Flood Forecasting Using Artificial Neural Networks in Black-Box and Conceptual Rainfall-Runoff Modelling

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Abstract: The paper presents a comparison of lumped runoff modelling approaches, aimed at the real-time forecasting of flood events, based on or integrating Artificial Neural Networks (ANNs). ANNs are used in two ways: (a) as black-box type runoff simulation models or (b) for the real-time improvement of the discharge forecasts issued by a conceptual-type rainfall-runoff model. As far as the coupling of ANNs with a conceptual model is concerned, feed forward neural networks are used as univariate time-series analysis techniques both for forecasting the future rainfall values to be provided as input to the hydrological model and for updating the river discharges issued by the model. A real-world case study is developed on the Sieve River basin (Central Italy) and future river flows are first predicted using artificial neural networks as black-box models, both with the only use of past flow observations and with the addition of exogenous inputs, that is previous rainfall depths. It is then applied the conceptual model and it is assessed the improvement allowed when integrating it with the ANN rainfall prediction and output updating modules. The results show that the ANN black-box model with exogenous input, when trained on a adequately representative data set, gives the best forecasting performances over the validation set. On the other hand, if the training set does not cover all the variety of events present in the validation set, for example if the major events are subtracted, the flood features were found to be better captured by the conceptual model coupled with pre and postprocessing ANN modules, thus demonstrating a greater generalisation ability of such approach.

***Keywords**: Artificial Neural Networks; Flood Forecasting; Conceptual Models; Black-Box Models*

1. INTRODUCTION

The mathematical models applied for real-time hydrological forecasting are broadly of two types: black-box and conceptual models.

Black-box, or *system-theoretic*, models are stochastically-based and empirical. They are based primarily on observations and seek to characterise system response from those data. A black-box model does not attempt in any way to represent the processes occurring within the catchment, not even in a simplified manner.

In a *conceptual* type model the internal descriptions of the various subprocesses are modelled attempting to represent, in a simplified way, the known physical processes. The input (precipitation values) is partitioned into components that are routed through the subprocesses either to the watershed outlet as streamflow or to the surface and deep storages or to the atmosphere as evapotranspiration. Even if not applying the exact differential laws of conservation, conceptual models attempt to describe large spatial and temporal scale conservation and response laws that are in accordance with the observed large-scale behaviour of water in hydrologic drainage basins.

Conceptual approaches were recognised able to improve the description of the hydrological response of a basin in comparison with black-box modelling and this generally implies a better performance in discharge forecasting (e.g. Brath and Rosso, 1993). In fact black-box models may obtain very good results in modelling events included in the calibration records but they often perform poorly in forecasting under out-of-sample conditions.

In the present work, an investigation of the real-time forecasting ability of a conceptual and of an ANN-based black-box model is presented. Both models are of the lumped type, that is, the watershed is considered as a whole, the input rainfall being the mean areal precipitation over the watershed and the output being the discharge measured at the closure section. The conceptual model is integrated with ANN operating as pre and post-processing modules that allow on one hand to forecast future rainfall values and on the other hand to exploit the measures of actual discharge up to the forecast instant.

Next section introduces the case study and the data set. Section 3 describes the black-box modelling approach, while in section 4 the conceptual rainfall-runoff model and the coupling of ANNs for improving its forecasts are exposed. Section 5 presents the features of the ANNs used in the applications. Sections 6 and 7 illustrate the results of the analysed forecasting approaches and offer the concluding remarks.

2. CASE STUDY AND DATA SET

The study catchment is the Sieve River basin, a tributary of the Arno River in Central Italy, with a drainage area of 830 km^2. The data set consists of five years (1992-1996) of hourly river discharges at the closure section of Fornacina and the spatial average of hourly rainfall depths in 12 gauges.
Given the interest in flood forecasting, the analysis of the river flow simulation was limited, both in calibration and validation phases, to the time intervals belonging to storm events. In the observation period a total of 84 storm events were identified and the corresponding precipitation and discharge observations were collected. The storm events were divided in two sets: a calibration (or *training*) set and a validation set, to test the performances of the calibrated model over out-of-sample occurrences. The calibration set (*training set 1*) contains twice the number of events of the validation set (56 versus 28 events) and the sets were chosen so as to have approximately the same proportion of major and minor events, in terms of flood peaks magnitudes. In order to investigate the influence of the calibration data on the generalisation ability of the trained networks, the ANNs were trained also on a subset (*training set 2*) of the above described set (*training set 1*), obtained setting aside the events reaching the highest flood peaks, that is the four events whose peaks are greater than 500 m^3/s.
In all the forecasting applications to be presented, in correspondence of each forecast instant, that is of each hourly step of the event, a discharge prediction is issued for the following 1 to 6 hours, based on the information available up to the forecast instant.

3. BLACK-BOX MODELLING

The most widely diffused application of ANN for flood forecasting is their use as a black-box hydrologic model, at time scales ranging from one year to one day.
Several studies have been dedicated to the prediction of river flows with no exogenous inputs, that is with the only use of past flow observations (e.g. Karunanithi et al, 1994; Atiya et al. 1999). The ANNs are used as univariate time series analysis techniques, forecasting the future discharge (output) on the basis of the last observed values (input).
But the large majority of hydrologic ANN applications consists in the prediction of future flows with exogenous input, that is, based on the knowledge of previous rainfall depths (and, rarely, other meteorological variables) along with past observed flows. The appeal of the use of ANNs as black-box rainfall-runoff models lies mainly in their capability to reproduce the highly non-linear nature of the physical phenomena dominating the rainfall-runoff transformation and encouraging results have been obtained in literature on both real and synthetic hydrologic data (among the others: Lorrai and Sechi, 1995; Campolo et al., 1999).
In a rainfall-runoff application, where the rainfall represents the exogenous input, in correspondence of each forecast instant the input consists of rainfall depths observed over a past time interval. In addition, the last observed discharges are generally included as inputs. In fact, the response time of the river depends on the state of saturation of the basin, which is a function of the rainfall history in the period preceding the flood event. If the model is not run in a continuous way, where the state of the catchment is represented by the moisture contents in the various stores, the only information available on the conditions of the basin before the current storm, and therefore on the capability of the system to respond to rainfall perturbation, is the ongoing runoff in the closing section (see Campolo et al., 1999).
In the present work, ANNs are first used without exogenous input, that is without the use of rainfall observations. Only the last measured discharges are provided as input to the networks, analysing the performance of the forecasts provided for the validation sets over the varying lead-times. It may therefore be identified the optimal number of inputs, that is the number of past discharge observations that seem to mainly influence the future occurrences. In the second type of application, the same optimal number of past discharges is given as input to the ANN, along with exogenous inputs, that is past rainfall values, thus testing a rainfall-runoff modelling approach.

4. CONCEPTUAL MODELLING

The deterministic rainfall-runoff transformation was simulated using a conceptual continuous simulation model called ADM (Franchini 1996). The catchment is assumed composed of an infinite number of elementary areas and the proportion of elementary areas that are saturated is described by a distribution function: the total surface runoff is

the spatial integral of the infinitesimal contribution deriving from the saturated elementary areas. The catchment is divided into two stores: the upper store produces surface and subsurface runoff, having as input precipitation and potential evapotranspiration, while the lower store produces base runoff. A parabolic type transfer of these components takes place first along the hillslopes towards the channel network, then along the channel network towards the basin outlet.
Even if the model is run in correspondence of the flood events, a simulation in continuous during the antecedent period is needed for updating the water contents in the stores, which in this way do not need to be subjectively initialised at the beginning of the storm. In the continuous rainfall-runoff simulation, an estimation of the potential evapotranspiration is needed: in the present case study it is based on hourly temperatures measured in 4 gauges and climatological data. Such temperature data are not used in the black-box approach, since as above said, the initial conditions of the watershed are represented by the last discharge observations.
The 11 parameters of the ADM model were calibrated for the Sieve river basin, on out-of-sample data, with the SCE-UA global optimisation algorithm (Duan et al., 1992).
Two possible ways for improving the real-time discharge forecasts issued by the conceptual model are here presented, both based on the coupling of the model with ANN-based forecasting modules.

4.1 Precipitation forecasting

The black-box model with exogenous input is calibrated on the same type of data that are provided to it when used in a real-time forecasting framework, that is rainfall and discharge values measured up to the forecast instant. In this way, the black-box model may, as long as it transforms the past rainfall in future discharge, somehow compensate for uncertainty sources in the input, first of all the ignorance of future rainfall occurrences. This is particularly easy for ANN models, which are extremely flexible and do not need any a priori identification of the input/output relationship. On the contrary, the conceptual approach, which is deterministic, assumes the knowledge of the future rainfall because it was parameterised on the basis of historical rainfall and runoff contemporary series, thus assuming the knowledge of actual rainfall values.
Being, in a real flood forecasting framework, the future rainfall unknown, the hydrological forecasts of the conceptual model must be based on a prediction of future rainfall, that is performed by an ANN having as input past rainfall observations and as output future rainfall values.

4.2 Discharge Updating

Any rainfall-runoff model discharge forecast, independently of the chosen modelling scheme, is only an approximation of reality, subject to different sources of error. In addition to input uncertainty, the forecasts are subject to uncertainties in both the model structure and in the parameters values.
Such uncertainty results in biased discharge forecasts, as shown by the difference between the simulated hydrograph and the hydrograph that is actually measured up to the time of forecast.
Black models, as above said, take into account the precious information coming from the real-time measurement of the actual discharge preceding the forecast instant. On the contrary, conceptual hydrologic models are generally formulated in a deterministic way, assuming that the input is sufficient to describe the evolution of the system and the measurements of the output (recent river flows) are considered redundant information.
For a more accurate real-time forecasting, it is instead extremely useful to exploit up-to-date observed system outputs in order to minimise the acknowledged errors due to model inadequacies. It was here chosen to update the output of the conceptual model with a postprocessing module, without the need to alter in any way the structure and implementation of the model. The correction consists in the addition to the modelled discharge of a prediction of the future error. Past discharge errors, as soon as they are measured by the tele-metering network, are processed by an ANN that issues predictions of the future errors, to be added to the discharge forecasts of the conceptual model.

5. ARTIFICIAL NEURAL NETWORKS

Neural networks distribute computations to processing units called neurons, grouped in layers and densely interconnected. Three different layer types can be distinguished: an *input layer*, connecting the input information to the network (and not carrying out any computation), one or more *hidden layers*, acting as intermediate computational layers, and an *output layer*, producing the final output. In correspondence of a computational node, each one of the entering values is multiplied by a connection *weight*. Such products are then all summed with a neuron-specific parameter, called *bias*, used to scale the sum of products into a useful range. The computational node finally applies an activation function to the above sum producing the node output. Weights and biases are determined by means of a non-linear optimisation procedure (*training*) that aims at minimising a learning function expressing a closeness between observations and ANN outputs, in the present case the mean squared error. A set of observed input and output (called a *target* to be distinguished from the network final output) data pairs, the training data set, is processed repeatedly, changing the parameters until they converge to values such that each input vector produces outputs as close as possible to the desired target vectors.

The following network characteristics were chosen for all the ANN applications described in the following:

- Architecture: multi-layer feedforward networks formed by only one hidden layer;
- Training algorithm: the quasi-Newton Levenberg-Marquardt BackPropagation algorithm (Hagan and Menhaj, 1994); the ANNS are trained starting from 10 different initial networks, randomly initialised, of which the best performing on training data is chosen as the *trained network;*
- The training did not consider an *early stopping* approach and only the training set was used for determining weights and biases;
- Activation functions: a tan-sigmoidal unit was chosen for the hidden layer:

$$f(x) = \frac{2}{(1+e^{-2x})} - 1, \quad (1)$$

where x is the input to the node, that is the weighted sum of the outputs from previous nodes and the bias of the node, and *f(x)* is the node output. A linear transfer function was instead chosen for the output layer: it was, in fact, preferred to choose an output activation function suited to the original distribution of targets, that in the present case are unbounded, rather than to force the data, with a standardisation or rescaling procedure, to conform to the output activation function;

- Multistep ahead prediction scheme*: direct multioutput* method, each output node representing one time step to be forecasted, so that the forecasts for all the lead-times are issued simultaneously.

The multioutput prediction scheme sets the number of the output nodes equal to the number of the lead-times of the prediction, in the present case equal to 6, having chosen to issue a prediction in correspondence of all the 6 hourly time steps following the forecast instant.

As far as the number of input and hidden nodes is concerned, the investigation of the performances of several combination of input and hidden layers dimensions will be described in the following sections.

6. ANALYSIS OF RESULTS

6.1 Black-box modelling results

Networks with a varying number of input and hidden nodes were first trained over *training set 1.* Their forecasting ability on the validation events was assessed through the mean of their *Efficiency coefficients, E_L,* over the six lead times,

$$mean(E_L) = mean\left[1 - \frac{\sum (Q_{o,t+L} - Q_{f,t+L})^2}{\sum (Q_{o,t+L} - Q_{o,mean})^2}\right], \quad (2)$$

where $Q_{f,t+L}$ is the discharge forecast for lead-time L issued in the forecast instant t, $Q_{o,t+L}$ is the value of the corresponding observed discharge and $Q_{o,mean}$ is the mean of the observed discharges. The summations are extended to all the issued forecasts, that is, to all the forecasts instants t belonging to all the validation events.

a) Without exogenous input									
			Lead-time (h)						
NI Discharge	*NI Rainfall*	*NH*	*1*	*2*	*3*	*4*	*5*	*6*	*Mean E_L*
2		6	0.982	0.932	0.857	0.774	0.693	0.615	0.809
4		**4**	**0.978**	**0.934**	**0.864**	**0.783**	**0.702**	**0.622**	**0.814**
6		9	0.976	0.932	0.861	0.778	0.695	0.615	0.810
8		6	0.976	0.933	0.862	0.779	0.696	0.616	0.810
10		6	0.976	0.930	0.859	0.779	0.697	0.618	0.810
12		4	0.973	0.929	0.857	0.773	0.690	0.610	0.805
15		2	0.957	0.908	0.831	0.742	0.656	0.576	0.778
b) With exogenous input									
4	2	6	0.985	0.956	0.920	0.883	0.838	0.779	0.893
4	**4**	**4**	**0.986**	**0.958**	**0.929**	**0.894**	**0.847**	**0.785**	**0.900**
4	6	9	0.985	0.960	0.931	0.894	0.843	0.779	0.899
4	8	6	0.986	0.962	0.934	0.898	0.842	0.773	0.899
4	10	6	0.984	0.959	0.930	0.889	0.831	0.765	0.893
4	12	4	0.985	0.956	0.921	0.878	0.824	0.761	0.887
4	15	2	0.938	0.949	0.925	0.876	0.811	0.738	0.873

Table 1. Efficiency coefficients of the validation forecasts issued by the black-box ANNs with varying numbers of input nodes. For each number of input nodes (*NI*) , only the networks with the number of hidden nodes allowing the highest efficiency are illustrated.

6.1.1 Without exogenous input

The ANNs with no exogenous input are fed only by past discharge values. Each past hourly value preceding the forecast instant corresponds to an input node. The number of such input nodes was varied from 2 to 18, with a number of nodes in the hidden layer, *NH*, ranging from 2 to 24. Table 1a shows that the highest efficiencies for the validation forecasts is obtained with 4 past discharge values (and 4 hidden nodes).

6.1.2 With exogenous input

The results on the networks with no exogenous input may be used to infer the number of past discharges that have more influence on the future values. The number of past discharge values to be given as input to the networks with exogenous input is thus set equal to 4. In addition, a varying number of past rainfall values (from 2 to 15) is also provided as input, again with *NH* ranging from 2 to 24. The best performance is provided by the network having as input 4 past discharge and 4 past rainfall values and with 4 nodes in the hidden layer. As shown in Table 1b, the improvement allowed by the addition of rainfall values is remarkable, especially for the longest lead-times.

6.2 Conceptual modelling results

As a standard of reference, the conceptual model was first applied without pre or post-processing modules. As a forecasting benchmark, the rainfall following the forecast instant was assumed to be persistent, that is equal to the last observed value for all the six hourly lead-times (*Conceptual A*).
ANN-based rainfall forecasting and discharge updating were first implemented separately.
An ANN module was trained for forecasting future rainfall depths on the basis of the last rainfall values. Rainfall forecasts for lead-times from 1 to 6 hours were issued in correspondence of each hourly time step belonging to all the events in the validation set. The performances of networks with varying number of input (from 2 to 24) and hidden (from 2 to 8) nodes were investigated and classified according to the RMSE (Root Mean Squared Error) of the hourly rainfall forecasts cumulated over the 6 steps ahead as compared to the 6-h cumulated observed rainfall depths. It was thus allowed to identify as the best performing networks for rainfall forecasting those with 12 to 18 input nodes and a small (2 to 4) number of hidden nodes. The predicted rainfall values were then provided to the conceptual model instead of the persistent rainfall values (*Conceptual B*), allowing an improvement (see Table 2a).

As far as the updating technique is concerned, the discharges issued by the conceptual rainfall-runoff model are corrected with the addition of an error value predicted by another univariate ANN, having as input past error values, up to the forecast instant. Networks with a number of input (past errors) ranging from 2 to 24 hours and a number of hidden nodes, *NH*, ranging from 2 to 8 were tested. In a first phase, in order to set apart the influence of input uncertainty, the future rainfall values were assumed to be known, that is the rainfall-runoff model was fed with actually observed future rainfall values. The networks with a medium input layer dimension (between 4 and 12) and a small number of hidden nodes allowed obtaining the highest mean coefficients of efficiency of the updated discharges over the six lead-times. The differences in the mean efficiencies of such networks were modest (around 0.1%), therefore the most parsimonious network was preferred and the ANN with 4 input nodes and 2 hidden nodes was chosen as the optimal configuration.
Following the separate implementation of rainfall forecasting and discharge updating techniques, an integrated flood warning approach was implemented, operating with both the input prediction and the output correction modules.
The second ANN (the one used for discharge updating) was thus re-calibrated on the simulation errors resulting when using as rainfall input to the hydrologic model, along with past observed values, the rainfall predictions issued by the first ANN.

	Mean Efficiency	*Mean Volume Error(%)*	*Mean Peak Error(%)*
	a) Training set 1		
Black-box	0.814	18.8	60.5
Black-box X	0.900	9.3	24.4
Conceptual A	0.781	36.6	56.3
Conceptual B	0.804	34.6	37.2
Conceptual C	0.883	13.1	25.7
	b) Training set 2		
Black-box	0.779	20.1	59.9
Black-box X	0.827	19.0	42.2
Conceptual B	0.805	31.1	43.4
Conceptual C	0.870	18.1	33.3

Table 2. Mean over the six lead-times of Efficiency, Volume error and Peak error of the forecasts of validation events for: black-box ANN without and with (X) exogenous input, conceptual model with persistent rainfall and no updating (*Conceptual A*), with ANN-based rainfall and no updating (*Conceptual B*) and with ANN-based rainfall and updating (*Conceptual C*).

Table 2a highlights the improvements of the performances of the fully integrated approach (*Conceptual C*) in comparison with those obtained when no discharge updating is performed and future rainfall is A) assumed to be persistent, B) predicted with the ANN module. Along with the mean over the six lead-times of the efficiency coefficients, Table 2 shows the average of the flow peak and volume percentage errors corresponding to each flood event in the validation set.

The comparison of the goodness-of-fit criteria of the black-box modelling with exogenous input (*Black-box X*) and of the conceptual model integrated with both rainfall and discharge error ANN predictions (*Conceptual C*) shows (Table 2a) better performances of the *Black-box X* modelling with respect to all the characteristics of the forecasted hydrograph: overall agreement (efficiency), volume and, to a less extent, flood peak.

6.3 Results with the reduced training set

The ANN-based models described in sections 6.1 (black box without and with, *X*, exogenous input), and 6.2 (conceptual model with ANN rainfall forecasting only, *B*, and with output updating as well, *C*) were successively trained over the reduced training set (*training set 2*), obtained abstracting the four events overpassing a flood peak of 500 m^3/s (peaks ranging from 535 to 715 m^3/s). The new trained networks were used for forecasting the events of the same validation set, which includes other four events with peaks between 514 and 725 m^3/s. The performances of the forecasts are summarised in Table 2b, and show how, on the reduced training set, the conceptual model with ANN pre and postprocessing modules is preferable to both black-box models.

7. CONCLUSIONS

The black-box application confirms the importance of the addition of the exogenous input. This appears to be more remarkable for increasing lead-times, as could be expected given the stronger influence of rainfall. The best performing networks have moderate hidden layers dimensions and are relatively parsimonious. In fact the analysis of the forecasts with varying number of input nodes indicates as most influencing the past four hourly values of observed flow and the past four values of rainfall.

As far as the conceptual model is concerned, the gain allowed by the introduction of ANN-based rainfall forecasts is sensible, but not as remarkable as the one given by the addition of the discharge updating, as it may be seen considering the differences in the goodness-of fit criteria between *Conceptual B* and *A* and between *Conceptual C* and *B* (Table 2a).

When comparing the forecasts of the black-box model with exogenous input with those of the conceptual model coupled with pre and postprocessing ANN modules, that is the best performing models within each modelling group, a difference is evidenced when training on the entire data set and when setting aside the major events. It seems in fact that if the ANN black-box model is trained on a adequately representative data set with respect to the events forming the validation set (*training set 1*), it outperforms the conceptual approach. On the other hand, if the training set does not cover all the variety of events present in the validation set (*training set 2*), the flood features are better captured by the conceptual modelling, thus demonstrating a greater flexibility and adaptability of such approach to out-of-sample forecasting. This conclusion may provide useful indications for the choice of the modelling approach in the operational implementation of real-time flood warning systems.

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