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An ANN Based Flood Prediction System

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Abstract

This paper presents a multilayer neural network in which there are selected entries and exits that will find the best solution of predicting the floods in the Prahova river basin, Prahova County. This system can be included in the emergencies management project for a river basin. Using artificial intelligence techniques in the prediction of floods will get better results than using conventional methods. The algorithm for solving the problem was implemented by using the facilities of MATLAB® programming environment.

Key words: *artificial intelligence, flood prediction, monitoring.*

Introduction

Practice has shown that global occurrence of floods cannot be avoided, but they can be managed, and their effects can be reduced through a systematic process that leads to a series of measures and actions aimed to reduce the risk associated with these phenomena. Flood management is easier by the fact that their event is predictable and often a prior warning can be made, and normally it is possible to clarify who and what will be affected by the floods.

The optimization of systems for monitoring and prevention of floods systems can be achieved using artificial intelligence techniques, because they have the capacity to solve difficult problems involved in river basin development, problems that can't be easily solved by conventional methods. Benefits can be found in reducing response time and improve efficiency of the system.

Artificial intelligence has fast and flexible techniques and tools to implement advanced solutions in the field of hydrology, techniques that use appropriate means of representation of knowledge, such as artificial neural networks (ANN) and neuro-fuzzy systems, which can be created for modelling of flow process and for flood prediction [1, 2, 3, 6, 8, 9, 10].

Artificial Neural Networks

Artificial neural networks are parallel distributed structures of processing with natural storage capacity and self-knowledge [5].

Typical neural networks are composed of layers of neurons with different weights that provide inter-neural connectivity for knowledge storage.

Among the many attributes of neural networks that have been noted in many areas of attachment can be observed the following:

- ❖ Parallel network architecture, due to repeated use of simple processing elements, neurons. This leads to the possibility of a simple hardware implementation of neural networks.
- ❖ The ability to learn from examples. The mechanism of learning is often represented by the right adjustment of the weights in model neurons.
- ❖ The ability to generalize to new inputs. For example, a trained network is able to calculate the desired output when the input data have not been used.
- ❖ Robustness with respect of data affected by noise encountered in real applications.
- ❖ Errors tolerance. Generally, network performances do not decrease significantly if some network connections are wrong.

Each neural input, $X_1 - X_n$ is weighted by $W_1 - W_n$ values. A bias, i.e. a compensatory is characterized by an additional constant input equal to 1 and weighted by the value W_0. Y output is obtained by adding weighted inputs and applying the result to a nonlinear activation functions [7]:

$$Y = f(\sum_{i=1}^{n} W_i X_i + W_0)\,. \tag{1}$$

The most popular architecture for neural networks is called multi-layer perceptron (MLP). The network is composed of an input layer, multiple hidden layers, typically using 1 or 2 layers, and an output layer and it uses as activation function for hidden and output layers a tansig function.

The output of each node of each layer is connected to each following layer entries. The data travels over the network in a single direction, from input to output. This network is called feedforward network [4].

The network is trained in a supervised manner, i.e. during training both inputs and desired outputs of the network are used. It has been proposed a large number of learning algorithms for networks of MLP, but the most popular algorithm is back propagation of error.

In short, this algorithm consists of applying a model of input and generating computed outputs which are then compared with desired outputs. Resulting error is propagated back to the network from exit to entry and network weights are adjusted to minimize the cost, usually the mean square error. The process is repeated for all of training data until the cost is reduced to a sufficient amount.

An important feature of MLP networks is that they can accurately represent any continuous non-linear function. Therefore, MLP networks have a good potential of application, including modelling and nonlinear process controlling.

Model Development

Further, we present a multilayered artificial neural network that will aim short flood prediction in Prahova river basin.

Input Vector Selection

A potentially critical issue in applying an extrapolative method of prediction in river stage management of floods is the choice of input variables.

Input vector used is given by the river basin features: rainfall (F), flood time (T_t), coefficient of drainage basin (α), basin area (X), the coefficient of form (γ).

The data used were obtained with "Romanian Waters" Agency - Water Management System Prahova help.

Neural Network Architecture

This work presents a neural network with 3 layers. The input layer consists of 5 neurons, one for each feature from the input vector (table 2). The hidden layer has also 5 neurons and the output layer has one neuron corresponding to the possibility of flood occurrence.

Each artificial neuron has a known input - output characteristic and implements a computing local process or a function. In general, the characteristic features for different neurons may be different, but rather that certain groups of neurons have the same characteristic features. Thus, for the output layer neurons a linear function was selected, and for hidden layer, in this study different activation functions were used (table 1). The functions are represented in figure 1.

Table 1. Activation functions

Hardlim function	Tansig function	Logsig function
$F(x)=\begin{cases}0, x=0\\-1, x<0\\1, x>0\end{cases}$	$F(x)=\dfrac{1}{1+e^{-kx}}$, k > 0	$F(x)=\dfrac{e^x-1}{e^x+1}$: R → [-1, 1]

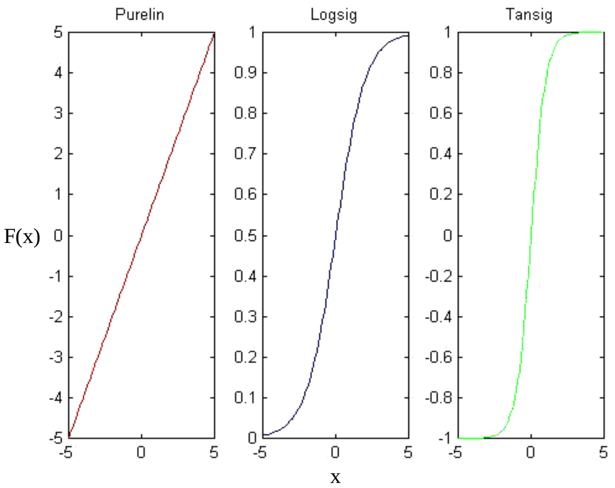


Fig. 1. Used activation functions.

After the weights and polarization of the network were initialized, the network is ready to be trained. Training is conducted by the back propagation of error algorithm. There are two ways of applying this algorithm: incremental way (training through forms), in which a gradient is calculated and weights are updated after each application of input vector from the training set and training through epochs, in which all the vectors of the training set are applied after the weights are updated once.

Case Study and Data Description

This research has flood prediction on Prahova River as main subject. Experimental data set is collected from Prahova basin river.

Length of watercourses crossing Prahova County is 1786 kilometres, the river basin is 3738 km^2, and the lake is 13 km^2. Prahova river is the main river of the country.

Prahova River crosses the county from north to south for a 161 km length. Water resources in the county have increased considerably due to the two large lakes Paltinu (Doftana Valley) and Măneciu-Izvoarele (Teleajen Valley).

Model simulation using MATLAB® programming environment

MATLAB® can be use for designing, implementing, visualizing, and simulating neural networks. Neural Network Toolbox software provides comprehensive support for many proven network paradigms, as well as graphical user interfaces (GUIs) that enable you to design and manage your networks.

The system developed in the MATLAB® programming environment is useful for prediction of floods in Prahova river basin, but it can be adapted for any other river basin.

Input data used were placed in the following limits (table 2):

Table 2. Input data limits

Input data	**Limits**	**Units of measurement**
Rainfall (F)	1..100	l/m^2
Flood time (T_t)	10..100	hours
Coefficient of drainage basin (α)	0,1..0,7	-
Basin area (X)	50..350	km^2
The coefficient of form (γ)	0,1..0,5	-

The output data are represented by short-term prediction values in {0, 1} (0 - the flood may not occur, 1 - the flood may occur). One example for the test data is represented in table 3:

Table 3. Test data set

Rainfall	**Flood time**	**Coefficient of drainage basin**	**Basin area**	**The coefficient of form**
38	67	0.29	115	0.32

As a statistical parameter it has been used the mean square error (MSE), which is different both in terms of changing the activation function for hidden layer, and the used training algorithm. This is calculated with the following formula:

$$MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_{obs} - O_{cal})^2} \ . \tag{2}$$

where n is the number of observations and O_{obs} and O_{cal} are the calculated and the observed value of neural network output data.

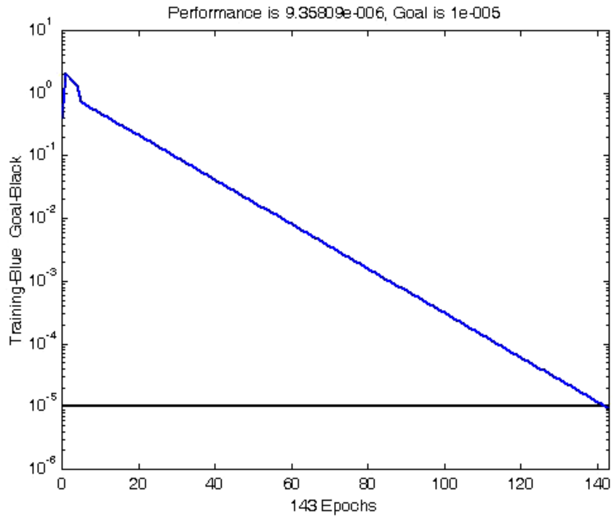
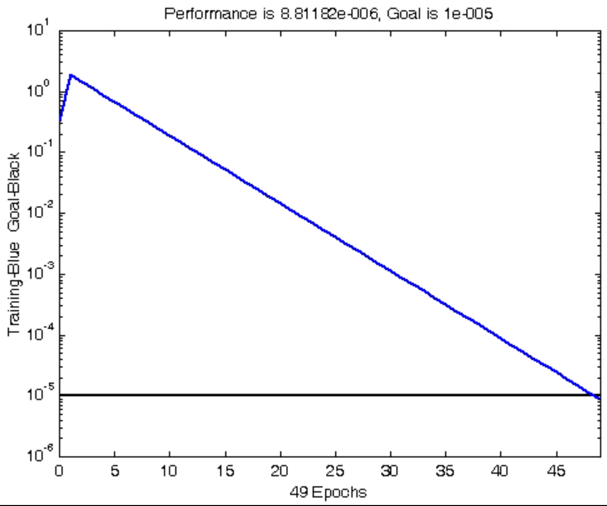
After the neural network training through gradient descending method, which leads to updating weights and polarization in the direction in which the performance decreases the fastest and by applying the two functions activation the error is:

Table 4. Resulted error after the training through gradient descending method

Activation Function	**Error**
Logsig	-2.1854e-005
Tansig	4.2309e-005

Another method for training the network for flood prediction has been training through epochs. In training through epochs the weights and polarization are updated only after all training set has been applied to the network. Calculated gradients are summed to determine the variation in weights and polarization.

Table 5. Resulted error after the training through epochs

Activation Function	Error	Epochs	Graphic
Logsig	-0,0031	143	
Tansig	0.0076	49	

As can be seen from table 5 the number of epochs is smaller when using the tansig activation function. Obviously, the backpropagation technique will not always find the correct weights and bias for the optimum solution.

Conclusions

By improving the prediction and viewing of speed, direction and expansion of water course during possible flooding, by monitoring the river basin using the techniques of artificial intelligence, they will provide all necessary information to take immediate measures related to defence against floods.

Knowing how evolution flow in different sections of the river is very important, because facilitate resolution of problems imposed by the practical needs.

This paper presented a multilayer neural network that aims flooding prediction. This network was trained by different methods, using different activation functions in order to compare the performance and to obtain more effective results.

Results obtained in this work lead to the idea that prediction models of neural networks performance depends on many factors, such as network structure, learning algorithm, the choice of network parameters. Of course, it is important to exercise caution in using artificial neural network for extreme flood events.

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Sistem de predicţie a inundaţiilor bazat pe tehnica rețelelor neuronale

Rezumat

Această lucrare prezintă o reţea neuronală multistrat în care se aleg intrări şi ieşiri care vor găsi o rezolvare optimă a predicţiei inundaţiilor în bazinul hidrografic al râului Prahova, judeţul Prahova. Acest sistem poate fi inclus intr-un proiect de management al situaţiilor de urgenţă dintr-un bazin hidrografic. Folosind tehnici de inteligenţă artificială în predicţia inundaţiilor se vor obţine rezultate mai bune decât folosind metodele convenţionale. Algoritmul de rezolvare a problemei va fi implementat folosind facilităţile mediului de programare MATLAB®.