Hybrid Systems for River Flood Forecasting Using MLP, SOM and Fuzzy Systems

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Abstract. This article presents an approach of data partitioning using specialist knowledge incorporated to intelligent solutions for river flow prediction. The main idea is to train the processes through a hybrid systems, neural networks and fuzzy, characterizing its physical process. As a case study, the results obtained with this models from three basins, *Três Marias*, *Tucuruí* and *Foz do Areia*, all situated in Brazil, are investigated.

Keywords: Modular Models, Hybrid Systems, Self-Organizing Map, Multi-Layer Perceptron, Fuzzy Systems, River Flood Forecasting.

1 Introduction

Artificial Neural Networks (ANNs) are increasingly used in the water resources field and environmental sciences, especially for river flow prediction, a classic case of temporal series. The use of ANNs presents a satisfactory performance in many fields, such as: classification, associative memory, temporal series processing, etc. However, in general, these networks are being used as tools to make flow predictions without considering their physical particularities over time.

Forecasting hydrological variables, like river flow, water levels and rainfall is necessary in planning, design, maintenance and operation of water resources systems and consists of a complex process since it is a highly non-linear phenomenon. Companies that generate electricity execute a *Monthly Operational Program* that defines the generation of each unity of the company and the commercialization of energy interchange between them. An important factor for an optimized service for energy demand is the presence of an efficient inflow prediction system, since the future system capacity is influenced by future inflows that has an intrinsic stochastic (random) nature. So, the development of a methodology that improves such predictions is very important.

Real time inflow forecasting has applications in operational flood as well as drought management. It can forewarn extreme flood as well as drought conditions, and can help in optimum operation of reservoirs and power plants. The process of modeling the hydric behavior of a reservoir has fundamental importance for the planning and operation of a flow prediction system of hydric resources. Traditionally, the flow predictions have been made through deterministic models that attempt to describe the water movement behavior by the laws of physics,

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resulting in a numeric system of differential equations. Alternatively, conceptual models have been used once they include equations that guide the drainage in a simplified way, but plausible enough to represent the desired behavior. However, these models in general require a big quantity of data, sophisticated optimization techniques for calibration and a detailed knowledge of the physical process. In the last years, many studies showed that neural networks presented themselves as efficient tools for flow prediction modeling [18,13,17,5,4,19,2,12,20,21]. The greatest advantage of using a neural network for flow prediction is its ability to learn the non-linear behavior of the transformation process of rainfall-runoff in a hydrographical basin by relating a set of entry variables (rain and/or past flows) and the output variables (generally, the flow itself) without the necessity of providing a mathematical equation or any consideration about the physical behavior of the hydrographical basin.

In a general way, the applications found in the literature try to represent the flow prediction process using a single neural network [5,12,15]. However, the flow presented in a hydrograph (flow as a function of time), exemplified in Fig. 1, is a product of different physical processes [7]. The hydrograph, in short, can be understood as a composition of an ascending branch that begins at point 1 (this point represents the end of the base flow, before the rain season). Between points 1 and 2, there are water infiltration and sub superficial flow, and at point 2, the superficial flow begins quickly increasing its value until moment 3 where it reaches its peak and then the descending branch of the hydrograph begins. The recession period of the hydrograph, between points 3 and 5, represents the gradual emptying of the rail river, but at points 3 and 4, there is a strong influence of the superficial flow still. Finally, from point 5, the flow returns to a general base flow from a superior point given the elevation of the water level.

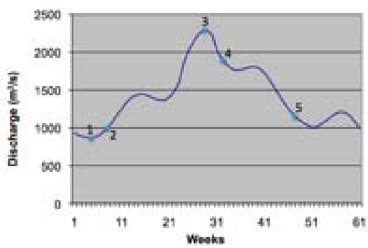

Fig. 1. Hydrograph (Discharge x Weeks)

Therefore, the use of a simple neural network may not be sufficient to represent this complex process of mapping between the inputs and outputs of a hidrogram. For that reason, the aim of this study is: implement two Modular Models that will be able to represent the physical process of ascent and descent of hidrogram for different events (high and low flows), then apply these methods to three basins located in the North, Northeast and South of Brazil, and finally, compare the two proposed methodologies with the traditional methodology, i.e., a single neural network to represent the overall process.

2 Problem Formulation

The process of developing a composed model, that has local ones, where each one of them represents an answer for the system behavior, results in a series of operations [6] that are listed below:

- Selection of the events: must correspond to different aspects of the system behavior, for example, high and low flows, up and downs.
- Selection of models: the selected events can represent models of the same nature or different nature.
- Objective function definition: expresses the simulation quality.
- Model calibration: the model parameters must be trained to optimize the selected objective functions.
- Model combination: the local models are finally integrated in a composed model.

In this article, we go through the whole process to develop two composite models. The steps will be emphasized throughout the text.

3 Methodology

The methodology used in this work consists of a modular modeling scheme where the hydrograph is decomposed in four parts that represents the ups (ascension) and downs (recession), the high and low flows of the process (Fig. 2). This work proposes to use two modular models: SOM and MLP, and MLP with Fuzzy objective function. However, in literature, other ANNs are heavily studied and used to forecast time series [16], as the network TDNN (Time Delay Neural Networks), which is an ANN with time delay, and the Recurrent Networks [8].

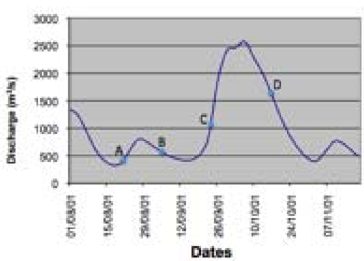

Fig. 2. Events of Hydrograph. A - Ascension low flow, B - Recession low flow, C - Ascension high flow, and D - Recession high flow.

For *Modular Model: SOM and MLP (MM_{SM})* we used two networks, self-organization map (SOM) and Multi-Layer Perceptron (MLP). The objective is to use the SOM network to characterize the various phenomena of the process and then use a MLP network for each of the groups defined by the SOM network.

For *Modular Model: MLP and Fuzzy objective function (MM_{MF})* we used Multi-Layer Perceptron network and Fuzzy logic in order to achieve the composition of the outputs of MLPs.

3.1 Self-Organizing Map (SOM)

The neural network self-organizing map (SOM) is classified as non-supervised and is characterized by the use of the input vector of each unit group as the prototype patterns associated with that unit [3]. During the process of self-organization, the unit vector whose weights most closely approximates to the input signal is chosen as winner. The winning unit and the units in their neighbourhood (according to the topology) have their weights updated.

The configuration of the SOM network is presented as follows: 14 inputs, where each entry corresponds to a daily flow and 4 neurons on the map, which determine the 4 groups of possible groups. Each entry is linked to all neurons.

3.2 Multi-Layer Perceptron (MLP)

The Multi-Layer Perceptron (MLP) networks are composed of interconnected computable nodes arranged in layers that, in theory, can approximate any mathematical function, linear or nonlinear [3]. The basic architecture of an MLP used in this project is described by: an input layer, hidden layer and output layer.

3.3 Modular Model: SOM and MLP (MM_{SM})

As previously mentioned, the focus is on modularization based on hydrograph, instead of building a global model that is responsible for representing the flow of water in all schemes. Thus, the MM_{SM} proposed, would consist of 5 neural networks, which are: SOM, MLP_1, MLP_2, MLP_3 e MLP_4, where each of these networks has settings that are described in the topic concerning the experiments. First, the input data are inserted in the SOM, to be separated into 4 groups, where each of these groups will be included in an MLP, and finally, the output of MM_{SM} is the output of these MLPs (Fig. 3).

3.4 Modular Model: MLP and Fuzzy Objective Function (MM_{MF})

In this model, the input data are divided into high and low flows. Each set is trained by a specific MLP, MLP_A will be called for high flows and MLP_B for low flows, where each of them has different configuration that will be shown in the experiment topic. After obtaining the results of the MLP_A and MLP_B, a concatenation is performed to obtain a single output using Fuzzy logic (Fig. 4),

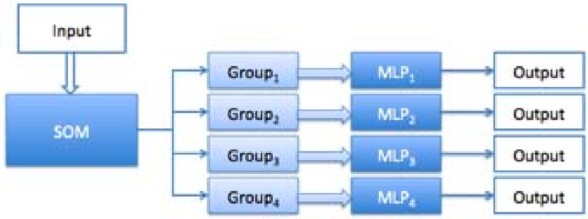

Fig. 3. Modular Model: SOM and MLP (MM_{SM})

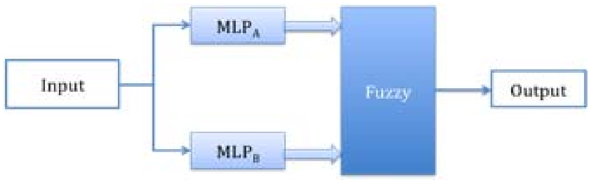

Fig. 4. Modular Model: MLP and Fuzzy (MM_{MF})

giving the impression of being an output of a global MLP. We use Fuzzy logic [1] in this model to admit intermediate values between high and low flows.

The hidrogram for high or low flows may be in a process of ascension or recession. So, to take into account this fact we used in this work a fuzzification error for training each neural network (MLP_A and MLP_B). Then, for process of ascension the objective function was considered:

$$OF_{Ascension} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{c,i} - Q_{o,i})^2(\frac{Q_{o,i} + \Delta Q}{Q_{o,max}})^2} \qquad (1)$$

Where: n = total number of examples; $Q_{o,i}$ = inflow observed in instant i; $Q_{c,i}$ = calculated inflow in instant i; $Q_{o,max}$ = maximum observed inflow; ΔQ = derivative of the hidrogram $(Q_{o,i} - Q_{o,i-1})$

The hidrogram was considered in a position to rise (ascension) when the Rate of increase is greater than a given value α pre-set depending on the basin analyzed. For recession the objective function considered was:

$$OF_{Recession} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{c,i} - Q_{o,i})^2(\frac{Q_{o,i} - \Delta Q}{Q_{o,max}})^2} \qquad (2)$$

In every moment of the training is calculated the Rate, as follow:

$$Rate = \frac{(Q_t - Q_{t-1})}{Q_{t-1}}100 \qquad (3)$$

Where: Q_t = current inflow; Q_{t-1} = previous inflow.

During the training an ascension is considered when the value of the Rate is more than α, which this article was considered 20%. On the other side a recession is considered when the Rate is less than 20%.

Thus, during the training of the neural network the error considered was one Fuzzy function, that uses $OF_{Ascension}$ and $OF_{Recession}$, according to the Rate. Therefore, when the Rate corresponds to a value x between the values α (20%) and $-\alpha$ (-20%) the error is fuzzificated according to Fig. 5.

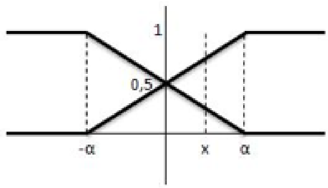

Fig. 5. Fuzzy Objective Function

In this case the composite objective function is:

$$OF_{Composite} = \frac{OF_{ascension}Coef_{ascension} + OF_{recession}Coef_{recession}}{Coef_{ascension} + Coef_{recession}} \quad (4)$$

Where:

$$Coef_{ascension} = \frac{x+\alpha}{2\alpha} = \frac{x+20}{40} \quad (5)$$

$$Coef_{recession} = \frac{x-\alpha}{-2\alpha} = \frac{x-20}{-40} \quad (6)$$

4 Case Studies and Results

For the case study we used data (discharge) from three power plants: Tucuruí (North), Três Marias (Northeast), and Foz do Areia (South), located in Brazil. Some information about the barrages can be viewed in Fig. 6. The horizon weekly was used because it is used for planning the national energy sector. The series of daily flow data were divided into three data sets: first is to adjust the weights (50%), second set is for cross-validation (25%) and third set (25%) to assess the performance of the proposed methodologies. The historic of average daily flow used here corresponds to the period 1968 to 2004. The MLPs networks (MLP_1, MLP_2, MLP_3, MLP_4, MLP_A and MLP_B) for Tucuruí, Foz do Areia and Três Marias had 14 input neurons (14 days previous), 5 neurons in hidden layer and 7 in the output layer, i.e., the forecasting horizon used was a week ahead. The learning-rate parameter (η) and momentum constant (α) were: $\eta = 0.30$ and $\alpha = 0.50$ for Tucuruí, $\eta = 0.30$ and $\alpha = 0.40$ for Três Marias and $\eta = 0.40$ and $\alpha = 0.60$ for Foz do Areia.

	Basin name		
Information	Três Marias	Tucuruí	Foz do Areia
Draining area (km^2)	50,732	757,577	30,127
Normal minimum level (m)	549.20	51.64	700.00
Normal maximum level (m)	572.50	71.93	742.00
Normal maximum volume (hm^3)	19,528	45,500	5,779
Useful volume (hm^3)	15,278	32,013	3,804
Period	1969-2004	1969-2004	1969-2004
Localization	Northeast	North	South
Total power (MW)	396	8,340	1,676

Fig. 6. Hydrological Characteristics: Três Marias, Tucuruí and Foz do Areia

To find out how good are the results of the proposed models, we made a comparison between the results of a simple MLP (MLP_S), the proposed methodologies (MM_{SM} and MM_{MF}) of Modular Model and the results of the statistical methodology used by the electricity sector. To compare these methods we calculated the Mean Absolute Percentage Error (MAPE), given by:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{(Q_{o,i} - Q_{c,i})}{Q_{o,i}} 100 \tag{7}$$

Methods		Três Marias	Tucuruí	Foz do Areia
MLP_S	Average	21,2%	8,7%	25,6%
	Standard deviation	18,0%	8,0%	9,0%
MM_{SM}	Average	20,8%	8,3%	19,1%
	Standard deviation	12,0%	7,5%	7,0%
MM_{MF}	Average	20,2%	8,3%	19,5%
	Standard deviation	11,0%	7,0%	6,5%
Statistician	Average	27,0%	11,5%	33,0%
	Standard deviation	19,0%	9,0%	15,0%

Fig. 7. Errors obtained in the reservoirs: Três Marias, Tucuruí and Foz do Areia

Looking at the table of errors found in Fig. 7, its possible to affirm that the results obtained with the proposed models are better than the other models. The graphs below (Fig. 8, 9, 10) that corroborates this assertion, show the comparasion results of the Modular Models (MM_{SM} and MM_{MF}) forecast, MLP_S forecast and of the actual outcome (observed).

In order to compare statistically the average results found by different models the test of hypothesis of difference between means was held. Thus, we conclude with 95% confidence (or a chance of error of 5%) that there is a difference between the average results of the statistical with MLP_S, and between MM_{SM} and MM_{MF} with MLP_S. Furthermore, we found no statistical differences between

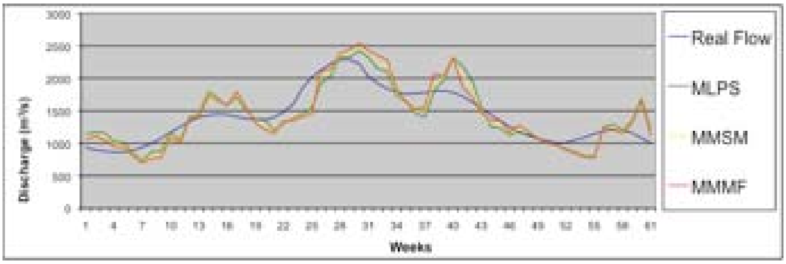

Fig. 8. Hydrograph of Três Marias: comparison of inflows

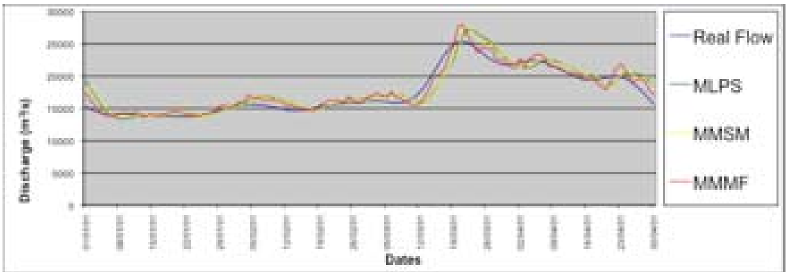

Fig. 9. Hydrograph of Tucuruí: comparison of inflows

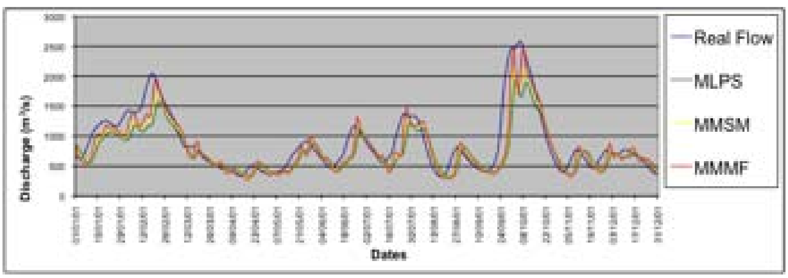

Fig. 10. Hydrograph of Foz do Areia: comparison of inflows

the Modular Models (MM_{SM} and MM_{MF}). This analysis was carried out for the three reservoirs studied and all leads to this conclusion. The time taken for the implementation of MM_{SM} was higher than the MM_{MF}, however, to obtain the results, both models showed similar performance.

5 Final Considerations

In this article, two approaches composed of neural networks and Fuzzy logic were presented: the Modular Models SOM and MLP, as well as the MLP and

Fuzzy, are used to represent the complex phenomenon of inflow forecast through the decomposition of its hydrograph. The genesis of the study presented here is based on the concept about which different segments of the complete hydrograph are a result of different physic processes that take place at the hydrographical basin and, therefore, need different modeling. The main conclusions of this study are:

1. The approach of decomposing the hydrograph in different segments can be a good alternative than trying to use a single neural network.
2. The results obtained through the use of different metrics shows that the proposed methodology has satisfactory results and that minimize problems of tendency (forecasts that are higher or lower than expected) in a particular portion of the flow mentioned by the authors [9,15,19].
3. Considering a fuzzy objective function allows a better representation of the physical phenomenon of ascension and recession of the hydrograph for high and low flows alike.
4. The obtained results for the three studied basins, Três Marias, Tucuruí and Foz do Areia, are satisfactory when compared with the use of a simple neural networks and very superior to statistical models used by the electric sector.

According to the achieved results, the following future works are proposed: consider a non-linear fuzzification; adopt four levels of fuzzification - soft up, abrupt up, soft down, abrupt down; and implement a Modular Model with a dynamic Neural Network, i.e., with memory.

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