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Artificial Neural Networks applied to flow prediction: A use case for the Tomebamba river

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Abstract

The main aim of this research is to create a model based on Artificial Neural Networks (ANN) that allows predicting the flow in Tomebamba river, at real time and in a specific day of a year. As inputs, this research is using information of rainfall and flow of the stations along of the river. This information is organized in scenarios and each scenario is prepared to a specific area. For this article, we have selected two scenarios. The information is acquired from the hydrological stations placed in the watershed using an electronic system developed at real time and it supports any kind or brands of this type of sensors. The prediction works very good three days in advance. This research includes two ANN models: Backpropagation and a hybrid model between back propagation and OWO-HWO (output weight optimization–hidden weight optimization) to select the initial weights of the connection. These last two models have been tested in a preliminary research. To validate the results we are using some error indicators such as MSE, RMSE, EF, CD and BIAS. The results of this research reached high levels of reliability and the level of error is minimal. These predictions are useful to avoid floods in the city of Cuenca in Ecuador.

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Keywords: Artificial Neural Networks, ANN, Forecasting, Hydrology, Floods

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1. Introduction

This model, can be used to predict water flow in a river in order to estimate the hydropower generation. Additionally, this model can be used to prevent disasters such as flooding and also to optimize the use of hydrological resources. This research used information from Tomebamba river basin. This data has been used to train and validate artificial neural network models in order to evaluate the results of those models.

In this context, this research can be considered as a primary tool for hydropower generation organizations to determine in the best way, the exact amount of water that has to be present in a reservoir when there is not too much water to generate electricity. The application of mathematical models in water management basins has very high requirements of information and commonly they are not applicable in the mountains regions. Computer techniques from artificial intelligence allow establishing relationships between input and output data in a hydrographical basin.

This paper has already evaluated different Artificial Neural Networks (ANN) to select one and implement it to allow control every connection inside the network. This, with the objective of obtaining a quick convergence and to reduce the overall error rate.

2. Background and related work

In this section, we provide a brief introduction to Neural Network and two specific types such as: Backpropagation and OWO-HWO (output weight optimization–hidden weight optimization) algorithms and genetic algorithms that will be used in order to obtain a good initialization of the weights of each connection. Additionally, a description of the current state of the art related to the rainfall forecasting.

2.1. Artificial Neural Networks (ANN)

Components

Artificial neural networks try to reproduce the human brain behavior, the model in which neurons are considered processing units [1],[2]. Typically, there are three types of neurons:

- Receive impulses or external signals, takes information from the outside, because if it, they are known as input units.
- Internal elements to process input information. These elements are called hidden units, because they don't have any relationship between input and output units.
- Output units, these units give the result to the system.

Each neuron has associated with a numerical value or activation state and there is an output function fi associated to each of this units. This function transforms the activation state of an output signal yi. This signal is sent to all communication channels of the network(connections). In this channels, the signal is modified because of the synapsis (connection weight) associated to each one of them based in a specific rule. Modulated signals arriving to the j-th unit joins each other generating the total Netj. An activation function F, determines the new neuron activation state aj(t+1), taking in account the total net input and the previous activation state aj(t)[1],[2].

Structure

Artificial Neural Networks are organized in function of:

- The number of levels or layers.
- The number of neurons per level.
- Connection patterns.
- Information flow.

The neurons distribution inside of the network is made creating levels/layer composed of a certain number of neurons in each layer. In this sense, can be identified three layer types [1]:

- Input: This layer receives the information directly from the external sources.
- Hidden: This kind of neurons are interns and don't have direct contact with the outside. The number of hidden level can be between zero and a very high number. Neurons in these layers can be interconnected in different ways
- Output: Transfer information from the inside of the network to outside of the system.

2.1.1. Algorithms

Backpropagation: This algorithm is based on the back propagation of the error, this is a supervised learning algorithm and it is based on the generalization of delta rule. Once a pattern has been used as an input, this pattern has to propagate from the input layers to the hidden layer in order to obtain an output[1].

The output is compared with desired output and an error rate is calculated in each of the output of the neurons. The error is, propagated backwards, starting from the output and through each neuron that contribute to the output layer. This is made with each neuron of the network until the error is distributed completely. With this, the connection weights can be manipulated in order to eliminate the error and obtain a correct approximation of the training patterns[1]–[4].

OWO-HWO: Is an alternative training algorithm used in networks with forward propagation. This algorithm solves linear equations for the weights in the outputs and reduces the separation in the error function of the hidden layers with the weights of the hidden layers. In this sense, a new function in the hidden layer has been proposed, which gives emphasis on error functions corresponding to a saturated value of the activation function. Moreover, an adaptive learning rate based in a local form of the error surface is used in the training process of the hidden layers. A quick convergence in the learning process has been noticed [5], [6].

In OWO-HWO, the output and hidden weights are modified alternatively in order to reduce the training error. The modification of the hidden weights is made based on the minimization of MSE (Mean Square Error) between the desired outputs and the current ones. Although OWO-HWO often converges rapidly it does not use some effective techniques, for example, prevention of premature saturation or adaptive learning rate[5], [6].

2.1.2. Backpropagation and related work

Several studies [1][2][4] state that Artificial Neural Networks (ANN) are probably the most successful machine learning technique because this kind of tool has a flexible mathematical structure in order to identify relationships between input and output data, this is important when a study needs to be executed in an certain area that does not have sufficient information.

Currently, artificial neural networks are widely used along of the world in order to predict any natural event [1], [4], [7]–[11] even those that are related to flow prediction[1], [4], [7], [8], [10]–[12]. This studies shown how to deal with this problem and also states that artificial neural networks can be a solution on similar problems. There are several neural network algorithms[13], but the most used in similar problems are: backpropagation[1], [4], [7], [8], [10], [11], [14] using different transfer functions and OWO–HWO (Output Weight Optimization–Hidden Weight Optimization) [6][5][15]. In this kind of networks, the main problem is related with the initial values of the connections between the neurons as well as the initial weights. A solution has been proposed[16]–[21] using genetic algorithms to select those ideal weights that were mentioned above.

3. Process for predicting flow

This paper includes research to determine the most suitable ANN model to obtain predictions with the highest reliability. With this a basis, research has been done to determine the most commonly used artificial neural networks applied in the flow level predictions. As a result of this, the following algorithms were identified:

- Backpropagation [2]–[4], [8], [17], [18]
- OWO-HWO [6], [5], [15]

- Genetic Algorithms [16]–[21]

Additionally, OWO-HWO and Genetic Algorithms can be used to include extra optimization in the connections weights of all the neurons that are present in each layer of the artificial neural networks.

3.1. Scenarios

Once an algorithm selection has been made, the next step is to establish scenarios to be used in the validation of each one of the selected algorithms. This article will use the information of Veintimilla et al. [2] and Cisneros et al. [4], [8] as an initial point. The aim is to predict the input flow level in the Tomebamba basin. The scenarios with the best results are shown in Table 1.

Table 1. Scenario 1

Flow / precipitation	Station	Input / Output
Flow	Tomebamba_en Ucubamba	Output
Precipitation	Est_Cancan_Soldados_1997_2009 i-3	Input
Precipitation	Est_Cancan_Soldados_1997_2009 i-2	Input
Precipitation	Est_Cancan_Soldados_1997_2009 i-1	Input
Precipitation	Est_El_Portete_1997_2001 i-3	Input
Precipitation	Est_El_Portete_1997_2001 i-2	Input
Precipitation	Est_El_Portete_1997_2001 i-1	Input
Precipitation	Est_Gualaceo_DJ_Pamar_1997_2009 i-3	Input
Precipitation	Est_Gualaceo_DJ_Pamar_1997_2009 i-2	Input
Precipitation	Est_Gualaceo_DJ_Pamar_1997_2009 i-1	Input
Precipitation	Est_La_Esmeralda_1997_2009 i-3	Input
Precipitation	Est_La_Esmeralda_1997_2009 i-2	Input
Precipitation	Est_La_Esmeralda_1997_2009 i-1	Input
Precipitation	Est_Matadero_en_Sayausi_1997_2009 i-3	Input
Precipitation	Est_Matadero_en_Sayausi_1997_2009 i-2	Input
Precipitation	Est_Matadero_en_Sayausi_1997_2009 i-1	Input
Precipitation	Est_Tarqui_DJ_Cumbe_1997_2009 i-3	Input
Precipitation	Est_Tarqui_DJ_Cumbe_1997_2009 i-2	Input
Precipitation	Est_Tarqui_DJ_Cumbe_1997_2009 i-1	Input
Precipitation	Est_Yanuncay_en_Pucan_1997_2009 i-3	Input
Precipitation	Est_Yanuncay_en_Pucan_1997_2009 i-2	Input
Precipitation	Est_Yanuncay_en_Pucan_1997_2009 i-1	Input
Precipitation	Est_Ucubamba_en_ETAPA_1998_2009 i-3	Input
Precipitation	Est_Ucubamba_en_ETAPA_1998_2009 i-2	Input
Precipitation	Est_Ucubamba_en_ETAPA_1998_2009 i-1	Input
Flow	Tomebamba_en Ucubamba i-3	Input
Flow	Tomebamba_en Ucubamba i-2	Input

The scenario shown in Table 2, its composed by mainly precipitation sensors and includes three days of data backward and gives a prediction of one day in advance.

Table 2. Scenario 2

Flow / precipitation	Station	Input / Output
Precipitation	Est_Cancan_Soldados_1997_2011 i-1	Input
Precipitation	Est_El_Portete_1997_2003 i-1	Input
Precipitation	Est_Gualaceo_DJ_Pamar_1997_2011 i-1	Input
Precipitation	Est_La_Esmeralda_1997_2011 i-1	Input
Precipitation	Est_Matadero_en_Sayausi_1997_2011 i-1	Input
Precipitation	Est_El_Portete_1997_2001 i-1	Input
Precipitation	Est_Tarqui_DJ_Cumbe_1997_2011 i-1	Input
Precipitation	Est_Yanuncay_en_Pucan_1997_2010 i-1	Input
Precipitation	Est_Ucubamba_en_ETAPA_1998_2011 i-1	Input
Flow	Tomebamba_en Ucubamba	Output

Scenario 2, has only data from the sensor where the prediction is made (Tomebamba river). Data used in this scenario includes two days backward and allows to have a prediction of one day in advance.

3.2. Algorithms evaluations

Ensure that you return to the 'Els-body-text' style, the style that you will mainly be using for large blocks of text, when you have completed your bulleted list. With the objective of model validation based on the artificial neural networks selected, data based on the scenarios and configuration parameters of the model were chosen in order to train and execute them. The results of those executions are shown in Fig. 1. From this figure, the best results are obtained with scenario 1 and as a conclusion: data normalization has no effect when ANN is based on backpropagation algorithms. However, when the networks is based in OWO-HWO it has a significant importance.

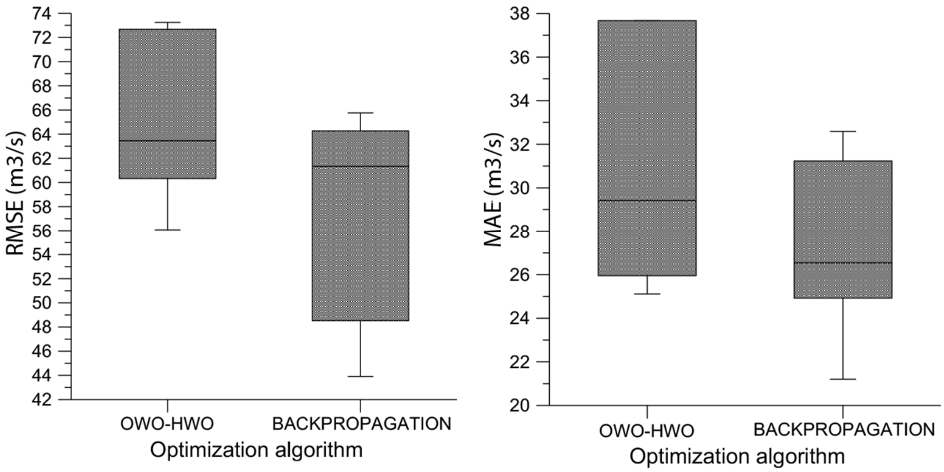

Fig. 1. Box-Whisker plot of the RMSE (right panel) and MAE (left panel) as a function of the OWO-HWO and BACKPROPAGATION optimization algorithm. The spreading per algorithm is due to the variation in scenario (1, 2 or 3), entries (4, 16 or 22), number of iterations (1000 or 9054) and normalization (yes or no).

To improve the results of the models, the iteration number has been increased in scenario 1 and using backpropagation algorithm. The results of this execution are shown in Fig. 2.

Based on the previous information, the backpropagation algorithm has been implemented in order to use other algorithms to control its characteristics and improve the weights of the connections of the neurons that belongs to the artificial neural network. Since backpropagation algorithms use random values to initialize the connection among neurons, one of these improvements is to use genetic algorithms to select the initial weights of the connections. With the combination of backpropagation neural networks and genetic algorithms, a hybrid algorithm has been created. This algorithm has been validating and in the following sections, the results are included.

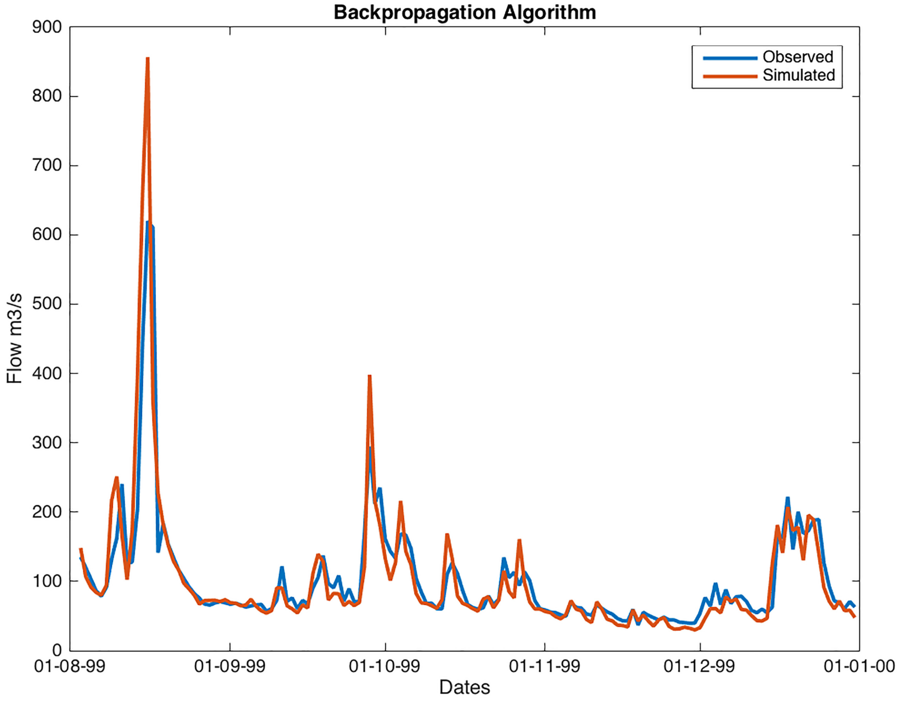

Fig. 2. Comparison of the daily flow generated by ANN in Tomebamba sensor from August 3th 1999 until December 31th 1999. Scenario 1, using backpropagation algorithm.

3.3. Algorithm implementation and setting an initial configuration

To validate the implementation of the hybrid algorithm, only scenario 1 and 2 have been selected because of the results of them in the previous tests. The main objective is to obtain the most suitable parameters for proper operation. In this sense, the following values has been varied:

- Hidden layers
- Neurons
- Learning rate
- Momentum
- Iterations
- Based on the previous tests of the model, the best results were achieved with the following values:
- Iterations: 5000
- Hidden layers: 2
- Neurons: 10 in the first hidden layer and 5 in the second one.
- Learning rate: 0.3
- Momentum: 0.2

- From the results, there are some conclusions can be summarized:
- As more iterations, better results are presented.
- The increase in the number of hidden layers improve the model results.
- In the beginning, the utilization of 0.1 as learning rate gave the best results. When this value is incremented, the MAE is incremented as too. With the inclusion of a second hidden layer the value of MSE was improved, and it produces an acceptable value of MAE. As a conclusion, the value of 0.3 as a learning rate combined with more than 1 as a hidden layer is the optimum for this model.
- The optimal value to be associated to the momentum parameter is between 0 y 0.2.

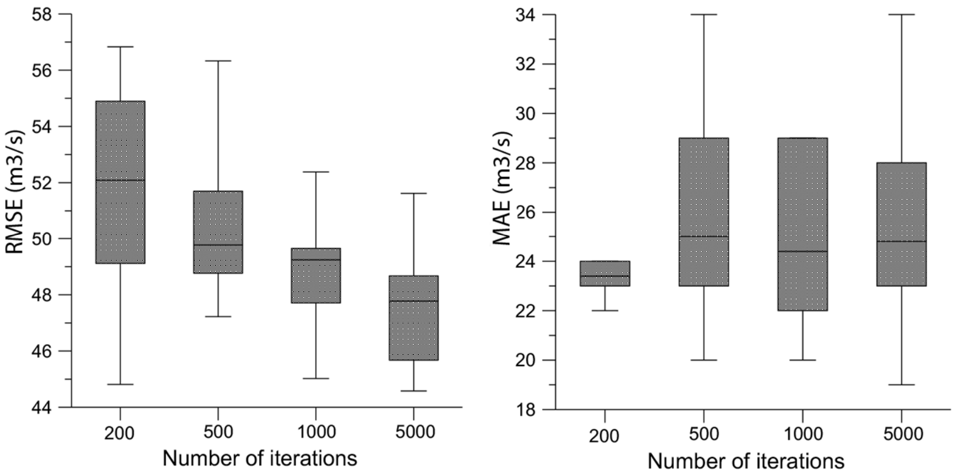

Fig. 3. Box-Whisker plot of the RMSE (right panel) and MAE (left panel) as a function of the number of iterations. The spreading per number of iterations is due to the variation in scenario (1 or 2), number of hidden layers (1 or 2), number of neurons (5, 10 or 13), learning rates (0.01, 0.1, 0.2 or 0.3) and momentum terms (0, 0.05, 0.1 or 0.2).

The coupling in the validation of this model it can be clearly seen in Fig. 4.

4. Conclusions and future work

OWO-HWO algorithm requires a large time of computation time in order to process the same number of iteration as well as Backpropagation algorithm. The Mean Square Error (MSE) is less in the backpropagation than in the OWO-HWO. When the training times are equals in both algorithms, is noticeable that backpropagation algorithm reduces drastically the MSE value.

Data normalization (values between 0 and 1) in training, helps OWO-HWO algorithm to reduce MSE. In this sense, the algorithm with the best performance based in MSE is backpropagation. Additionally, it has to mention that with the use of genetic algorithms in the weights initialization process has obtained the best results in the validation process. In order to continue this research, the next step is to use machine learning techniques such as support vector machines and/or data mining techniques. This, because almost all Ecuadorian regions does not have enough information and this computer based techniques can work with small sets of data.

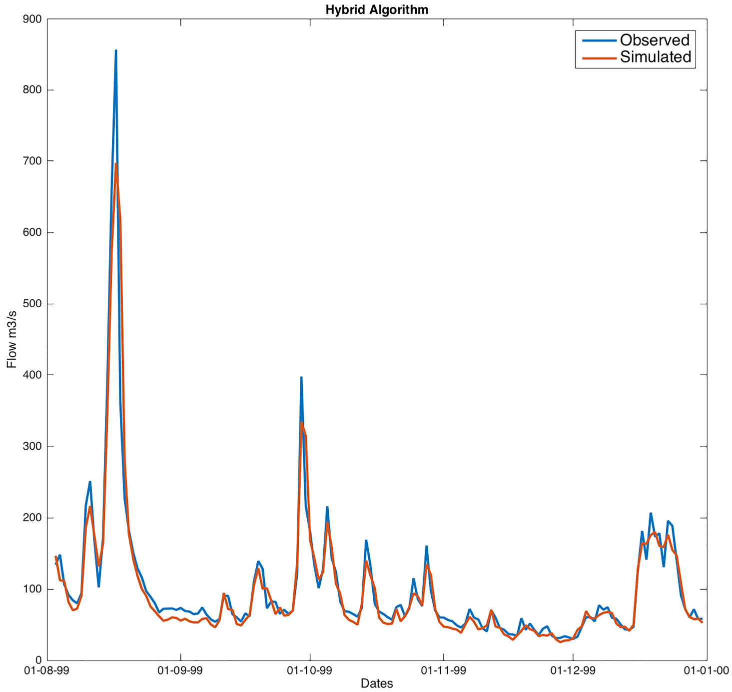

Fig. 4. Results: (1000 iterations): Scenario 1, fixed parameters 2 hidden layers (5 and 10 neurons each), learning rate 0.3, momentum 0.2, RMSE 30.52 and MAE 14.75.

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