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Neural networks for daily mean flow forecasting

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Abstract

A neural network is developed to model the rainfall-runoff behaviour of the Tiber River basin. Performances of the neural network are then compared with the ones gained through an autoregressive model with exogenus input (ARX) and via the persistence hypothesis. The comparison shows that the neural scheme is able to provide very accurate discharge forecasts and performances quite superior to the other two approaches.

1.Introduction

The subject of rainfall-runoff modelling affects a wide spectrum of topics ranging from water resources management to areal flooding and dam safety analysis. Fundamental to each topic is the problem of how to accurately compute runoff at a point from meteorological data consisting mainly of rainfall and temperature measurements over the catchment area. The fact that there is no single universally accepted approach to computing runoff and that several models have been developed within different frameworks (for a review, see Franchini and Pacciani,[1] Todini,[2] Hromadka II,[3] Karlsson and Yakowitz,[4]) clearly indicates that a definitive solution has yet to be found and that research in the field is still active.

The purpose of this work is to assess the possibility of employing a new approach based on a neural network scheme, whose use is becoming more popular among scientists involved in hydraulic and hydrometeorological activities (French et al.,[5] Ranjithan et al.,[6] Dartus et al.[7]), for forecasting the daily mean discharge in the hilly basin of the Tiber River in Central Italy.

Forecasts obtained with the neural network are then compared with the discharges gained through a black box transfer model, formulated as an autoregressive model with exogenus inputs (ARX) (Box and Jenkins,[8]) and finally with the results obtained via the persistence hypothesis. The comparison clearly shows that the neural scheme, if "properly" trained (for the meaning of "properly" see the following sections) is able to provide very accurate discharge forecasts and performances quite superior to the ARX approach.

Although additional research is obviously required these preliminary results indicate that the neural network (NN) approach could well constitute an efficient and reliable alternative for runoff forecasting.

2 Description of the basin and available hydrologic data

The basin chosen to test the capability of runoff forecasting by neural networks is the upper Tiber River basin, located in Central Italy (Fig.1)

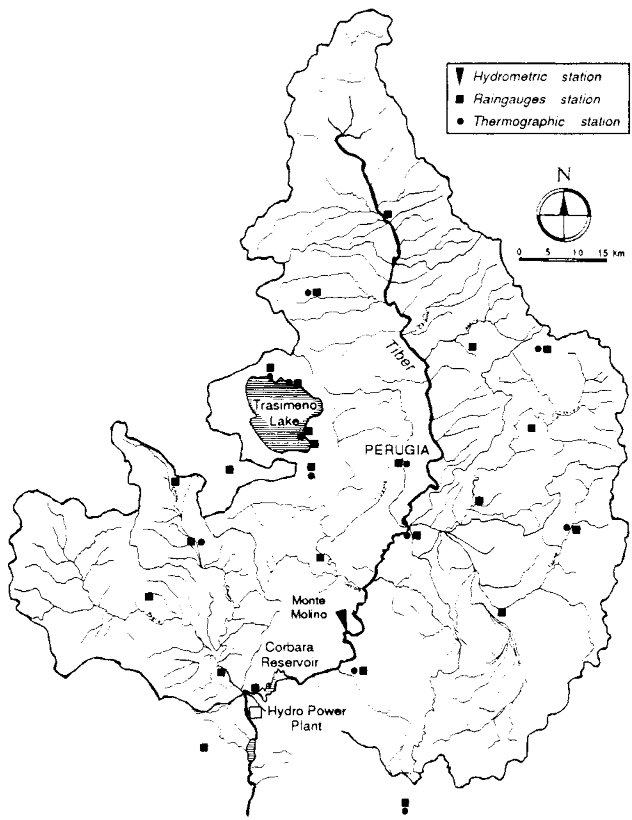

Figure 1. *The upper Tiber River basin*

The basin has a complex mainly hilly orography (200÷800 m a.s.l.), yet shows higher peaks (1000÷1500 m a.s.l.) over a wide area of the boundary. The really mountainous area is in the northern zone, while the southwestern part of the basin is mostly level; a worth noting karst is located to the east. Given the basin's limited mean altitude and the reduced areal range of zones at altitudes ≥ 1000 m a.s.l., the role of nival precipitations and the subsequent spring melt is negligible so that floods generally occur during the November-May period and are caused by widespread rainfall. Daily discharge forecasting is required for the management of the Corbara reservoir which supplies the Baschi hydroelectric power plant, the most important hydro plant along the Tiber River, with an installed power of 100 MW and a maximum turbine discharge of 200 m^3/s.

Available hydrometeorological data covers the period from 1/8/1988 to 31/12/1992, and are composed of:

- daily precipitation values from 26 raingauges located inside the basin;
- daily mean temperature from 13 thermographic stations;
- daily mean discharge values at the section of Monte Molino, just upstream of the Corbara reservoir.

To test the performance of the various models, the period 4/8/1988÷ 31/12/1991 was chosen as the calibration period, leaving the whole 1992 as the trial or validation period. Since 1992 witnessed numerous flood episodes of particular significance (daily mean flow $Q \geq 500$ m^3/s) and in particular the maximum flood ($Q=880$ m^3/s) measured over the entire investigation period, this trial is particularly probative.

3. The neural network structure

The term "neural network" means a set of basic units, or nodes, which communicate with each other through a closely-woven network of interconnections. As a general concept, neural networks are mathematical models of theorized mind and brain activity which attempt to exploit the massively parallel local processing and distribution storage properties believed to exist in the brain (Grossberg,[9]). Different possibilities exist for the neural network structure and neuron forms (see for instance Lippman,[10] for a more complete discussion). In this particular network the various nodes are arranged in three layers, an input layer, a hidden layer and an output layer; each node is interconnected with all the nodes in the adjacent layers, but not with the ones in the same layer.

Each interconnection between two units indicates transmission of data whose importance is proportionate to the value of the weight **w** of the interconnection itself. Once the number of nodes has been fixed, weights **w** are determined in the "learning phase" where the network output value x_k' is compared to the real value x_k so that the error (x_k-x_k') can be used to adjust the interconnection weights. The mathematical adopted method for this purpose is known as "error back-propagation" and is based on a non-linear optimization approach which uses a descendent gradient method over the error surface (Jones and Hoskins,[11] Sforna, [12]).

4 Application of the neural network

The training phase of the NN, i.e. the definition of weights **w** which regulate the interconnections, is of primary importance to achieving accurate performances in the reconstruction phase of the discharges. From the experience gained in this particular application, it is worth highlighting the following points:
a) Great care should be taken in accurately preparing the "learning" data. The observations set should be constructed to include, as far as possible, the different conditions the network will have to operate under. If "holes" are left in the training set, once the network is operating it is likely to come up against unfamiliar situations to analyze, or at least ones which differ greatly from the cases trained for, and this would therefore increase the likelihood of considerable errors in the supplied forecasts. In this case it means that if the network is supposed to be capable of forecasting discharges between 0 and 1000 m^3/s, the training values should be distributed as uniformly as possible over this interval.
b) The number of examples which represent very similar hydrological conditions should be limited; in fact, by supplying the network with a great number of very similar examples and which contain significant errors, the "back-propagation" method may lead the network to a local minimum of the error function which is much higher than the absolute minimum.
c) The training process should be followed very closely in the evolution phase. The network's learning rate should be decreased gradually to values close to zero. In this way it is possible to make the solution stable and to annull the effect the order the examples are supplied in has on the final values of the weights **w**.
d) When deciding on how many inputs to supply to the network, excess should be avoided as surplus information entails needlessly long computing times or worse still could produce an erroneous interpretation of the data. For this reason a test period is indispensable in order to verify the validity and accuracy of the training phase. In the Tiber case, a series of trials were carried out on different training sets representative of different possible subdivisions of the basin into subzones (from 1 to 5) based on altimetric and geological characteristics. This following optimal set came to be defined:

$$Q_t = f(Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}, P_{tot5gg}, T_{t-1}, T_{med10gg}) \quad (1)$$

where t indicates the current day, Q the mean daily discharge, P the total daily precipitation (areal mean over the entire basin), T the mean areal

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temperature, P_{tot5gg} total rainfall (areal mean) measured between t and t-4, $T_{med10gg}$ the mean areal temperature in the period t, t-9.

e) The choice of the number of nodes in the hidden layer is fundamental for the correct use of the network. In fact, the mean square error which the network commits in the training period generally diminishes as the number of hidden nodes increases. However, it does not mean that a larger-sized network is better at learning the complex relations which regulate the different phenomena under investigation. This clearly emerges from an analysis of Fig. 2 where the RSME trend is shown for different numbers of hidden nodes: while this function tends to decrease for the training period, in the test period it presents a minimum which is then followed by a new increase.

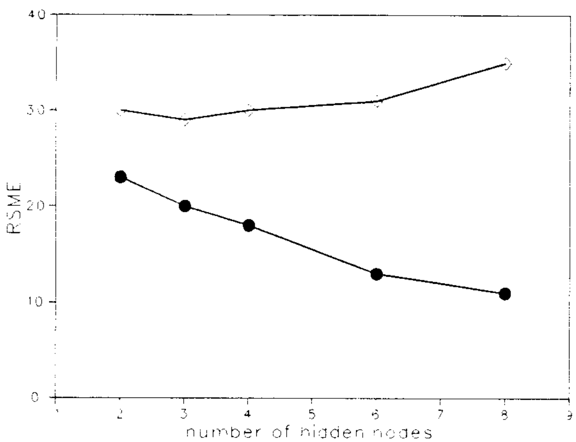

Figure 2. *RSME for different numbers of hidden nodes : ● training period, ◇ test period*

In the case under investigation the optimal number of hidden nodes is found to be threee. Once again it is important to stress that a test period is vital to ensure the network has been constructed properly. To sum up, the network to be chosen is composed of 8 input nodes, corresponding to the physical variables recorded above, and 3 hidden nodes.

5. The ARX rainfall-runoff model

The stochastic black box model implemented to compare the NN scheme is a non linear transfer function rainfall-runoff model with autoregressive component and exogenous inputs represented by the areal rainfall. Non linearity is achieved by the threshold value S based on the Antecedent Precipitation Index (API) (Linsley at al,[13]) as computed in Todini and Wallis,[14] which tries to take the soil saturation degree into account.

In the calibration phase of the model, different possible subdivisions of the basin based on the altimetric and soil characteristics were tested, as occurred with the neural networks; 1,2,3,4 and 5 zones respectively, were considered, corresponding to a number of rainfall inputs between 1 and 5. Since the performances of the different models were essentially equivalent, in terms of time-saving the model with the lowest number of parameters, the one characterized by just one rainfall input, was chosen. This choice is consistent with the one made regarding the neural network. The selected rainfall-runoff model is:

$$Q_t = \omega_1 Q_{t-1} + \omega_2 Q_{t-2} + \alpha'_1 P'_t + \alpha'_2 P'_{t-1} + \alpha''_1 P''_t + \alpha''_2 P''_{t-1} + E \qquad (2)$$

where Q = daily mean discarge (m^3/s)
P' = rainfall input if function API $\leq$ S (mm)
P'' = rainfall input if function API $>$ S (mm)
E = residual error (m^3/s)

The model parameters were calibrated with the widely documented CLS method (Erlich,[15]) imposing the positiveness of the transfer function coefficients. The final parameters, identified by trial and error on the basis of the minimum standard deviation of residuals were :

$$\omega_1 = 0.682,\ \omega_2 = -0.0281,\ \alpha'_1 = 0.6389, \alpha'_2 = 1.229, \alpha''_1 = 2.508,\ \alpha''_2 = 6.341$$

6. Comparison of the results

The performances of the three models can be compared by analyzing Fig.3 where the efficiency of the reconstruction of the discarges obtained with the various method is shown up and Tab.1 where the following statistical parameters are given for both the calibration and the validation periods:

- Number of data — ND
- Maximum error [m^3/s] — E_{max}
- Minimum error [m^3/s] — E_{min}
- Mean error [m^3/s] — E_{mean}
- Standard deviation of the Error [m^3/s] — σ_e
- Root mean square error [m^3/s] — RSME
- Determination coefficient — R^2

	Neural network		ARX model		Persistence	
	Training	Test	Training	Test	Training	Test
ND	585	365	1245	365	1245	365
E max	125.5	177.4	210	220.3	392.7	502.7
E min	-173	-234.9	-382	-399.3	-516.7	-610.6
E mean	-1.2	-4.3	-0.8	-3.2	0	0.1
σ_e	20.2	29.2	29.3	41.3	40	57.9
RSME	20.2	29.5	29.3	41.4	40	57.8
R^2	0.95	0.9	0.8	0.79	0.63	0.59

Table 1. *Comparison of the statistical performances of NN, ARX model and persistences hypothesis.*

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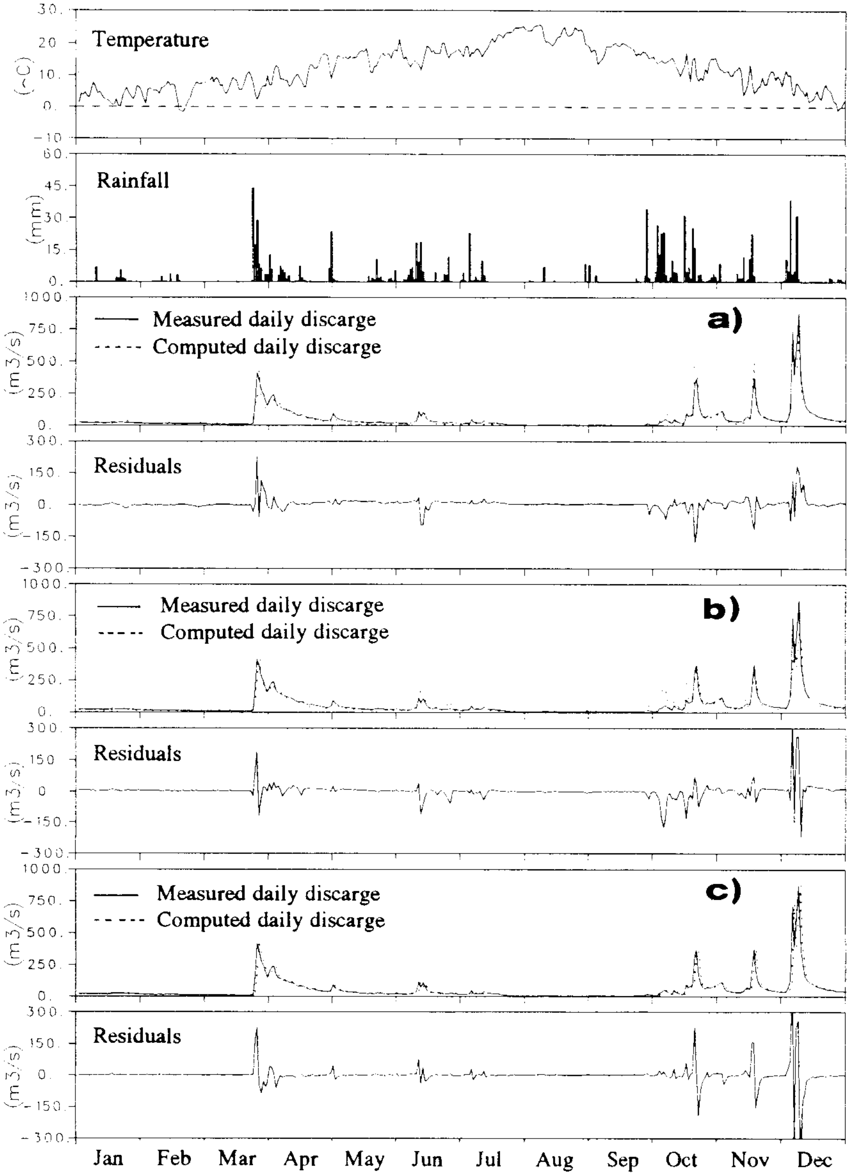

Figure 3. *One-step-ahead daily discarge forecast at Monte Molino: a) Neural network, b) ARX model, c) Persistence hypotesis*

7. Conclusions

The application of a neural network scheme for the forecast of the daily mean discharge which fills the Corbara hydroreservoir, located along the Tiber River in Central Italy, has shown that the proposed method, if properly built and trained, may provide highly accurate runoff reconstructions. The forecast is constructed on the basis of the previous discharge, the daily precipitation and the daily mean temperature; additional inputs which try to take the degree of soil saturation into account are represented by the total rainfall of the previous five days and the mean temperature over the previous ten days. Finally, the method is compared with both the simple persistence hypothesis and with an ARX rainfall-runoff model. The comparison clearly shows that the neural network is able to provide much better performances. Even if wider experience must be gained to confirm the results, this preliminary experience indicates that the neural approach may constitute an efficient alternative to the more classical rainfall-runoff modelling approaches.

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