The Neural Network-Based Forecasting in Environmental Systems

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Abstract: - The forecasting problem is one of the main environmental problems that need efficient software tools. More concrete, it can mean meteorological/weather forecasting, air/soil/water pollution forecasting, flood forecasting and so on. Several methods based on artificial intelligence were proposed by taken into account that they can offer more informed methods that use domain specific knowledge, and provide solutions faster than the traditional methods, those based on a mathematical formalism. In this paper we present the application of neural network-based forecasting methods, as well as their combination with fuzzy logic in air pollution forecast and flood forecast in a hydrographic basin. The neuro-fuzzy based forecasting can be integrated in a more complex real time monitoring, analysis, and control system for environmental pollution or hydrological processes.

Key-Words: - Artificial Neural Network, Fuzzy Logic, Air Pollution Forecast, Flood Forecast, Hydrographic Basin

1 Introduction

More applications of Artificial Intelligence (AI) methods in environmental sciences were reported in the literature. The problems varied from modelling to implementing monitoring, analysis, forecasting, and control modules in different environmental systems, such as meteorology, ecology, ecosystems, environmental protection, hydrology, seismology, geology etc.

The forecasting problem is one of the main environmental problems that need efficient software tools. In particular for environmental systems, it can mean meteorological forecasting, air/soil/water pollution forecasting, flood forecasting and so on. Several methods based on AI were proposed by taken into account that they can offer more informed methods that use domain specific knowledge and can provide solutions faster than the traditional methods, those based on a mathematical formalism [19]. In particular, computational intelligence (e.g. artificial neural networks - ANN, fuzzy logic etc) provides good solutions to forecasting problems. In this paper we present two case studies of applying feedforward artificial neural networks (FANN) and their combination with fuzzy logic to air pollution forecast and to flood forecast in a hydrographic basin. The two solutions given by the neural approach and the neuro-fuzzy approach can be applied with success in various scenarios. The experimental results obtained so far are also discussed. The neuro-fuzzy based forecasting can be integrated in a more complex real time monitoring, analysis, and control system for environmental pollution or hydrological processes.

2 Environmental Forecasting Systems

In our research work we have considered two environmental forecasting systems for two types of applications, one in the area of environmental protection for air pollution forecasting in urban regions, and the other, in the area of hydrology, for flood forecasting in a given hydrographic basin. Both applications have a higher degree of complexity which can be reduced by using specific computational intelligence techniques.

2.1 The architecture of a neural based environmental forecasting system

We have used FANN that were trained with different improved backpropagation algorithms (e.g. with variable learning rate and momentum). The architecture of a neural network was chosen by taken into account the specific parameters of the forecasting system in each case study, air pollution and flood forecast. The generic architecture of a forecasting ANN is shown in Figure 1.

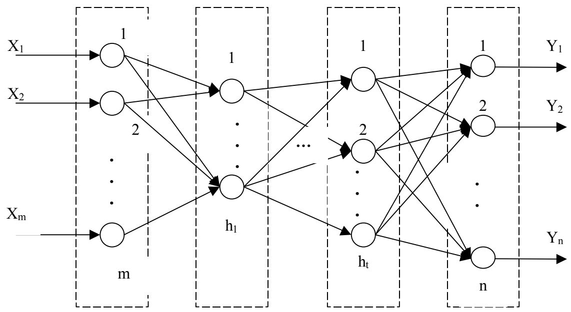

Figure 1 The generic architecture of a feedforward artificial neural network used in an environmental forecasting system.

The input vector X of the neural network has *m* components, corresponding to *m* parameters that can be measurements of the same parameter from different sites or terms of timeseries corresponding to the same parameter measured in the same location, but in different time windows. The output vector Y has *n* components, corresponding to the forecast horizon of the parameter that is forecasted. Between the input layer and the output layer of the feedforward neural network there are *t* hidden layers. Usually, one hidden layer is enough to solve forecasting problems. However, for more complex patterns two hidden layers are needed. The number of hidden layers as well as the number of nodes in each hidden layer is determined by experiments. In the next section we shall describe the two environmental forecasting systems, after describing briefly in the next subsections the neuro-fuzzy approach and some related work.

2.2 The neuro-fuzzy approach

The performance of a neural network depends on a set of parameters such as the size of the network, the learning rate, the training strategy and so on. Two solutions for the improvement of the forecasting NN performance are given by the combination of several neural networks and the combination of the neural network with fuzzy logic in a so called neuro-fuzzy network. A feed forward neuro-fuzzy network has first hidden layer that realize the fuzzification (i.e. the association of physical crisp inputs to linguistic terms, named also fuzzy terms), next layers compute the fuzzy inference and, if needed, additional layers will cope with defuzzification. An example of such neuro-fuzzy network is given by ANFIS (adaptive network based fuzzy inference system) introduced in [8], and included in Matlab. The neuro-fuzzy approach has been applied with succes also to modeling and control problems [9].

2.3 Related work

Several artificial neural networks were used either for environmental quality forecasting [4] or for environmental pollution analysis. Some feedforward neural networks were applied to environmental air pollution forecasting in urban regions (see e.g. [2], [15], [16], [17], [18], [22]). Moreover, various comparisons between different approaches were also presented (see e.g. [2] – a comparison between statistical and neural network approaches applied to urban air quality forecasting, [23] – a comparison of neural networks model and qualitative models applied to environmental engineering). There are also some neural networks that were used in hydrology and flood forecasting [1], [6], [17]. Some recent neuro-fuzzy systems applied in environmental sciences are presented in [3], for environmental pollution, and [16], for hydrology.

3 Case Studies

In this section we describe two environmental forecasting systems that are based on a feedforward neural network. For the second case study it is presented also the neuro-fuzzy solution.

3.1 Air pollution forecasting system

The air pollution forecasting system, RNA_AER, is fully described in [10]. The architecture of the feedforward neural network has *m* input nodes, one hidden layer and one or two nodes in the output layer. The data that were used are timeseries of air pollutants concentrations measured in the period 2005-2007 in the Târgovişte town from the Dâmboviţa country. The pollutants that were analyzed are NO_2, SO_2, NH_3, CH_2O, PM (particulates matters), and TSP (total suspended particulates). The experiments were made by using the FANN library [5] with a C++Builder programme.

The application interface is presented in Figure 2. Several training algorithms, as well as neural network architectures were experimented in order to obtain the optimum one for a short-medium forecasting of a specific air pollutant concentration. Three training algorithms were used, the classical backpropagation algorithm, RPROP algorithm (the resilient back-propagation), and QuickProp algorithm. The training parameters, specific to each training algorithm, were also varied during the experiments.

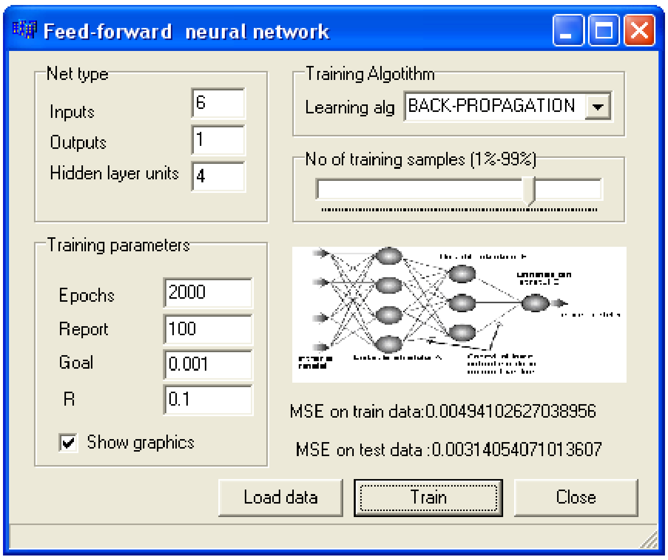

Figure 2 The interface of the air pollution forecasting system (based on the FANN library [5]).

Figure 3 and 4 show the forecasting results for timeseries of daily concentrations of PM_{10} in case of using a neural network with the architecture of 2×4×1 and 6×4×1, respectively. The length of the PM_{10} timeseries is of 101 terms. In Table 1 it is shown the dependency between the training and validation errors and the input nodes number of the feedforward neural network as obtained in the experiments presented in [10].

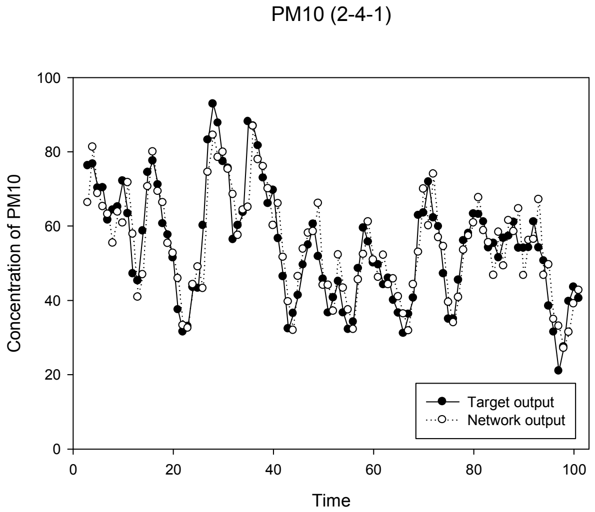

Figure 3 The concentration of PM_{10} obtained by a feedforward neural network with the architecture 2×4×1.

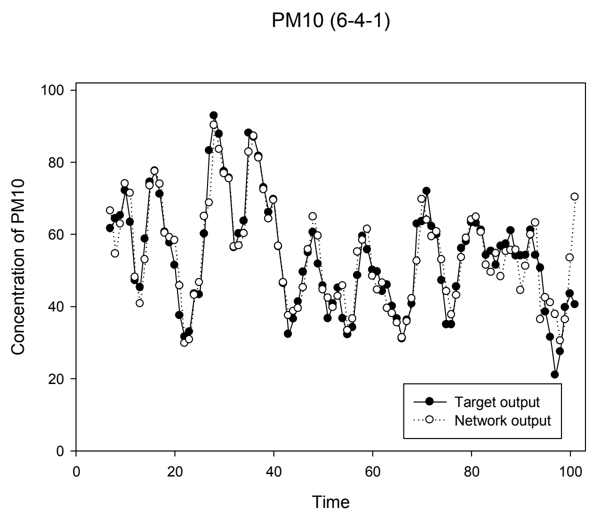

Figure 4 The concentration of PM_{10} obtained by a feedforward neural network with the architecture 6×4×1.

Due to their efficiency, we have used two training algorithms, RPROP and QuickProp. By analysing the mean square error for the PM_{10} air pollutant (as given in Table 1) we can conclude that the best feedforward neural network architecture was 6×4×1.

Table 1. The dependency between the training and validation errors and the input nodes number of the feedforward neural network.

Training Algorithm	RPROP		QuickProp	
Network topology	MSE Training data	MSE Validation data	MSE Training data	MSE Validation data
2×4×1	0.00984	0.01085	0.01143	0.00858
4×4×1	0.00494	0.01644	0.00948	0.00942
6×4×1	0.00408	0.02051	0.00873	0.00941
8×4×1	0.00311	0.02265	0.00731	0.01356

Table 2 corresponds to a neural network architecture of 2×4×1, and shows the dependency between NN training/validation errors and the number of samples used during the training phase. We have used 99 samples for all experiments done in the case of PM air pollutant.

Table 2. The dependency between the training/validation errors and the number of samples used during neural network training.

Training Algorithm	RPROP		QUICKPROP	
No of training samples	MSE Training data	MSE Validation data	MSE Training data	MSE Validation data
70	0.01053	0.00961	0.01233	0.00743
80	0.00984	0.01085	0.01143	0.00858
90	0.00955	0.01297	0.01068	0.01261

Figure 5 shows the concentration of TSP obtained by using a feedforward neural network with the architecture 2×4×1. The neural network was trained with the RPROP algorithm.

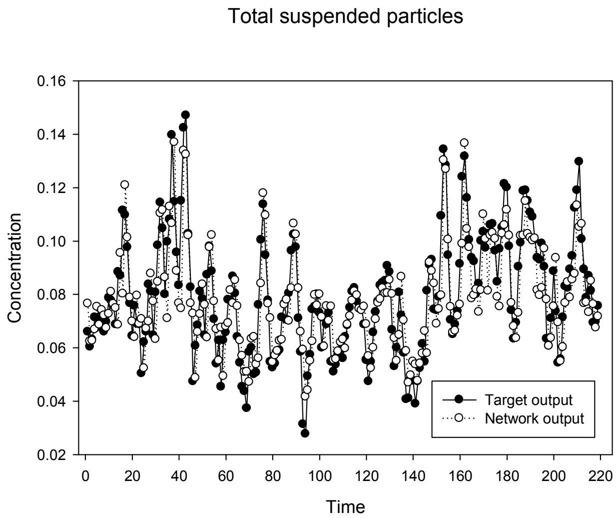

Figure 5 The concentration of TSP obtained by a feedforward neural network with the architecture 2×4×1.

Some of the experimental results are presented in [11]. The use of the neuro-fuzzy network is briefly described in [10]. In this paper we present the neuro-fuzzy solution only for the second case study from the hydrology

domain, where the results obtained so far are better than those obtained by the feedforward neural network.
The conclusion of this first case study was that the concentration of different air pollutants can be forecasted in urban regions with a good degree of accuracy when we choose the proper neural network architecture, and the best neural network training algorithm. Such a forecasting software instrument can be used by Environmental Protection Agencies in order to identify sites in the urban region where the concentration of some air pollutants can exceed the national air quality standards in some periods of time, and to send warnings or to propose to the decision makers some measures or counter-measures in order to limit the exceedance of the air pollutants concentrations over their maximum admisible values.

3.2 Flood forecasting system

Worldwide practice has shown that global occurrence of floods can't be avoided, but they can be managed, and their effects can be reduced through a systematic process that leads to a series of measures and actions aimed to contribute to the reduction of the risk associated with these phenomena [20]. Flood management is eased by the fact that their manifestation is predictable and often a prior warning can be made, and usually it is possible to clarify who and what will be affected by the floods (see e.g. [1], [14], [20]). All the specialists dealing with hydrological processes analysis admit that they are complex stochastic processes. Therefore, even if some methods and techniques are not specific for studying stochastic processes, all are related to probabilistic processing of results. Using artificial intelligence techniques opens promising prospects in this field. Simulation methods are still the main method of to analysis hydrological processes in a given river basin. Artificial neural networks are used for modeling, in a discrete domain, of the hydrological process (as shown in [6], [7], [12], [13]), because they work with sequences of samples of the sizes of input - output, most often being used input-output representation.

A very important aspect of flood prediction is represented by the knowledge of the way of the manifestation for the phenomenon in the river's basin over a long period of time. Although, during the last years, research concerning the application of artificial neural networks has been made, a model for flood prediction and analysis was not yet developed. This is because of the fact that the hydrological response and especially the flow regime during the flood are influenced by physiographic characteristics of the basin [22].

In this work there have been described two types of artificial neural networks with the help of the programming environment Matlab 7.1. Both of them have the function to predict the flow of the river downstream with help of the flow time series measured upstream (Figure 6). Initially, we have created a feed-forward neural network, model integrated with the fuzzy logic for the development of an Adaptive Network based Fuzzy Inference System (ANFIS). ANFIS is a neuro-adaptive learning technique which provides a fuzzy modeling method. Also, this paper presents a comparative analysis of the results obtained by applying these two methods.

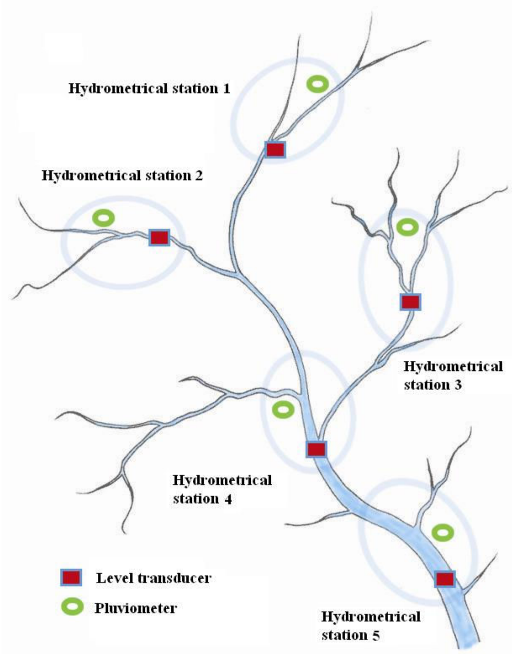

Figure 6 The Prahova river hydrographic basin form.

The entire Prahova – Teleajen catchment basin (shown in Figure 7) covers an area of 3738 km^2, between Predeal and Adâncata, and is part of the Ialomița hydrographic basin. This area covers 79% of the administrative area of Prahova County. The hydrographic network forms a basin in a palm form flowing NW-SE. The main rivers that compose the Prahova sub-basin are the Prahova river and its main tributaries: Azuga, Doftana, Teleajen and Cricovul Sărat.

Figure 7 The Prahova river basin and major hydrometric stations

The Prahova river basin is characterized by three types of climates: mountain, hill, and plain. The annual quantity of precipitation is 1000-1400 mm in the mountains, 500-1000 mm in the hills and 550-600 mm in the plain. During summer rainfall is more abundant and the flood waves may occur in the hydrometrical stations of Moara Domnească and Adâncata.

The main gauging stations located in Prahova catchment are represented in Figure 8.

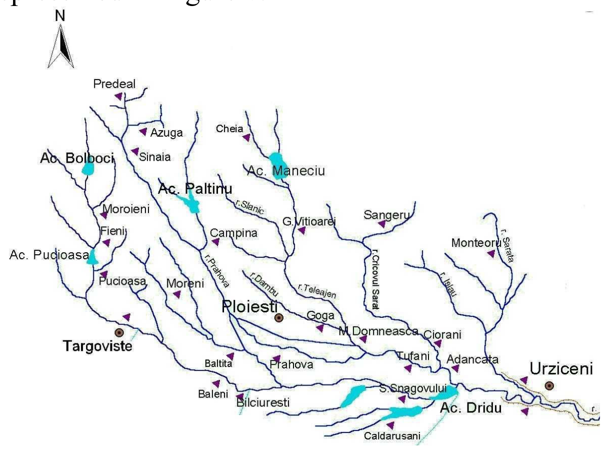

Figure 8 Main gauging stations

Gauging station specific rates of Prahova river basin are presented in Table 3.

Table 3. Rates hydrological stations

River	Gauging station	Attention Rate	Flood rate	Danger Rate
Azuga	Azuga	90	130	150
Valea Cerbului	Buşteni	70	100	150
Prahova	Buşteni	100	150	200
Prahova	Câmpina	250	300	400
Prahova	Prahova	250	250	400

A potential critical aspect in applying an extended prediction method in the flood management stage is represented by choosing the input variables.

The used input vector is given by the daily average liquid flow measurements made in Prahova river basin at the hydrometrical stations like: Azuga, Buşteni, Buşteni-Valea Cerbului, Campina. They are time series of river flow in the period from 2005 to 2008. This period was chosen because lately our country has faced a series of floods. The average flow of liquid is expressed in m^3/s and it represents the volume of water drained through a river section. The system serves to analysis the input vector and predicts the flow in Prahova hydrometric station. The data used were obtained with the help of the Romanian Waters National Agency - Prahova Water Management System.

The reason for choosing the period between the years 2005-2008 is that it includes both time series of normal river flow and flood flows. Figure 8 shows one of the floods produced in 2008 Prahova hydrometric station.

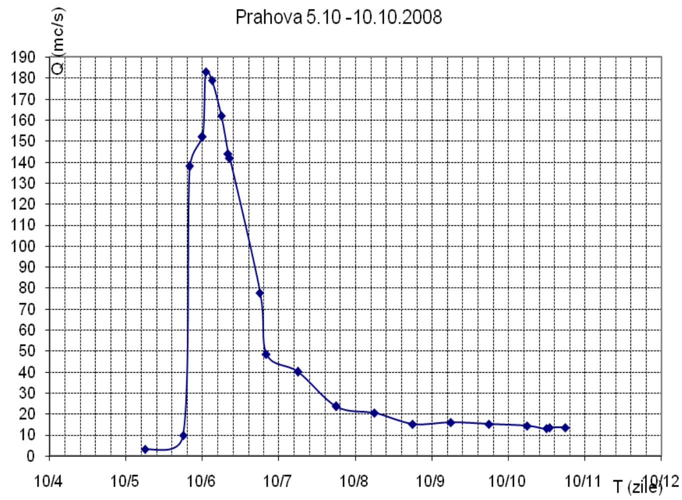

Figure 8 Flood wave produced during 5.10-10.10.2008 in Prahova hydrometric station.

The artificial neural network could be trained for different sets of values, aiming to be able to correctly predict the flow in Prahova hydrometric station near 10 hours earlier, time which can be used for operational applications, such as warning population. Some examples of time series used for training the artificial neural network are presented in Table 4.

Table 4. Time series of the Prahova river flow.

Q_{Azuga} (m^3/s)	$Q_{Busteni}$ (m^3/s)	$Q_{Valea\ Cerbului}$ (m^3/s)	$Q_{Câmpina}$ (m^3/s)	$Q_{Prahova}$ (m^3/s)
1.77	2.71	0.43	5.94	3.95
1.44	1.59	0.22	4.76	4.24
1.55	3.49	0.49	6.4	5.44
1.87	3.72	0.53	6.12	3.89
6.55	9.37	1.06	13.6	20.5
2.7	2.71	0.41	8.11	6.62
0.91	1.62	0.96	7.54	4.86
0.81	1.62	1.04	7.16	4.93
0.38	1.09	0.42	4.4	2.82
14.1	22.4	0.4	35.5	34.3

For reasons related to the design of the artificial neural networks (for which usually output sizes are usually scaled on the interval [0, 1]), input data were normalized in the interval [0, 1] before being placed in the network by the formula (1).

$$data_{[0,1]} = \frac{data}{data_{\max imum}} \tag{1}$$

An important aspect in developing the artificial neural network was to choose the number of hidden layers and the number of neurons in each hidden layer. If there are too few neurons in the hidden layer, the network may be unable to predict the flood because of the insufficiently parameters. In contrast, if they are too many neurons in the neural network it may lose the ability to generalize. We have used for the Prahova river basin flood prediction, a 4 layered neural network feed-forward: (1) - An input layer: the number of input neurons corresponds to the number of input data (average flow rate measured in each hydrometric station upstream); (2) - Two hidden layers with 8 neurons in each layer; (3) – The output layer with one neuron - Prahova flow in Prahova hydrometric station.

The number of hidden layer neurons was inferred by error. It increased by 2 neurons and it was observed that for 8 neurons in each hidden layer resulted smallest error. Each artificial neuron has input / output characteristic and implements a local process or a function. In general, the characteristic functions for different neurons may be different, but it is preferred that a certain group of neurons have identical functions. The tansig activation function given by equation (2) was selected for all four layers.

$$F(x) = \frac{1}{1+e^{-kx}} \tag{2}$$

Once the weights and polarization were initialized with random values, the network is ready to be trained. Network training was accomplished with Cascade-correlation algorithm. Initially, it was used the reverse error propagation algorithm, but it was not providing good results in training the network.

Learning accuracy and good generalization heavily dependent on the network topology chosen. Determining the best topology for a problem and training set are based on empirical criteria, it requires a long process.

It was used as statistical parameter the mean square error, which may be influenced both by the activation function for hidden layer and the network training method used. It is calculated with the equation (3):

$$EMP = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{obs} - Q_{cal})^2} \tag{3}$$

where, n is the number of observations and Q_{obs} and Q_{cal} are the observed value and the calculated value of flow.

The second approach is the introduction of fuzzy logic to predict the river flow. This system has the main property of being able to simultaneously handle numerical data and empirical knowledge.

This system uses Sugeno type fuzzy inference. Systems which are using the Sugeno type inference allow the use of adaptive techniques for constructing fuzzy models. These techniques allow for adaptive fuzzy systems to "learn" information about a data set to calculate the membership functions that are best adapted to the problem [6]. They resemble best to the neural networks.

This consists of the implementation of an Adaptive Network based Fuzzy Inference System (ANFIS) system, which is based on the learning algorithms of neural networks and fuzzy knowledge based characterization of the input output function.

ANFIS is a rules-based system and consists of three main components:

- database – there have been used around 1000 time series of Prahova river and its tributaries flow;
- a fuzzy rule-based if-then type (Figure 9);

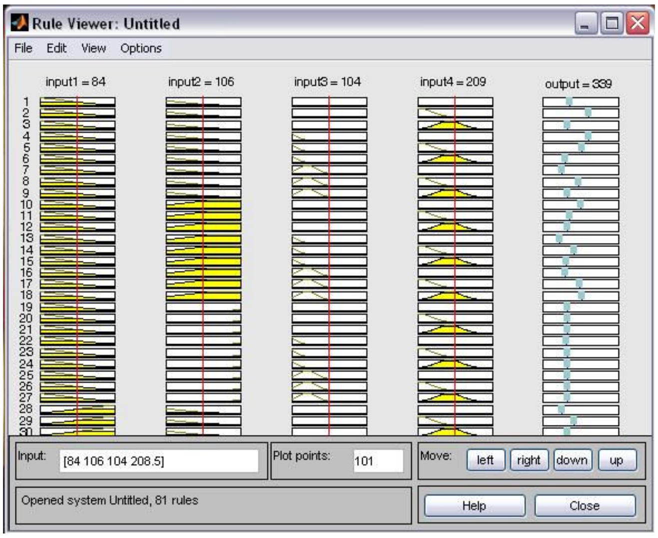

Figure 9 The fuzzy rule-based

- an inference system that combines fuzzy rules and produces the system's results (Figure 10);

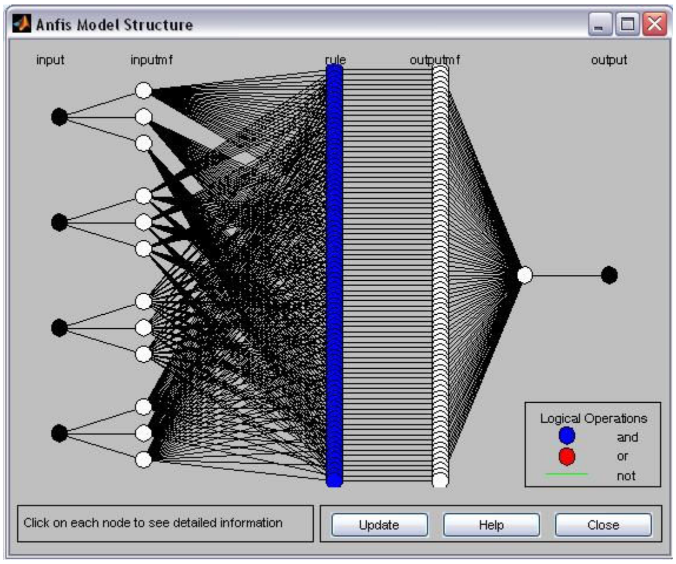

Figure 10 The ANFIS model structure

Both models were tested with the same set of data from the training of 5000 epochs and with the same set of input data.

Examples of the errors that were obtained are shown in Table 5.

Table 5. Examples of the resulted errors obtained with the ANN.

Error	1	2	3	4	5	6
ANN	-0.0018	-0.0016	-0.0007	-0.0282	-0.0014	-0.0014
ANFIS	0.94482					

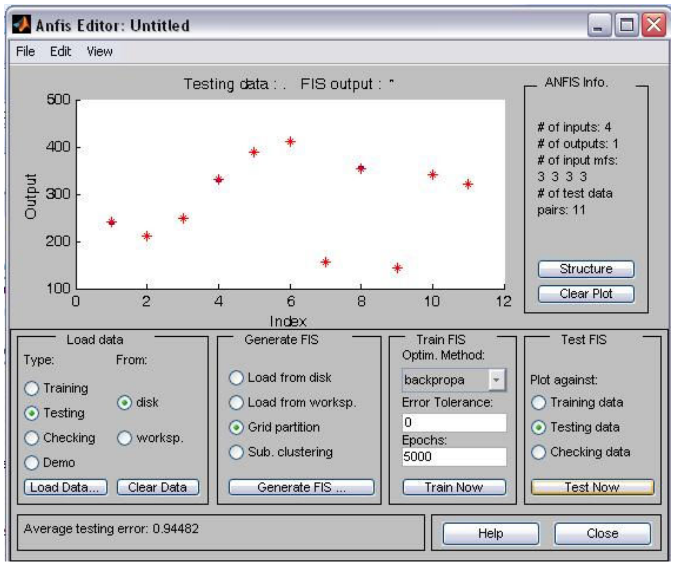

Figure 11 ANFIS system error resulting

The results obtained so far showed a random behavior behavior of both the neural network and the ANFIS system when used to predict floods, according to data from the different hydrographic stations. It may work very well in some cases but not guaranteed for all times. Therefore, to prevent false predictions, the network should be tested over a long period.

Artificial neural networks that are configured properly extend flood forecasting capability by using the correct input. Caution should be exercised in case of extreme situations. In this case study there have been problems concerning the response of the network when flood waves succeed at short intervals.

In table 6 are presented the comparative results of the flood prediction system that uses a classical method and a neural based algorithm (ANN).

Table 6. Comparative analysis of flood prediction systems.

Hydrometric station flow [m^3/s]	Classical method	ANN	ANFIS
Azuga	44.83	45	45
Valea Cerbului	56.08	56	56
Buşteni	43.45	43	43
Câmpina	108.8	109	109
Prahova	156.66	155.99981	156.94482
Error	0.66	- 0.00019	0.94482

The error was determined based on the value obtained from measurements made in Prahova hydrometrical station, the flow obtained is equal to 156. The classical method - requires the improvement of the conventional mathematical model used. This requires a fairly long time and a consistent and sustained effort from specialists in hydrology. The results obtained lead to the idea that the performance of neural network prediction models depend on many factors, such as the network structure, the learning algorithm, the choice of network parameters. Thus, artificial neural networks properly configured can extend the ability of flood forecasting by using the correct input.

ANFIS fuzzy technique combines artificial neural networks using human expert knowledge in designing and training neural networks [7].

Artificial neural networks are used for modeling, in discrete process, they worked with sequences of samples of the sizes of input - output of the process, most often being used input-output representation [21].

For the ANFIS system, establishing rules and their adaptation is performed by an online mechanism. Simulation results obtained show that the ANFIS structure does not increase performance of the neural network.

In this work we have described an artificial neural network for flood forecasting that was developed by using Matlab 7.1 programming environment. The network has the role of downstream river flow prediction with upstream river flow series. A very important aspect of flood prediction is the knowledge of the way that the phenomenon manifests itself in the catchment basin, which was studied over a period of time. This approach has the main advantage that it is not necessary to develop a basin-type model, or to integrate all of the characteristics of the river basin in the system. Here there may be listed a number of disadvantages. Since it is necessary to use a complete set of data for network training, system implementation complexity increases. Also, because of flood waves produced, may change the topology of the river, a factor that leads to the modification of the parameters in the hydrological process of water leakage. Another disadvantage is the statement that artificial neural networks do not allow the extraction of a model on hydrological process. This implies the system's malfunctioning in some extreme cases (cases which can not be found in the data from which the network was trained).

4 Conclusion

The application of artificial neural networks and of neuro-fuzzy networks to solve forecasting problems in environmental systems can provide potential benefits. In this paper, we have presented two such case studies, one from the environmental pollution domain and the other from the hydrology domain. The first forecasting system was a feedforward neural network that was applied to air pollution forecast in urban regions. The experimental results showed a good behaviour of the forecasting system for the timeseries that were used. Several neural network architectures were experimented in order to find the optimum one. The second prediction system was a feedforward neural network that was used to flood forecasting in a specific hydrographic basin. The artificial neural network could be trained for different sets of values, aiming to be able to correctly predict the flow in Prahova hydrometric station near 10 hours earlier, time which can be used for operational applications, such as warning population.Further, this model was integrated with the fuzzy logic for the development of an Adaptive Network based Fuzzy Inference System (ANFIS). The experimental results showed a satisfactory behavior of the prediction system. However, this system needs to be improved with some heuristic knowledge, specific to the hydrographic basin that is analyzed. Both forecasting systems are real world applications and they proved that computational intelligence provides more efficient methods than the traditional ones.

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