fuzzy Neural Network for Urban Environment Monitoring System: the Villa San Giovanni Study Case", in Proceedings of the WIRN workshop, pp. 323-328,1999.

[7] L.A. Zadeh, "Knowledge representation in fuzzy logic", IEEE Transactions on Knowledge and Data Engineering, vol. 1, no. 1, pp. 89-100, 1989.

[8] S.L. Chiu, "Fuzzy Model Identification Based on Cluster estimation", Journal of Intelligent and Fuzzy Systems, no. 2, pp. 267-278, 1994.

[9] J.S.R. Jang, "ANFIS: Adaptive Network-based Fuzzy Inference Systems", IEEE Transaction on Systems, Man, and Cybernetics", vol. 23, no. 3, pp. 665-685, 1993.

[10] J.A. Dickerson, B. Kosko, "Fuzzy Function Approximation with Ellipsoidal Rules", IEEE Transactions on Systems, Man, And Cybernetics - Part B: Cybernetics", vol. 26, no. 4, pp. 542-560, 1996.

[11] B. Kosko, Fuzzy Engineering. New Jersey: Prentice Hall, Intl. Edition, 1997.

[12] W. Bach, Atmospheric pollution. New York: McGraw-Hill Book Company, 1972.

[13] T. Kolarik, and G. Rudorfer, "Time series forecasting using neural networks", in Proceedings of the International conference on APL, pp. 86-94, 1994.

[14] M.B. Kennel, R. Brown, H.D.I. Arbarbanel, "Determining embedding dimension for phase-state reconstruction", Phys. Rev., vol. A45, pp. 3403-3411, 1992.

[15] F. Takens, "Detecting strange attractors in turbulence", in D.A. Randand L.S. Young (Eds.) Lecture Notes in Mathematics, pp.366-381, 1981.

[16] L. Cao, "Practical method for determining the minimum embedding dimension of a scalar time series", Physica, no. D110, 43-50, 1997.

[17] A. Lay-Ekuakille, P. Vergallo, N.I. Giannoccaro, A. Massaro, D. Caratelli, "Prediction and Validation of Outcomes from Air Monitoring Sensors and Networks of Sensors", Proc. V International Conference on Sensing Technology , in Proc. of ICST2011, 2011.

[18] J. Milford et al., "Total reactive nitrogen (NO) as an indicator for the sensitivity of ozone to Nox and hydrocarbons", J.Geophys. Res., vol. 99, pp. 3533-3542, 1994.

[19] M. Sugeno, "Fuzzy measures and fuzzy integrals: a survey", in M.M. Gupta, G. N. Saridis, and B.R. Gaines (Eds.) Fuzzy Automata and Decision Processes, pp. 89-102, 1977.

[20] E. Gandolfi, M.Masetti, C. Vitello, S. Zannolli, "Adaptive Fuzzy Systems for Gas Microsensor Arrays to be Implemented in Air Pollution Monitoring Station: First Results", in Advances in Fuzzy Systems and Intelligent Technologies, Proc. of the WILF'99,pp. 139-148, 2000.