River flood forecasting with a neural network model

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Abstract. A neural network model was developed to analyze and forecast the behavior of the river Tagliamento, in Italy, during heavy rain periods. The model makes use of distributed rainfall information coming from several rain gauges in the mountain district and predicts the water level of the river at the section closing the mountain district. The water level at the closing section in the hours preceding the event was used to characterize the behavior of the river system subject to the rainfall perturbation. Model predictions are very accurate (i.e., mean square error is less than 4%) when the model is used with a 1-hour time horizon. Increasing the time horizon, thus making the model suitable for flood forecasting, decreases the accuracy of the model. A limiting time horizon is found corresponding to the minimum time lag between the water level at the closing section and the rainfall, which is characteristic of each flooding event and depends on the rainfall and on the state of saturation of the basin. Performance of the model remains satisfactory up to 5 hours. A model of this type using just rainfall and water level information does not appear to be capable of predicting beyond this time limit.

1. Introduction

Forecasting river flow after heavy rain is important for public safety, environmental issues, and water management. For these purposes, mathematical models have been developed based either on physical considerations [e.g., Garrote and Bras, 1995; Refsgaard and Knudsen, 1996; Todini, 1996; Buchete et al., 1996] or on a statistical analysis [see Hsu et al., 1995; Mukherjee and Mansour, 1996; Raman and Sunilkumar, 1995]. Both approaches are difficult, and the type of forecast they provide is not completely satisfactory. During heavy rain periods, some of the terms of the hydrological balance (evaporation, infiltration, and storage variation) can be neglected since they give no relevant contribution to the river flow rate in the short period. In contrast, accurate information on rainfall and on the state of the basin must be available. The rainfall gives a measure of the amount of water gathered by the basin and represents the perturbation experienced by the river system. The state of the basin, which is correlated, albeit indirectly, to the flow rate or, alternatively, to the water level, represents the capability of the river system to respond to rainfall perturbation. However, even in these simplified conditions, the usual approaches prove to be inefficient or too burdensome [Woolhiser, 1996]. In this paper we develop a fairly simple neural network model to predict the flow rate in a river during heavy rain periods.

In the hydrological context, as in many other fields, artificial neural networks (ANN) are increasingly used as black-box, simplified models [Bishop, 1994]. For hydrological applications, ANN models can take advantage of their capability to reproduce the unknown relationship existing between a set of input variables descriptive of the system, for example, rainfall, and a set of output variables, for example, river flow rate [Chakraborty et al., 1992].

Previous work has demonstrated that ANNs are adequate to model the rainfall-runoff process [Zhu et al., 1994; Minns and Hall, 1996; Shamseldin, 1997]. A comparison between ANN models and traditional models has been made by Hsu et al. [1995], who concluded that the ANN approach is more effective and more efficient whenever explicit knowledge of the hydrological subprocess is not required and when the object is to predict streamflow behavior from customary monitored time series of rainfall and flow rate.

Most of the previous work considered rainfall data averaged over the basin scale; this has the advantage of reducing the number of input variables but does not allow identification of the contribution of runoff routed from different subbasins. Recently, Shah et al. [1996] and Smith and Eli [1995] established the importance of considering the effect of spatially distributed rainfall. However, they used synthetic, stochastically generated rainfall patterns and runoff data.

In the present work we use an ANN to predict the occurrence of floods from available distributed rainfall and hydrometry data collected in the basin of the river Tagliamento, in Italy. The geography of the basin, which features various subbasins contributing to the main flow in different circumstances, is such that distributed rainfall information is required to obtain accurate streamflow prediction [Shah et al., 1996].

2. Database

The data used in this work refer to the river Tagliamento, in Friuli, Italy, shown in Figure 1. The basin of the river (overall area is about 2480 km²) includes various subbasins, and the monitoring system consists of a network of rain gauges and a series of hydrometers. A subset of rain gauges (located at Paularo, Ampezzo, Pesariis, Resia, and Moggio) and one hydromter (located at Venzone) were used in this work.

A database of 20 different flooding events was selected from available historical records relative to the last 20 years. These events represent periods in which variation of the water level
The earthquake, which caused the site to be evacuated, occurred at 12:15 PM local time. Aftershocks were felt for several days afterwards. The tremors were so strong that the instruments on the site were able to detect them. The epicenter of the earthquake was located about 10 miles from the site.

The damage caused by the earthquake was significant. The buildings on the site were severely damaged, and many of the instruments had to be repaired. The tremors were so strong that the site was evacuated for several days. The aftershocks continued for several days after the main event. The earthquake was felt throughout the region and was reported on television and radio stations.

The data collected during the earthquake were important for understanding the effects of seismic activity on the site. The data were analyzed to determine the magnitude of the earthquake and the epicenter. The data were also used to assess the effects of the earthquake on the instruments on the site. The data were used to improve the models used to predict future earthquakes.

Table 1: Results of Correlation Analysis, Expressions in Terms of Rain Gauge Data

<table>
<thead>
<tr>
<th>Rain Gauge Sites</th>
<th>Mean Rainfall (in)</th>
<th>Maximum Rainfall (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.2</td>
<td>1.5</td>
</tr>
<tr>
<td>2</td>
<td>1.0</td>
<td>1.2</td>
</tr>
<tr>
<td>3</td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>4</td>
<td>0.6</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>0.4</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Figure 1: Map of the Rainfall Monitoring Stations

The map shows the locations of the rain gauge stations on the site. The stations were evenly spaced throughout the site to ensure that the data collected were representative of the entire site. The data collected from the stations were used to calculate the average rainfall for the site.

Conclusion

The earthquake caused significant damage to the site. The data collected during the earthquake were important for understanding the effects of seismic activity on the site. The data were used to improve the models used to predict future earthquakes.
\[
x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (0.9 - 0.1).
\]

3. Methodology

3.1. Neural Network Based Model

The model is based on a feed-forward neural net, with logistic activation function. The net is feed-forward in the sense that propagation of the signal is unidirectional, without feedback cycles between nodes. Input information coming into the model through special, nonprocessing input nodes is fed to a number of inner, hidden nodes. Hidden nodes perform a two-fold function: First, they compute a signal \( z_i \) from all incoming information using the following relation:

\[
z_i = \sum w_{i,j} x_j - \sigma_j
\]

where \( w_{i,j} \) is the weight associated with the connection from node \( i \), the input node, and node \( j \); \( x_j \) is the input variable value; and \( \sigma_j \) is a threshold value, which is different for each node. Second, they transform this signal using a nonlinear activation function \( f \). In this work, \( f \) is the logistic or sigmoid function and has the following form:

\[
f(z_i) = \frac{1}{1 + \exp(-z_i)}, \quad f(z_i) \in [0:1].
\]

The outgoing signal is then fed to the subsequent layer of nodes (this may be a hidden layer or an output layer, depending on the problem complexity) and transformed in the same way as described by (2) and (3).

The transformation of the input variables array, \( I \), into the corresponding output variables array, \( O \), can be expressed synthetically as

\[
\bar{O}_e = F(\bar{I}, \bar{W}, \bar{\sigma}, N, f).
\]

The adjustable parameters of the model are weights \( \bar{W} \), thresholds \( \bar{\sigma} \), and number of hidden nodes \( N \) for each hidden layer eventually present.

3.2. Calibration of the Model

Implementation and calibration of the neural model were realized using the software Stuttgart Neural Network Simulator (SNNS), developed by the University of Stuttgart and available as free software from the Internet. The calibration of the model, also called training, is performed by minimizing the function \( E(\bar{W}) \), representing the square of the error of the model with regard to real data, using the back propagation error algorithm to correct the weights [see Bishop, 1994; Haykin, 1995]. The error of the model is computed on all the calibration data at a time (batch training). In brief, variation of the weight \( w_{i,j} \) from node \( i \) to node \( j \) is calculated as

\[
\Delta w_{i,j} = -\eta \frac{\partial E}{\partial w_{i,j}},
\]

where \( \eta \) is the learning rate. Correction of the value of the weights corresponds to moving along the error surface \( E(\bar{W}) \) toward the local minimum following the direction of the steepest gradient.

In this work a decreasing learning rate (from 0.5 to 0.01) was used to accelerate convergence toward a global minimum. For each model the training procedure was repeated starting from independent initial conditions in order to select the best performing of the trained nets. The trend of \( E(\bar{W}) \) calculated using data from the training and testing sets was used to determine when learning was optimal. Training was stopped when no more sensible improvement in performance was found, i.e., the variation of \( E(\bar{W}) \) was negligible with proceeding of time, or when overtraining started, i.e., \( E(\bar{W}) \) calculated on the testing set started rising even if \( E(\bar{W}) \) calculated on the training was still decreasing [Bishop, 1994; Haykin, 1995].

4. Results and Discussion

4.1. Input Data and Structure of the Model

In this work we developed two models to predict the water level of the river at short times (1 hour in advance) and at longer times (up to 10 hours). Input data differ depending on the prediction to be made. For short-range prediction at time \( T \) we used (1) the water level at times \( T - 1, T - 2, T - 3, \) and \( T - 4 \); and (2) the rainfall at times \( T - \Delta_i, T - \Delta_i + 1, T - \Delta_i + 2, \) and \( T - \Delta_i + 3 \), where \( \Delta_i \) is the mean time lag of each rain gauge. The temporal trend of precipitation is used as input to better characterize the response of the basin, since cumulated rainfall and rate of variation of intensity are important as well as the intensity itself [Mason et al., 1996]. The temporal trend of the water level is important since it determines the response of the basin to rainfall perturbation. For prediction at longer times, from time \( T \) to time \( T + 9 \), we used (1) the water level from time \( T - 1 \) to time \( T - 5 \); and (2) the rainfall depths recorded by the rain gauges from time \( T - 15 \) to time \( T - 1 \). This time interval includes the mean time lag of each rain gauge and has been extended up to present time since prediction of the water level of future time intervals also requires rainfall information about the recent past.

On the basis of the structure identified for the input-output transformation, patterns, i.e., related couples of input-output data, have been generated from each data set. For the short-term prediction model the numbers of patterns generated were 1113, 333, and 591 from the training, testing, and validation data sets, respectively. For the long-term prediction model the numbers of patterns generated were 969, 268, and 503 from the training, testing, and validation data sets, respectively. These numbers are smaller than those of the short-term prediction model because the time string required in input was longer. Generated patterns describe the input-output transformation during the rising limb and the falling limb of the flood, with consecutive patterns representing a shift in time of the input and output temporal windows.

The selection of the final structure for the models, i.e., the number of hidden nodes, was a trial-and-error procedure. Starting from an oversized hidden layer of 15 nodes, neural network models were trained until a minimum for \( E(\bar{W}) \) for the particular configuration was obtained. A different error function \( E(\bar{W}) \) was used for short- and long-term prediction. For short-term prediction, \( E(\bar{W}) \) was calculated on a single output node, and minimizing \( E(\bar{W}) \) was equivalent to minimizing the error on the water level predicted 1 hour in advance. For long-term prediction, \( E(\bar{W}) \) was calculated over 10 output nodes, thus representing the error in prediction over the entire time horizon. Once the minimum for \( E(\bar{W}) \) was found, the number of hidden nodes was progressively decreased and the training repeated. The process continued until
Figure 3. Comparison of measured and computed water level.

For more from validation sec. Water level is normalized.

As shown in Figure 2, the model predictions are also compared to the measured data. The relatively small differences between the predicted and measured water levels suggest that the model is performing well. The root mean square error (RMSE) and the coefficient of determination (R²) are used to quantify the performance of the model. The RMSE is calculated as:

\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \]

where \( y_i \) and \( \hat{y}_i \) are the measured and predicted water levels, respectively.

The coefficient of determination (R²) is given by:

\[ R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \]

where \( SS_{res} \) and \( SS_{tot} \) are the sum of squares of residuals and total sum of squares, respectively.

Table 2. Error Standards Used to Evaluate Model

<table>
<thead>
<tr>
<th></th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.85</td>
<td>0.84</td>
</tr>
<tr>
<td>R²</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>( \frac{\text{mean error}}{\text{mean value}} )</td>
<td>0.10 x 10^{-1}</td>
<td>0.10 x 10^{-1}</td>
</tr>
<tr>
<td>( \frac{\text{max error}}{\text{max value}} )</td>
<td>1.01 x 10^{-1}</td>
<td>1.01 x 10^{-1}</td>
</tr>
<tr>
<td>( \frac{\text{min error}}{\text{min value}} )</td>
<td>1.01 x 10^{-1}</td>
<td>1.01 x 10^{-1}</td>
</tr>
</tbody>
</table>

The model performance is deemed satisfactory if both RMSE and R² values fall within acceptable ranges.
also reported for each time step, and no preferential distribution of the error can be noted with respect to the value of the water level. An important characteristic of level behavior is the peak height. The error in the prediction of peak height, defined as the absolute difference between the observed and computed water level over the observed water level at the peak, can be used to evaluate the reliability of the model in forecasting floods. The peak error percent on predicted peaks is less than 10% on the validation data.

Results obtained with this model proved that information given as input is sufficient to capture the transformation. However, if our target is to predict the water level at time $T$, supplying the experimental value of the level at time $T - 1$ is too stringent a requirement for the model and makes it impractical to use for flood risk warning. As previously described, the model uses water level at times $T - 1, T - 2, T - 3$, and $T - 4$. In order to assess the importance of the level information, we examined the performance of the model in the cases in which (1) no water level data are supplied, (2) water level at $T - 4$ only is supplied, and (3) water level at $T - 4$, $T - 3$, and $T - 2$ is supplied. The results of this analysis are presented in Figure 4 relative to data from calibration and validation sets. Consider first Figure 4a, in which the model makes use only of rainfall information; results are extremely poor. In this condition it is impossible for the neural model to give good results because input-output mapping is not single-valued. Since the network is trained by exploiting data corresponding to the rising and falling limbs of the flood, during the rising limb the input information represented by zero rainfall should be mapped into a varying water level. This cannot be learned by the model, which associates to this input an output value most frequently found in the data set in the given conditions (about 0.22 normalized units for the water level). This is clearly visible in Figure 4a, where the flat distribution of points represents water level at time intervals in which the same value is calculated even if different values were measured. In Figures 4b and 4c the accuracy of the prediction increases, but results are not as satisfactory as those in Figure 2. This means that information about the capability of the basin to respond to a rainfall perturbation is more accurate when recent water level values are used.

4.3. Forecasting at Longer Times

In order to forecast the water level at longer times, from time $T$ up to time $T + 9$, the parameters of the model introduced in section 4.1 were optimized again. The water level at the closing section measured at time $T$ depends on the rainfall that occurred a few hours before in the mountain. The time required for the rain pulse to induce a change in the water level at the closing section was calculated with the correlation analysis, the results of which are presented in Table 1. The results are averaged over each single event history and over all events. 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 days or weeks preceding the flooding event. In a model of the type developed in this work, the only information available on the state of the basin before the heavy rain period is the water level at the closing section. This information is not sufficient to characterize the initial conditions of the basin and explains why water level forecasts for longer times become inaccurate.

In Figures 5a and 5b the trends of RMSE and $R^2$ are presented versus the prediction time horizon $\Delta T_p$. As was expected, RMSE increases with $\Delta T_p$, whereas $R^2$ decreases with $\Delta T_p$. In particular, in Figure 5a the increase in RMSE is almost linear as the prediction time horizon increases, and a slight difference in the average rise rate of RMSE for calibration and validation is found. From comparison of the results obtained during calibration and validation, it can be observed that the rate of variation of $R^2$ (Figure 5b) increases slightly at 5 hours, i.e., the minimum time lag from the correlation analysis, for the validation set. Displacement between the two $R^2$ curves increases as the prediction time horizon becomes greater than 5 hours. This confirms previous considerations about the relation between the time horizon of prediction and information available for prediction (section 4.2). However, if we consider a prediction of water level 5 hours in advance to be satisfactory, we have a model efficiency of about 85%, which is more than adequate for this type of problem [see Shamseldin, 1997], and a root mean square error of about 0.04, which corresponds to 28 cm.

Results obtained in predicting the water level 1 hour in advance using the short-term or the long-term prediction models are different. This can be expected, since different evaluation criteria are used to decide when learning is optimal. For short-term prediction, minimizing $E(\hat{W})$ is equivalent to minimizing the error in the water level predicted 1 hour in advance. For long-term prediction, minimizing $E(\hat{W})$ is equiva-
5. Conclusions

This paper addresses the problem of forecasting the river flow rate for the basis of rainfall. The objective of the study was to improve the predictive capability of the model, thereby reducing the error in predicting the river flow rate for the basis of rainfall.

Figure 6: Time series trend of measured and computed water levels; real data, model prediction 1, 3, and 5 hours in advance, and error on 3 hours forward prediction.
basis of rainfall information and previous water level with a sufficient lead time in order to reduce the consequences of floods. The model is based on an artificial neural network and has the advantages of low cost and simplicity with respect to complex physically based models. The database on which the model was assessed comprised field data collected on the river Tagliamento, in northern Italy. To obtain a precise characterization of the floods, we used the rainfall information distributed over the basin, i.e., not averaged information. This introduces significant changes with respect to previous flood forecasting models [Hsu et al., 1995; Bertoni et al., 1992].

Predictions of the model for 1-hour forecasting are accurate, with a minimal error of the order of 4%. When trying to use the model to forecast water level with a longer time horizon, performance decreased rapidly. The main reason for this depends on the physical response time of the river basin to rainfall. In our model, rainfall is used as input and the river level is used to characterize the capability of the model to respond to rainfall. The water level at the closing section starts to respond to rainfall after a certain time lag characteristic of each rain gauge, i.e., distance, of the conditions of the basin and of the type of rainfall. The way in which the river responds to the rainfall depends first on the perturbation and then on the state of saturation of the basin. The information on the level at the closing section seems to be able to represent the state of the basin only after river flow rate started to be affected by the rainfall event under consideration.

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References

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