Integration of neural networks in a geographical information system for the monitoring of a catchment area

Frédérik Thiéry, Stéphane Grieu, Adama Traoré, Mathieu Barreau, Monique Polit

INTEGRATION OF NEURAL NETWORKS IN A GEOGRAPHICAL INFORMATION SYSTEM FOR THE MONITORING OF A CATCHMENT AREA

Frédérik Thiery, Stéphane Grieu[1], Adama Traoré, Mathieu Barreau, Monique Polit

Laboratoire de Physique Appliquée et d'Automatique, Université de Perpignan, 52 avenue Paul Alduy, 66860, Perpignan, France.

Abstract

The present work takes part in a global development of reliable and robust tools allowing real-time controlling and supervising of the Têt catchment area, the main river of the Pyrénées-Orientales department (Southern France). The impact of the Têt on the department life is significant and the management of its water quality must be largely improved and better supervised.

The main purpose of the work was to develop "rain flow" predictive models, using Elman recurrent neural networks and based on the identification of localized rain events. These neural models allow understanding the dynamic evolution, according to rain events, of the Têt flow at a selected point and of the Perpignan WWTP (WasteWater Treatment Plant) influent flow. Their most interesting characteristic is their capability to predict big increases in river flow and in plant influent flow.

The neural models have been integrated as thematic layers in a Geographical Information System (G.I.S.) allowing an efficient management and update of the records used to develop the models.

Keywords: Elman neural network; "rain flow" predictive model; monitoring; Geographical Information System.

1. Introduction

For many years, hydraulic resources management, wastewater treatment plants efficiency improvement and natural environment protection are major concerns. Indeed, a bad management of water resources, as well qualitative as quantitative, or a plant malfunction can have an extremely negative impact on both environment (fauna and flora) and health fields.

The present work takes part in a global development and evaluation of reliable and robust tools allowing real-time controlling and supervising of the Têt River catchment area. The main river of the Pyrénées-Orientales department (south of France, main city: Perpignan) has a significant impact on the life of the department and the management of its water quality must be largely improved and better monitored [8].

As much of other Mediterranean coastal rivers, the hydrological system of the Têt River presents periods of low water level, intercepted by violent and devastating short rising period, essentially due to rain. This kind of contrasted systems needs to be better understood. These flash-risings highly contribute to the sea pollution level and are very difficult to follow by means of both classical sampling strategies and reliable mathematical models [12].

The main purpose of the presented work was to develop "rain flow" predictive models, using Elman recurrent neural networks and based on the identification of localized rain events. These neural models allow understanding the dynamic evolution, according to rain events, of the Têt flow at a selected point (Perpignan Pont-Joffre) and of the Perpignan WWTP (WasteWater Treatment Plant) influent flow. Their most interesting characteristic is their capability to predict big increases in river flow and in plant influent flow. With these tools, it's possible to both highlight river floods and adapt the plant operation and its capability to treat all the incoming water.

These "rain flow" predictive models have been integrated as thematic layers in a Geographical Information System (G.I.S.) allowing an efficient management of the records used during the development phase. It also allows updating the data base according to new measurements and/or predictions [1, 13].

[1] Corresponding author, grieu@univ-perp.fr, Tel. 33 4 68 66 22 40; Fax 33 4 68 66 22 87

2. The Têt River catchment area

A catchment area, or drainage basin, is an area drained by a stream or other body of water. The limits of a given catchment area are the heights of land (often called drainage divides, or watersheds) separating it from neighboring drainage systems. The amount of water reaching the river, reservoir, or lake from its catchment area depends on the size of the area, the amount of precipitation, and the loss through evaporation (determined by temperature, winds, and other factors and varying with the season) and through absorption by the earth or by vegetation; absorption is greater when the soil or rock is permeable than when it is impermeable. A permeable layer over an impermeable layer may act as a natural reservoir, supplying the river or lake in very dry seasons. The catchment area is one of the primary considerations in the planning of a reservoir for water-supply purposes.

The Têt river which originates from the Carlit Mountain, is the main coastal river located in the eastern part of the Pyrenees, tributary of the Mediterranean Sea. It extends on 120 km and covers a catchment area of 1380 km². It presents a lengthened form, of east-west orientation. Two quite distinct parts can be considered for this catchment area:

- Its upstream part: the starting point of the Têt is the "Pique Rouge" and water is running until the Vinça dam. Average altitude is about 1026 m and average slope is about 22.6°.
- Its downstream part: from the city of Vinça to the Mediterranean Sea. The river joins the sea close to city of Canet-en-Roussillon. Average altitude is about 280 m and average slope is about 8.9°.

The Têt river has many tributaries. Some of them have an important flow contribution during rain phenomena. It is important to distinguish the river right bank from the left one. The right bank tributaries drain 548 km² and the left bank tributaries drain 304 km². Their impact on the river flow is not equivalent, also because of their orientation. So, the river left bank presents lowest water level because of its lowest slope than the right one, bringing a less abundant tribute to the Têt course. For these mentioned reasons, and to clear the water network, small tributaries were neglected on Figure 1. These small tributaries have a weak influence primarily during rising periods. Tributaries with a weak quantitative impact but with an important qualitative influence were kept [8].

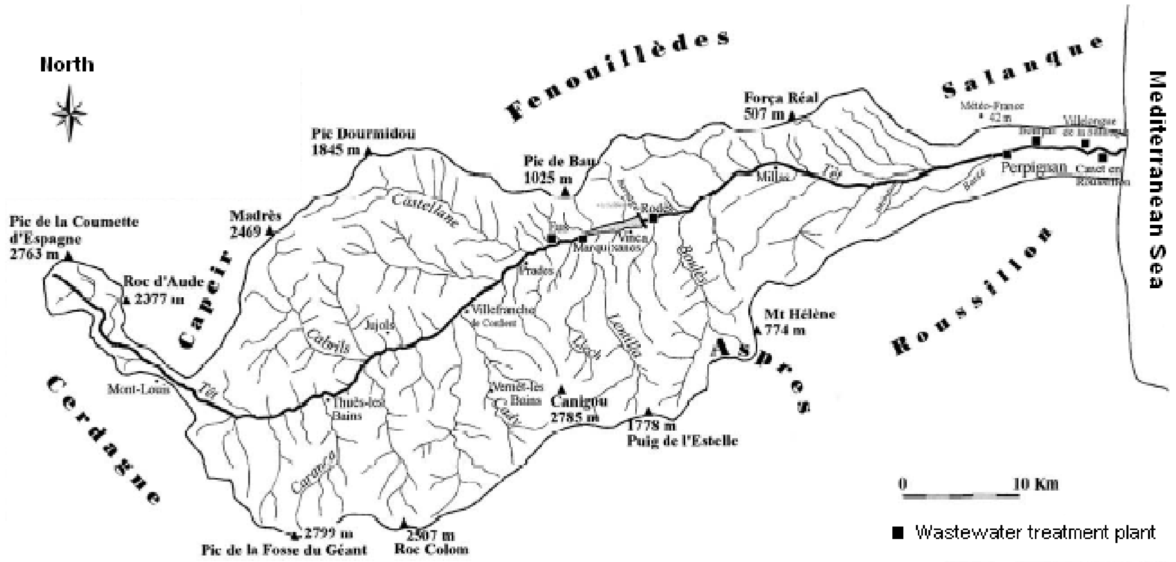

Fig. 1. The Têt catchment area

3. The Perpignan wastewater treatment plant

Perpignan is the capital of the Pyrénées-Orientales department. The current population of the city is about 100 000. It is located in a privileged environment: on one side, the Mediterranean coast with its beaches and rocks, and on the other side, the mountains with the Canigou, one of the highest mountains in French Pyrénées.

Six towns are connected to the Perpignan WWTP able to treat the wastewater of 160 000 inhabitants: Bompas, Canohès, Perpignan, Saint-Estève, Le Soler and Toulouges. The plant effluent goes into the Têt river and have a significant impact on its ecological state. This WWTP uses a Biocarbone process to eliminate organic matters. The water line consists of a primary treatment (clarifiers) and a biological treatment (activated sludge) [3]. The sludge line consists of a sludge dehydration and chemical treatment.

4. Materials and methods

4.1. Elman neural network

Feedforward neural networks have been successfully used to solve problems that require the computation of a static function i.e. a function whose output depends only upon the current input, and not on any previous inputs. In the real world however, one encounters many problems which cannot be solved by learning a static function because the function being computed changes with each input received.

It should be clear from the architecture of feedforward neural networks that past inputs have no way of influencing the processing of future inputs. This situation can be rectified by the introduction of feedback connections in the network [4]. Now network activation produced by past inputs can cycle back and affect the processing of future inputs. The class of neural networks which contain cycles or feedback connections are called recurrent neural networks. While the set of topologies of a feedforward networks is fairly constrained, an RNN can take on any arbitrary topology as any node in the network may be linked with any other node (including itself).

The Elman network commonly is a 2-layer network with feedback from the first-layer output to the first layer input [11].This recurrent connection allows the Elman network to both detect and generate time-varying patterns. A 2-layer Elman network is shown below (Fig. 2).

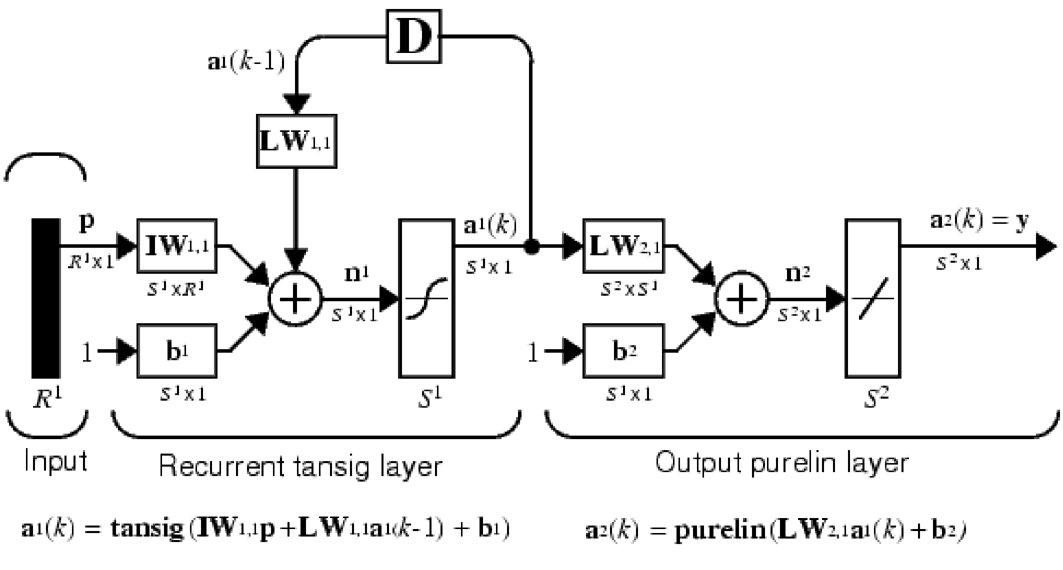

Fig. 2. A 2-layer Elman neural network

The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity.

The Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step.

Thus, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different due to different feedback states. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained, using an iterative process, to respond to, and to generate, both kinds of patterns [9]. At each iteration:

a. The entire input sequence is presented to the network, and its outputs are calculated and compared with the target sequence to generate an error sequence.

b. For each time step, the error is backpropagated to find gradients of errors for each weight and bias. This gradient is actually an approximation since the contributions of weights and biases to errors via the delayed recurrent connection are ignored.

c. This gradient is then used to update the weights with a backpropagation training algorithm. Like the Levenberg-Marquardt algorithm.

4.2. The Levenberg-Marquardt algorithm

Several training methods were used, but the Levenberg-Marquardt algorithm proved to be the fastest and the most robust. It is particularly adapted for networks of moderate size and has memory reduction feature for use when the training set is large [2].

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as:

$$\mathbf{H} = \mathbf{J}^T \mathbf{J}$$

The gradient can be computed as:

$$\mathbf{g} = \mathbf{J}^T \mathbf{e}$$

where **J** is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and *e* is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T \mathbf{J} + \mu \mathbf{I}]^{-1} \mathbf{J}^T \mathbf{e}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

The main drawback of the Levenberg-Marquardt algorithm is that it requires the storage of some matrices that can be quite large for certain problems. The size of the Jacobian matrix is Q x n, where Q is the number of training sets and n is the number of weights and biases in the network. It turns out that this matrix does not have to be computed and stored as a whole. For example, if we were to divide the Jacobian into two equal submatrices we could compute the approximate Hessian matrix as follows:

$$\mathbf{H} = \mathbf{J}^T\mathbf{J} = \begin{bmatrix}\mathbf{J}_1^T & \mathbf{J}_2^T\end{bmatrix}\begin{bmatrix}\mathbf{J}_1 \\ \mathbf{J}_2\end{bmatrix} = \mathbf{J}_1^T\mathbf{J}_1 + \mathbf{J}_2^T\mathbf{J}_2$$

Therefore, the full Jacobian does not have to exist at one time. The approximate Hessian can be computed by summing a series of subterms. Once one subterm has been computed, the corresponding submatrix of the Jacobian can be cleared.

4.3. Rainfall records

Pluviometers	Localization	Pluviometers	Localization
Baillestavy	Têt river catchment area	Le Tech EDF	Tech river catchment area
Caixas	Têt river catchment area	Le Tech La Llau	Tech river catchment area
Canet-en-Roussillon	Têt river catchment area	Col d'Ares	Tech river catchment area
Canohès	Têt river catchment area	Saint Laurent de Cerdans	Tech river catchment area
Eus	Têt river catchment area	Serralongue	Tech river catchment area
Fillols	Têt river catchment area	Tresserre	Tech river catchment area
Mont-Louis	Têt river catchment area	Vives	Tech river catchment area
Mosset	Têt river catchment area	Dorres	Sègre river catchment area
Nohèdes	Têt river catchment area	La Tour de Carol	Sègre river catchment area
Olette	Têt river catchment area	Porté-Puymorens	Sègre river catchment area
Perpignan Mas Nérel	Têt river catchment area	Sainte Léocadie	Sègre river catchment area
Perpignan Pont Joffre	Têt river catchment area	Valcebollère	Sègre river catchment area
Py	Têt river catchment area	Villeneuve les Escaldes	Sègre river catchment area
Railleu	Têt river catchment area	Formiguères	Aude department
Saint Michel Cuxa	Têt river catchment area	La Tour de France	Agly river catchment area
Thuir	Têt river catchment area	Opoul	Agly river catchment area
Vernet les Bains	Têt river catchment area	Mas La Roque	Agly river catchment area
Vinça	Têt river catchment area	Sournia	Agly river catchment area
Amélie les Bains	Tech river catchment area	Torreilles	Agly river catchment area
Brouilla	Tech river catchment area	Alenya	Réart area
Ceret	Tech river catchment area	Argelès sur Mer	Côte Vermeille
Corsavy	Tech river catchment area	Banyuls sur Mer	Côte Vermeille
Le Boulou	Tech river catchment area	Cap Béar	Côte Vermeille
Le Perthus	Tech river catchment area	Cerbère	Côte Vermeille

Tab. 1. Rainfall records localization

Rainfall records from year 2002 were used during the model development. These records were available for 48 geographical precise places localized in the Pyrénées-Orientales department and equipped with pluviometers (Tab. 1). Three places localized in the Têt catchment area were selected and used as networks inputs after a statistical study because of their significant impact on the river flow at Perpignan Pont-Joffre and on the Perpignan WWTP influent flow:

(I) Perpignan Pont-Joffre ; (II) Vinça ; (III) Thuir

4.4. Evapotranspiration (ET)

Water can exist in the natural environment in three different forms or states: solid (ice), liquid and gas. The process by which water changes from a liquid to a gas is known as evaporation. Evaporation from vegetation is generally given a more specific term: evapotranspiration (ET for short). By definition, ET is the loss of water from a vegetated surface through the combined process of soil evaporation and plant transpiration. Both soil evaporation and plant transpiration represent evaporative processes; the difference between the two rests in the path by which water moves from the soil to the atmosphere.

Evapotranspiration data are usually presented as a depth of water loss over a particular time period in a manner similar to that of precipitation. Evapotranspiration records were available at the city of Rivesaltes (about 10 km from Perpignan) and were used, jointly to the rainfall records, to develop the "rain flow" models.

4.5. Geographical Information System (G.I.S.)

A G.I.S. is a computer system capable of capturing, storing, analyzing, and displaying geographically referenced information; that is, data identified according to location. Practitioners also define a G.I.S. as including the procedures, operating personnel, and spatial data that go into the system. The power of a G.I.S. comes from the ability to relate different information in a spatial context and to reach a conclusion about this relationship. Most of the information we have about our world contains a location reference, placing that information at some point on the globe. When rainfall information is collected, it is important to know where the rainfall is located. This is done by using a location reference system, such as longitude and latitude, and perhaps elevation. Comparing the rainfall information with other information, such as the location of marshes across the landscape, may show that certain marshes receive little rainfall. This fact may indicate that these marshes are likely to dry up, and this inference can help us make the most appropriate decisions about how humans should interact with the marsh. A G.I.S., therefore, can reveal important new information that leads to better decision-making [1, 13].

A G.I.S. uses layers, called "themes" to overlay different types of information, much as some static maps use Mylar overlays to add tiers of information to a geographic background. Each theme represents a category of information, such as roads or forest cover. As with the old Mylar maps, the layers which are underneath remain visible while additional themes are placed above. The design can be developed in the following way:

- Abstraction: consisting of the modelling of information.
- Acquisition: allowing to recover existing information by various sources, and to feed the data base.
- Filing: stores the data in order to find them and question them easily.
- Analysis: allowing to answer the requests, it is the heart even SIG.
- Posting: allowing the graphic restitution.

5. Results and discussion

The Elman neural network, thanks to its recurrent connections, allows a dynamic treatment of information. According to its structure, this kind of network learns past information characterizing subjective inputs.

For this work, the Elman network structure as been adapted in order to exploit and treat, as well as possible, the considered system dynamic. Thus, to carry out the Têt river prediction at day d+1, the network uses as inputs the pluviometry of the previous day (i.e. day d) measured at the four selected places, the evapotranspiration of the previous day and the error done when predicting the river flow at day d (Fig. 3). This structure allows implicitly taking into account the pluviometry and the evapotranspiration of days d-1, d-2, d-3 ...: the network keeps in memory past information to carry out its prediction.

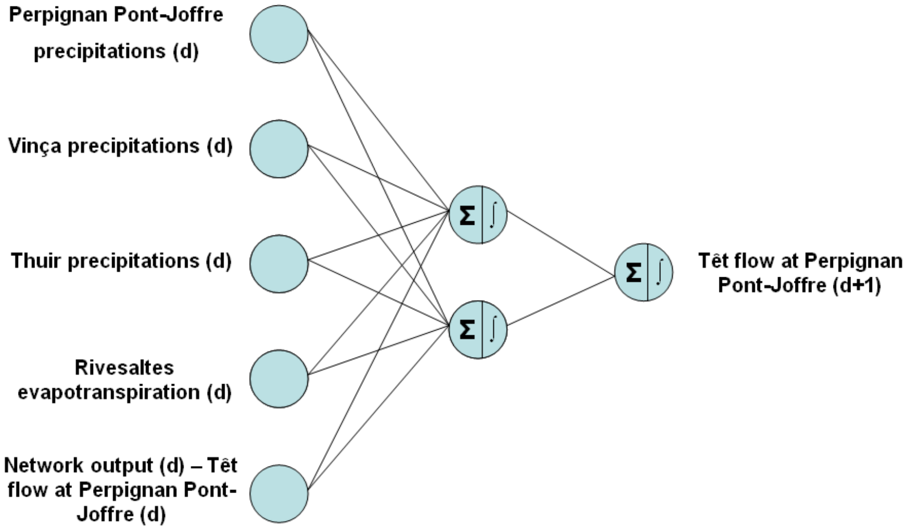

Fig. 3. Simplified representation of the network used for the prediction of the Têt flow

To predict the Perpignan WWTP influent flow, the same inputs were used (Fig. 4).

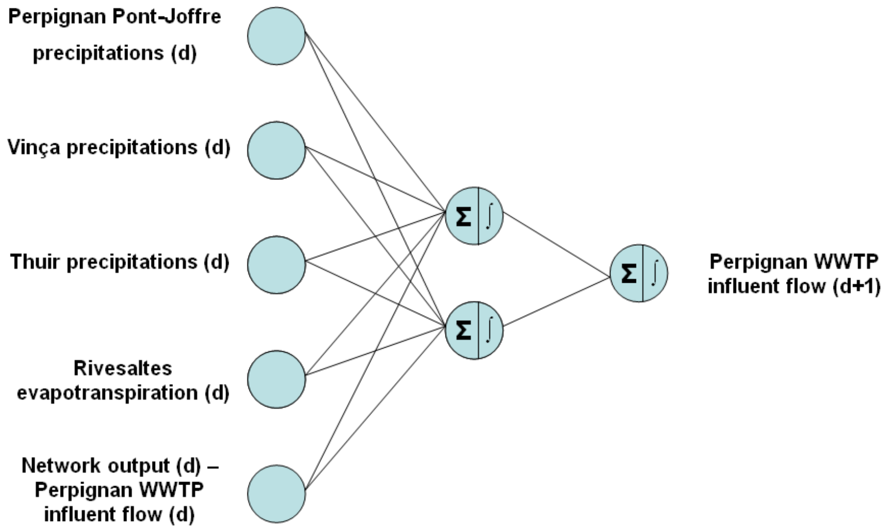

Fig. 4. Simplified representation of the network used for the prediction of the Perpignan WWTP influent flow

For the Têt flow prediction, the network training phase has been carried out by means of a database composed of 80 daily average values characterizing or not rain situations. The validation phase was done with the 20 daily average values immediately following in time the data used during the training phase. For the Perpignan WWTP influent flow prediction, 42 daily average values characterizing or not rain situations were used. The validation phase has been carried out with the 22 daily average values immediately following in time the data used during the training phase. By their structures, the networks dynamically handle the in-time rain phenomenon impact on both Têt flow and Perpignan WWTP influent flow.

Although the relationship between the network performance and its hidden layer size is not well understood, a principle can be used as a guide: the principle of generalization versus convergence. Generalization means the network ability to produce good results with a data set that has not been seen during the training phase. Convergence is the ability to learn the training data. Thus, the two following user-definable parameters, because of their great influence on the learning phase efficiency, were optimized [5, 6]:

- The number of iterations completed during the training phase: 500 for both predictions of Têt flow and Perpignan WWTP influent flow.
- The number of neurons placed in the network hidden layer: 15 hidden neurons for the Têt flow prediction and 6 hidden neurons for the Perpignan WWTP influent flow prediction.

The number of iterations to complete during the training phase and the number of hidden neurons are very important parameters in the field of neural computation. They increase the network calculation capability during the training process. However a network can become specialized on the training data and only on those. Thus, the objective is to use as many hidden neurons as needed for convergence without inhibiting the network ability to generalize. So the network will be able to focus on the important features in the data rather than fitting the noise, an inherent component of any environmental field data set.

Figures 5, 6, 7, 8 and 9 present an example of results obtained with the developed "rain flow" model. These results can be considered as satisfactory because they always highlight the network ability to predict big increases in river flow and in plant influent flow in case of rain events. Average relative errors are about 10 % for the predictions.

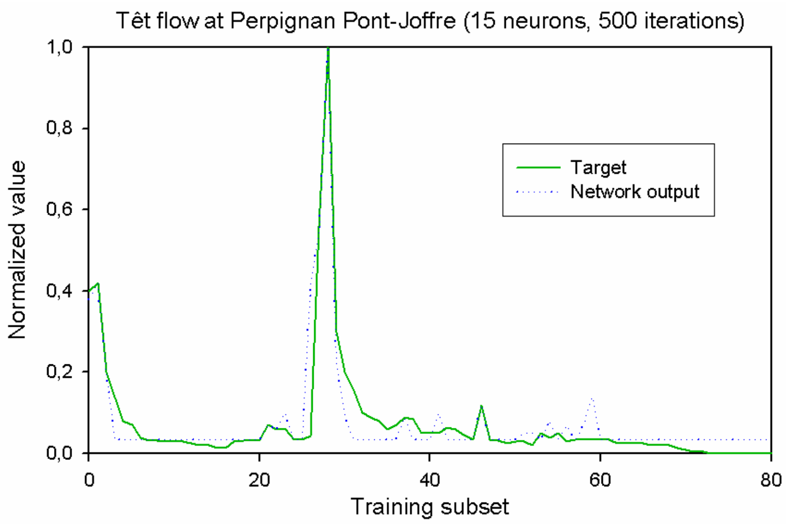

Fig. 5. Estimation results for the Têt flow at Perpignan Pont-Joffre (training phase)

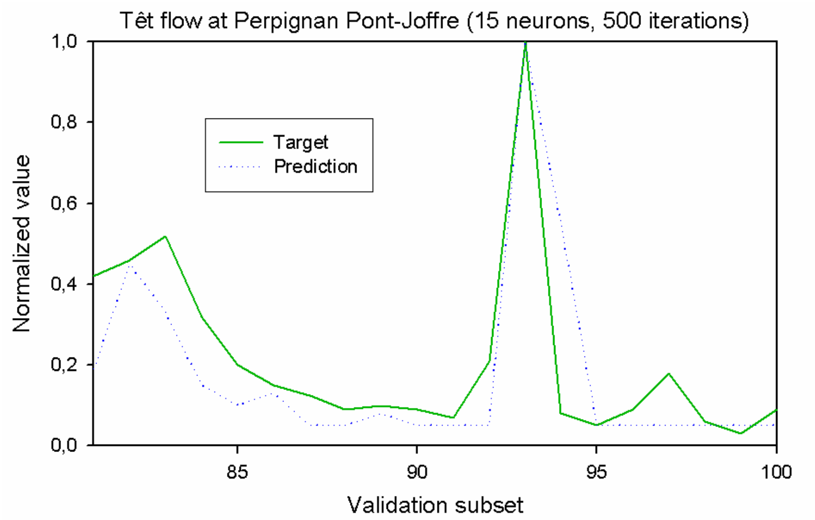

Fig. 6. Estimation results for the Têt flow at Perpignan Pont-Joffre (validation phase)

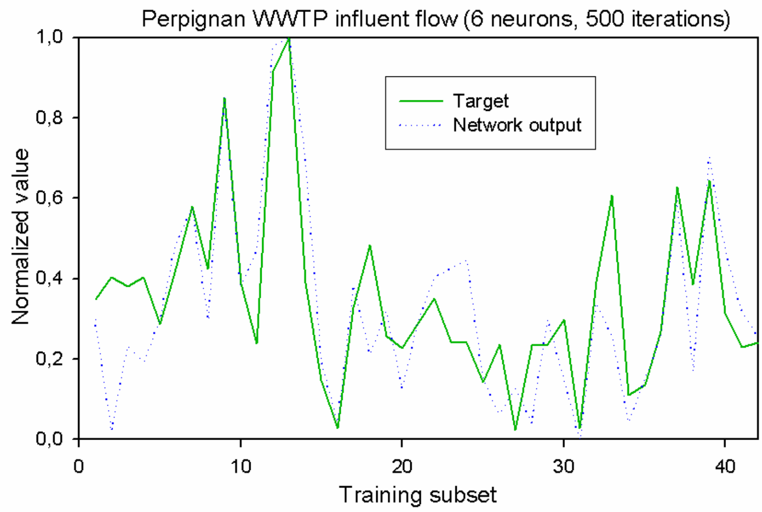

Fig. 7. Estimation results for the Perpignan WWTP influent flow (training phase)

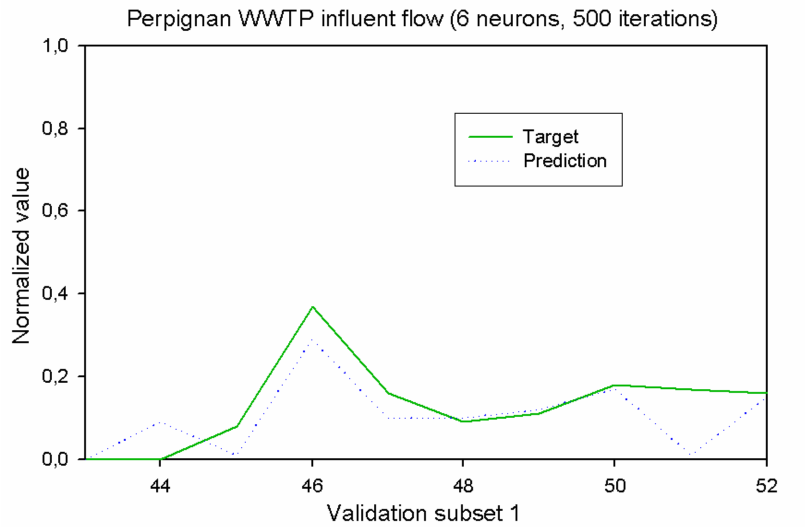

Fig. 8. Estimation results for the Perpignan WWTP influent flow (validation phase 1)

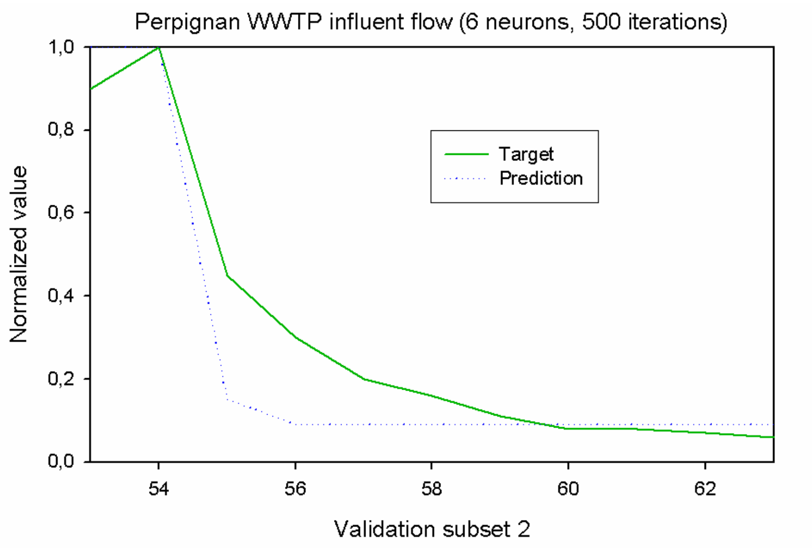

Fig. 9. Estimation results for the Perpignan WWTP influent flow (validation phase 2)

6. Conclusion

The present work takes part in a global development of reliable and robust tools allowing real-time controlling and supervising of the Têt River catchment area. The Têt is one of the main river in Southern France and its ecological state needs to be highly improved.

The main purpose of the work was to develop "rain flow" predictive models based on the identification of localized rain events and allowing understanding the dynamic evolution of the river at a selected point and of the Perpignan WWTP influent flow. To take into account the influence in time of rain events, an Elman recurrent neural network has been used. Its structure has been adapted and optimized to be the most efficient possible.

The results can be considered as satisfactory. They provide useful information about consequences of localized rain events and will contribute to the improvement of the catchment area monitoring. The most interesting characteristic of the models is their capability to predict both river floods and big increases in Perpignan WWTP influent flow.

Future works will focus on the on-line implementation of the models and on the development of qualitative models describing the working of the main catchment area WWTPs [5, 6, 7].

References

[1] R. Aspinall, D. Pearson, Integrated geographical assessment of environmental condition in water catchments: linking landscape ecology, environmental modelling and GIS, Journal of Environmental Management 59 (2000) 299-319.

[2] C. Charalambous, Conjugate gradient algorithm for efficient training of artificial neural networks, IEEE Proceedings 139 (1992) 301-310.

[3] W. Eckenfelder,J. Musterman, Activated sludge treatment of industrial wastewater, Technomic, 1995.

[4] J.L. Elman, Finding structures in time, Cognitive Sciences, N° 14, pp. 179-211, 1990.

[5] S. Grieu, F. Thiery, A. Traoré, T.P. Nguyen, M. Barreau, M. Polit, KSOM and MLP neural networks for on-line estimating the efficiency of an activated sludge process, Chemical Engineering Journal 116 (2006) 1-11.

[6] S. Grieu, A. Traoré, M. Polit, J. Colprim, Prediction of parameters characterizing the state of a pollution removal process, Eng. Appl. Artif. Intell. 18 (2005) 559-573.

[7] M.M. Hamed, M. G. Khalafallah, E.A. Hassanien, Prediction of wastewater treatment plant performance using artificial neural networks, Environ. Modell. Software 19 (10) (2004) 919-928.

[8] W. Ludwig, P. Serrat, L. Cesmat, J. Garcia-Esteves, Evaluating the impact of the recent temperature increase on the hydrology of the Têt river (southern France), Journal of Hydrology 289 (2004) 204-221.

[9] D.T. Pham, D. Karaboga, Training Elman and Jordan networks for system identification using genetic algorithms, Artificial Intelligence in Engineering 13 (1999) 107-117.

[10] C. Schittenkopft, G. Deco, W. Brauer, Two strategies to avoid overfitting in feedforward networks, Neural Networks 10 (1997) 505-516.

[11] S. Seker, E. Ayaz, E. Türkcan, Elman's recurrent neural network applications to condition monitoring in nuclear power plant and rotating machinery, Eng. Appl. Artif. Intell. 16 (2003) 647-656.

[12] P. Serrat, W. Ludwig, B. Navarro, J.L. Blazi, Spatial and temporal variability of sediment fluxes from a coastal Mediterranean river: the Têt (France), Earth and Planetary Science 333 (2001)389-399.

[13] M. Todorovic, P. Steduto, A GIS for irrigation management, Physics and Chemistry of the Earth, 28 (2003) 163-174.