Learning and Nonlinear Models (L&NLM) – Journal of the Brazilian Neural Network Society, Vol. 9, Iss.3, pp. 148-156, 2011.

AN APPLICATION OF ELMAN NETWORKS IN TREATMENT AND PREDICTION OF HYDROLOGIC TIME SERIES

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Abstract - Brazil has an available hydrograph to build great dams. This shows that sophisticated runoff control systems with hydrological data prediction functionalities are necessary to deal with physical processes of high complexity and variability. A modeling of hydrological series according to conceptual methods is an expensive process and requires a lot of intervention from the experts. The application of Artificial Neural Networks is an alternative to capture the existing standards in hydrological time series, since it reduces such intervention and the cost of building a model. This paper presents the application of Elman Network for modeling of hydrological time series (imputation and prediction) through the construction of Rainfall-Runoff models and certifies its ability on generating reliable predictions of future values of river discharge based only on rainfall data.

Keywords - Artificial Neural Network, Elman Network, Data Imputation, Time Series Prediction

1. Introduction

The lack and high demand for natural resources have been demanding from managers, engineers and scientists, some rational and efficient decision making. In this context, it is essential the development of computational tools to enhance the processes of decision-scale projects of infrastructure, as well as analyze theories or understand physical phenomena, which may demand unknown and updated information. However, much of this information can only be obtained through mathematical inference from historical data. A set of information, collected sequentially in a certain domain (time, space or frequency), characterizes a time series (Morettin and Toloi, 1985). If it is taken into account the great amount of time series, found in nature (e.g. in a hydrographic area), as well as the constant need of new information, modeling and predicting these series are essential tasks to scientific development.

The beginning of a modern prediction series area is assigned to Yule, who, in 1926, proposed the technique of auto-regressive modeling (Makridakis et al., 1983; Makridakis, 1994). Other researchers proposed techniques to predict time series, which consisted on searching, in a limited universe of models, those ones that best represented the generating processes of the series (Widrow et al., 1994). So, due to the study of Artificial Neural Networks (ANN) and computer technology, longer and more complex time series could be explored. This allowed to extract relations in large data sets and to infer the generating process of series, by adaptive search methods (Makridakis, 1994).

For the effective representation of time, an ANN needs to represent dynamic signals through time (Haykin, 1999). Such models, called Recurrent Artificial Neural Networks (R-ANN), use their memory system to capture temporal patterns such as trends and seasonality (Valencia, 2005) and have at least one feedback loop among their neurons that can be structured in different ways, featuring local (recursive feedback in each neuron) and globally recurrent networks (feedback among different neurons) (Haykin, 1999; Schreiber et al., 1988).

Since the first studies on ANN-R, which were carried out by Rumelhart et al. (1986), several networks models have been developed, including the Elman Network (Elman, 1990). In this artificial neural network architecture, the time representation occurs in internal units, called context units. Such units carry out the feedback for the hidden layer (globally recurrent network) and are responsible for memorizing previous activations of intermediate units. In Figure 1, the feedback is represented by lines in blue and red. The blue lines are responsible for spreading the output signals of neurons in the hidden layer to context units (memory layer), while the red ones are responsible for considering the (feedback) values in the temporal network processing.

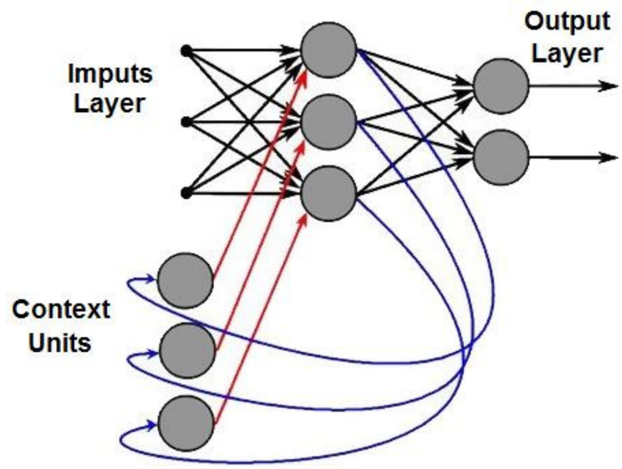

Figure 1: Elman ANN Architecture. Source: **Adapted from Haykin (1999).**

The use of feedback in the hidden layer allows that all samples, already presented to a network, influence in the network response as well as emphasizes the influence on most recent inputs (Braga et al., 2007). In Elman networks, the context units are used only to memorize the previous activations of intermediate units and can be considered as one step delay (Elman, 1990). The learning or weight adjustment is carried out through the backpropagation algorithm. This is possible because, at a specific time interval *t*, the activation of intermediate units (*t* - *1*) and the current inputs (*t*) are used as single entries.

The ANNs, able of capturing temporal patterns, can be seen as an available alternative to Rainfall-Runoff modeling (Minns and Hall, 1996; Jain and Indurthy, 2003), since this task requires the representation of a lag time (time between rainfall and its respective runoff). Nowadays, the ANNs have highlighted in applications related to water resources, as they propose several advantages in comparison to other statistical and mathematical methods. Some of these advantages are samples based learning (or experience based learning); independence of a problem; distributed, parallel and local processing and a realistic implementation.

Raman and Sunilkumar (1995) applications are highlighted to generate symmetrical series of runoffs in Bharathapuzha River, Southeastern India. Zhu et al. (1994) predicted runoffs of 1, 2 and 3 hours into Butternut Creek Basin River in New York. Dawson and Wilby (1998) studied the comparison of models based on ANN and conventional runoff prediction models. Ballini (2000) analyzed the prediction of runoff time series through Fuzzy ANNs, using data collected in the Furnas Dam and Emborcação Dam (basin of the Paraná River, Brazil) and Sobradinho Dam (basin of the São Francisco River, Brazil). Machado (2005) worked in a rainfall-flow model, monthly accumulated from the basin of Jangada River, on the border of Paraná and Santa Catarina - Brazil, and Jain and Kumar (2007) draw a hybrid model (ANN and statistical models) to predict fluviometric series from the Colorado River in Lees Ferry. It is noteworthy that some of the analyzed studies were not restricted to hydrological series. They also observed meteorological data as solar radiation, temperature, humidity and wind speed.

This paper presents a design of a rainfall-flow model of the basin of Piquiri River basin[1], based on time pluvial and fluvial series. This model was designed using an Elman Network for pre-processing (imputation) and to predict some fluvial runoffs at intermediate and long terms. In order to better showing the design and tests of such model, this text is structured as follows: Section 2 describes the concepts involved in rainfall-runoff model; Section 3 presents the proposed rainfall-runoff model, the experiments and the reached results. Section 4 presents the conclusions and, finally, the bibliographic references are listed.

2. Problem Definition: Rainfall-Flow Models

Rainfall-runoff models describe, depending on rainfall, losses (flow) through evaporation, interception, infiltration and percolation of groundwater and calculate the superficial and runoffs (Tucci, 1998). According to these models, it is possible to predict some situations that have not occurred in nature yet, offering support to built applications on managing water resources, see (Linsley and Franzini, 1978). Such prediction, generally, occurs with a time delay, i. e., after the occurrency of the rain, the correspondent effect on the flow in the control section will occurs after a time interval Δ_t.

Flow distribution versus time in a given section of a stream is usually called as hydrograph and is interpreted as the answer of a basin or drainage area when stimulated by rains that fall in that area (Righetto, 1998). This response usually occurs with a time delay - the basin's time delay. In Figure 2 is shown the time delay of a hypothetical river basin, which does not depend only on intensity and spatial distribution of precipitation, but also on physical characteristics of a basin, such as area, geographic and topographic conformation, soil classification and the land uses (Tucci, 1998). Assume a rainfall (Q*a*), its corresponding effect on the flow rate (Q*b)* in the control section[2] will occur after a time interval Δt.

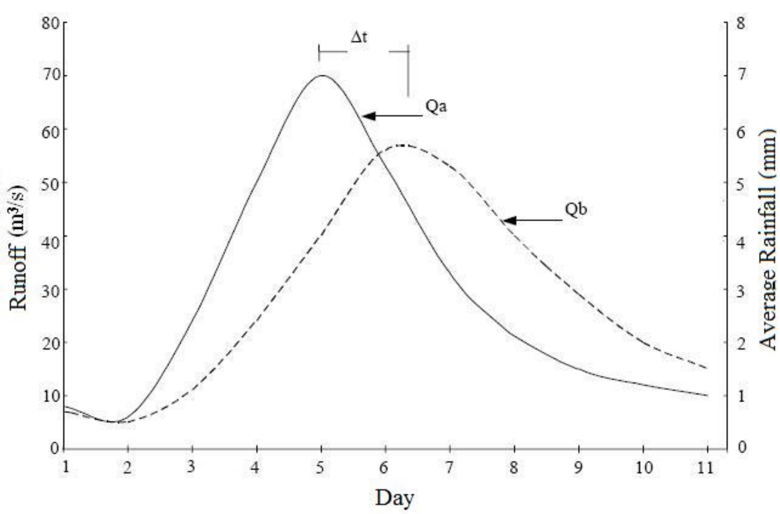

Figure 2: Graphical representation of lag time in a river basin.
Source: Adapted by Tucci (1998): Qa represents the average rainfall that is accumulated; Qb represents the resulting runoff. After the occurrence of rainfall (the highest point of Qa), its resultant in a flow (the highest point of curve Qb) occurs only after a time delay. In this case, it means more than one day (Δt = 1, 3).

3. Experiments and Results

This section reports the proposed model, experimental and analyzed procedures, with emphasis on the data imputation and time series prediction, and reached results.

3.1. Data Set

The data used to design the rainfall-flow model come from fluviometric and pluviometric ranks of the

[1]A large hydrographic basin (24,731 km^2 of drainage area) located in the western region of Paraná State/Brazil.

[2] The control sections correspond to the river's transversal section where the flow is measured.

basin of Piquiri River, monitored by SUDERHSA (2008). There are 102 historical series of rainfall (1956 to 2008) and one serie of runoff (1971 to 2003), all of them with a daily frequency. Due to an availability of a single serie of flow, it was considered as a reference-cut in relation to the other hydrological series[3], limiting them to 22 series.

For the supervised training of ANN, 22 rainfall series were used as input and the flow series as expected value (output). The available flow series has three periods of missing data: 01/04th/1982 to 01/31st/1982; 05/01st/2002 to 05/31st/2002; and 12/1st/2002 to 12/31st/2002. If it were considered only the period without failure, the series would be limited to a period of 18 years (1983 to 2001). In order to increase the scope of this series[4], the failures were imputed by a distributed neural hydrological model[5], in such a way that the rainfall data and runoff rate were used to train an Elman Network and estimate data runoff.

3.2. Proposed Model and Experiments

For networks training (imputation and prediction), different sets of parameters were tested and the best answers were obtained from:

- Randomized initialization of weights to minimize the problem of local minimum, caused by the initial conditions. Each network was initialized and trained three times;
- Dynamic adjustment of *Momentum*, with a rate = 0.1 in a range of [0.001, 1*e*10];
- Learning rate is defined in according to the Levenberg-Marquardt learning algorithm (Ardrib, 2003);
- Evaluation of performance, according to the measurement of Mean Square Error;
- Training stop condition determined in 600 epochs or by a progressive growth of cross validation procedure's errors, during ten consecutive epochs (to avoid loss of generalization) or even, reach an error rate of zero;
- Number of neurons[6] in the hidden layer is 35.

Because there were several peaks on flow series and also to avoid those future values of flow rates extrapolate threshold imposed by normalization, the runoff series was not normalized. Therefore, a positive linear function was adopted as the activation function of output neurons, representing the data among [0, + inf]. The chosen normalization process for the input data was a linear transformation, re-scaling them to a width range [-1,1]. Thus, to better represent the ANNs internal structure, the input layer and the hidden ones use a hyperbolic tangent activation function.

The data set (series), used in the experiment, were divided into three sequential sub-sets: a) Validation - the first 15% data of each series; b) Training - the next 70% data of each series; and c) Test, the remaining 15% of each series.

3.3. Imputation Results

After both phases, network's parameters adjustment and network training, the Elman Networks showed consistent results when compared to hydrologic basin behavior. Imputation of missing data provided similar results to the hydrograph behavior, mainly because their highest values[7] were not undersized and the basin's time delay was reproduced.

Elman networks have been successful, with small errors in minimum and average runoff rates, maintaining stability in the predictions (Figure 3). This network showed a cumulative difference of 0.0162%, concerning the observed volumes (real runoff) in relation to predicted volumes (simulated runoff).

Although the local of failures have happened in short periods, the ones in May 2002 showed a critical point, characterized by a high incidence of rain. In Figure 4, the vertical bars represent accumulated rainfalls in the studied area. The full line represents the discontinuity of flow collection, while the dotted one shows an interpolation generated by the Elman Networks after training. An analysis of this figure highlights a correct delayed response associated to the flow after a rainfall period. In this context, the Elman network represents

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[3] Observe that the rainfall-flow model with ANN support (supervised training) requires that all time series present the same period of data collection.

[4] Righetto (1998) recommends the application of periods equal or superior to 20 years to understand how hydrological series work out.

[5] Distributed models are those in which the parameters of input also vary according to geographical area (Morettin and Toloi, 1985).

[6] Networks with more layers and more neurons were not considered due to computational complexity of the training process.

[7] River runoff data are used to scale hydraulic project, therefore, the highest runoffs shoud not be undersized (Barbosa, 2006).

an adequate tool for prediction regarding to large periods, mainly due to its generalization ability.

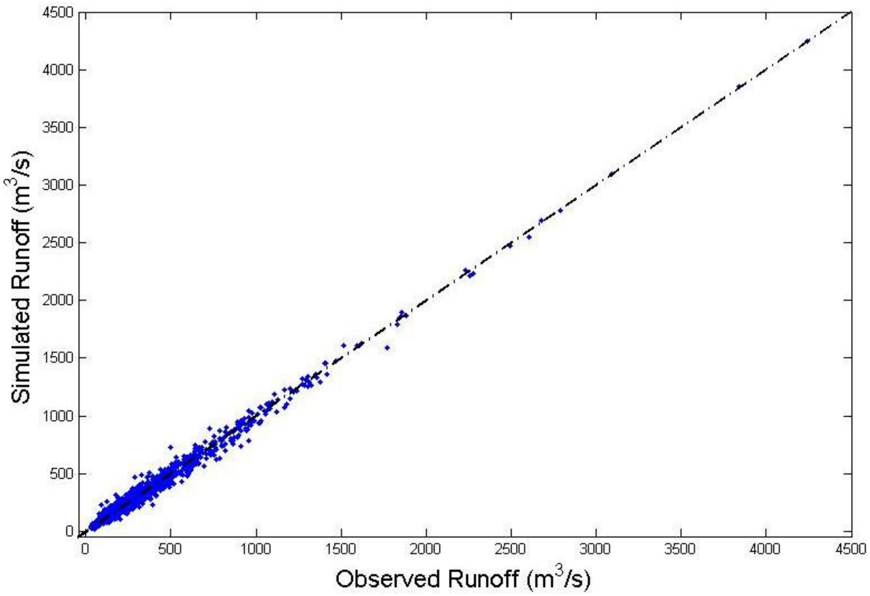

Figure 3: Illustration of collected data (abscissa axis) versus the results predicted by the best Elman network (vertical axis) for the training datasets.

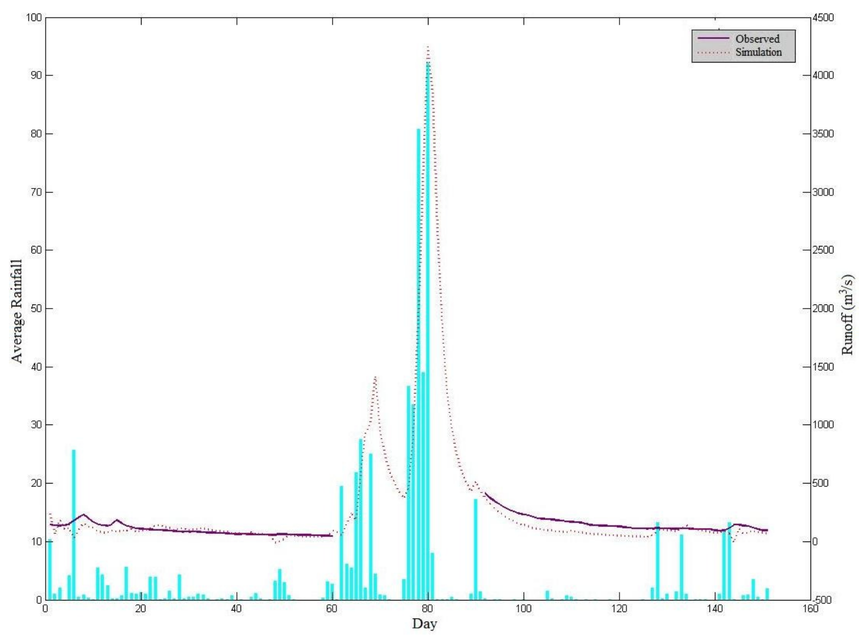

Figure 4: Interpolation for the failures in May, 2002. Axles: Average Rainfall X Days X Flow (m3/s).

If it is taken into account the short periods and failures as well as according to the good results produced by the Elman Network, the reached results were considered available to support an interpolation of missing data. This resulted in an extending period of time series from 18 to 32 years.

3.4. Prediction Results

For the prediction task, the Elman Networks were trained with pre-processed series (imputation results). The training time of the networks was almost 180 hours8. This time is due to the length of each

8Tests were performed using the Operational System Windows XP, a Pentium IV 3,000MHz processor and 1,024MB of RAM memory.

training epoch, in which it is necessary to input, in the network, 22 time series. Each time series has a period of 27 years of daily data, so that 5 years belong to the validation set and 22 years to the training set.

Following this step, the test set was presented to the networks in order to obtain their answers (predictions). These answers show the networks ability to predict values with a horizon of up to 5 years, which is pre-determined by the size of test set. A summary of network performance is presented in Table 1, where the best results are highlighted in bold.

Table 1: Performance of Elman Networks

Elman Network - Mean Square Error			
Performance			*Architecture*
Validation Error	Training Error	Test Error	Hidden number
1,8360and05	1,9Sland05	1,809and05	20
S,4216and04	9,1523and04	S,5534and04	25
6,9S10and03	7,4739and03	6,219Sand03	30
1,3327and **03**	**1,3204**and**03**	**1,2313**and**03**	**35**

When only Mean Square Error (MSE) is evaluated, the good results that were obtained by ANN can not be seen. One reason is the wide runoff variation. In May and October, the observed flows reached 9.6 times the average flow (up to 4,759m^3/S). This contributes to increase the MSE. However, when the graphical representations for the prediction results and the expected values are analyzed, the correct time series prediction obtained by ANN can be observed.

The Elman Network with the best result showed the best representations on maximum of runoff; however, the highest frequency of errors occurred in the average runoff. These errors may have been caused by the high number of possible combinations of inputs that reach an average value. This makes the network's time generalization process more difficult.

Based on the nonlinearity of the studied flow series and analyzing the Figure 5, it can be registered how close the expected data (dotted line) are to the collected ones (full line), especially regarding periods of extreme flow rate. The results qualify the model to be used in simulations of long periods of runoff.

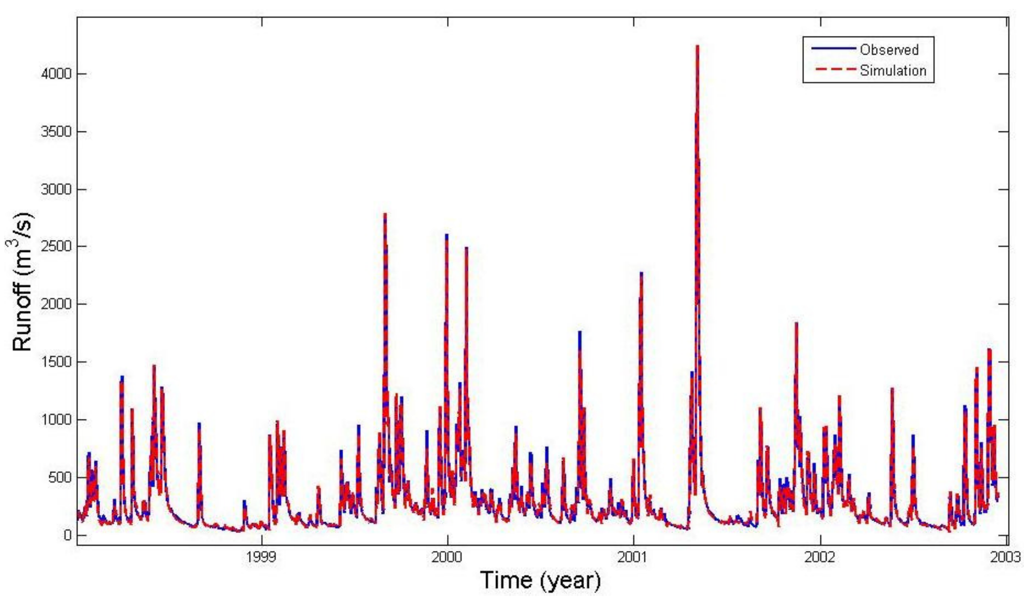

Figure 5: The best result of Elman networks for prediction of 5-year flow (1998 to 2003).

There is an apparent overlap concerning the observed flow (full line) and expected one (dropped line) (Figure 5), but when the image is enlarged, it is possible to observe some errors in predictions of lower flow (Figure 6).

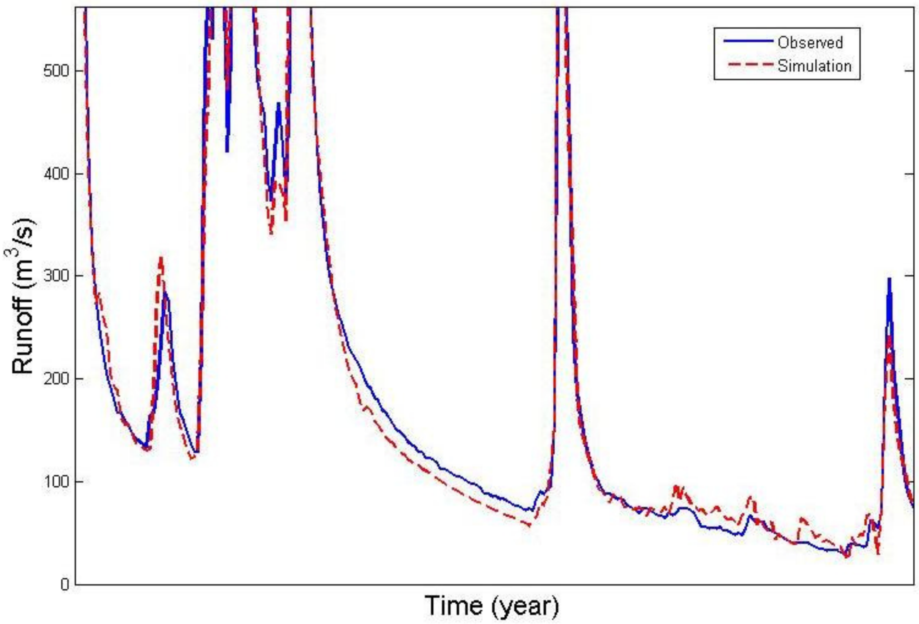

Figure 6: Enlargement of the reached results by Elman Network along the period of prediction: June 1998 to August 1998.

According to the expert's point of view, those differences are considered normal because, for the model built with a great drainage area, many pluviometric series are needed to represent the basin behavior. This fact may have inconsistencies caused by errors during the collection, due to conditions changes or some real physical agent. When the average annual flow of basin is taken into (524 m^3/s), the average error was small and varied 24.141 m^3/s.

Despite the use of 22 pluviometric series, they may not have been enough to get the most perceptible answers of watershed basin. Thus, an increase on the number of series, mainly from collection ranks near the main stream runoff (Piquiri River) may be an option to improve the results, but it also will require more computational resources.

4. Conclusions

The results obtained by Elman Networks have been promising, since they have raised reliable predictions for long periods (5 years) and shown a high capacity for time generalization. They also indicate such network as a useful and efficient tool for solving problems of research and water resources management of Piquiri River basin.

Although it was demanded a long time on ANN arranging and training in a computer, it is still short when compared to design conceptual hydrological models, which can take years to be done and calibrated. Moreover, after data preparation, training takes place automatically, reducing the expert's effort and influence in such models design. A decreasing on subjectivity imposed by an expert increases the confidence of results and validates the modeling.

Some required parameters in conceptual modeling are related to physical characteristics of a watershed basin, so, a data collection is required in field. This kind of collection asks for more time and results in large economic costs. ANN-based models capture physical relationships of a basin that are implicitly included on data, reduce the number of parameters needed for modeling as well as to reduce time and costs.

For future directions of this research is intended to:

- Testing other ANN-R architectures in the same problem, especially investigating different training algorithms, normalizing procedures and input and output data representation in order to reach better results;
- Selecting precipitation series by consistency checks, in order to avoid some series that contribute negatively to ANN generalization process. This can be realized by the correlation analysis among the input series and their contribution to the resulting flow;

- Carrying out other imputation models of missing data in order to compare the accuracy of the results;
- Use statistical indexes to validate the estimated results, such as Camargo coefficient (De Camargo, 1993) that allows evaluating precision and accuracy of predictions, as well as promotes a hydrological metric for validation of Rainfall-Runoff models. In this method, the precision is considered a degree of data dispersion according to the average (this evaluation is obtained by calculations of correlation), and accuracy as the deviation degree of estimated values in relation to the observed ones (Willmott coefficient), (Willmott et al, 1985).

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