A NUMERICAL AND EXPERIMENTAL MODEL OF A SEPARATIVE CATCHMENT IN THE NORTH OF SPAIN

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ABSTRACT

This paper presents two different methodologies for a hydrological study of the runoff generated in an urban watershed with a separate sewer system during storm water events. The first approach is based on the use of a numerical model (SWMM), a process simulator, and a non-linear parameter estimation tool (PEST), while the second deals with a concept of artificial neural networks.
A pilot project of a subcatchment in the city of Santiago de Compostela called "Fontiñas" (45 hectares) was studied using the two methodologies and the most relevant conclusions are presented in each case. Also included is the comparison of the two methodologies, using data collected with a rainmeter located in the watershed under study and the continuous measurement of the flow in a control section.

KEYWORDS

Artificial neural network; calibration; non linear parameter estimation; PEST; SWMM; urban drainage modeling

INTRODUCTION

The runoff generated by rainfall in an urban area has been widely studied. There are many mathematical models and computer programs that address this problem, based generally on conceptual watershed models, that either draw on the unitary hydrograph method, or on the pure hydraulic modelling method such as cinematic wave equations. Regardless of the method, the idea is to attempt to give a physical sense to the modelling and to the parameters that describe these phenomena later used in the calibration and verifications processes.

On comparing the data obtained using the model with actual data, there are parameters that need to be adjusted, and whose optimum values sometimes differ from what would be expected if the theory is strictly applied. Thus we would assume that, as we are dealing with a set of parameters that is smaller than what is actually involved (given that the problem in all its complexity has infinite degrees of freedom), some of the parameters used answer to more than one physical phenomenon, which means that their intrinsic physical sense loses validity. This is especially true in models that use unitary hydrographs. In fact, some of the synthetic unitary hydrographs used most frequently have parameters with a questionable physical sense.

To extricate ourselves from the parameters is only the first step in a process whose target is to establish the superiority of real data over conceptual models. This process, which has its supporters and its detractors, advances another step by completely ignoring the conceptual model -there are no watersheds, no channels, no equations- entrusting the adjustment structure to the data measured in the field. The models based on artificial neural networks follow this line of thought.

The purpose of this paper is to present the results obtained using one of the more widely accepted conceptual models for the hydrological simulation of urban runoff (SWMM), whose parameters have been calibrated using field data and a specific software program for non-linear parameter estimation (-reverse problem-) and the data obtained by means of the neural network, fitting the same data.

MORPHOLOGY OF THE STUDIED CATCHMENT

The catchment that has been studied, "Fontiñas", has a separate sewer system and an area covering about forty five hectares, 65% of which is urbanized and mainly used for residential purposes. Figure 1 shows an outline of the catchment.

One of the main characteristics is the steep slope of its streets, which averages 6%. This fact is quite important in the behaviour of the runoff, and has therefore been considered in the model. The effect is that there are very steep rising limbs in our hydrographs when rainfall events occur and the time it takes to reach the peak flow will range from 30 to 35 minutes.

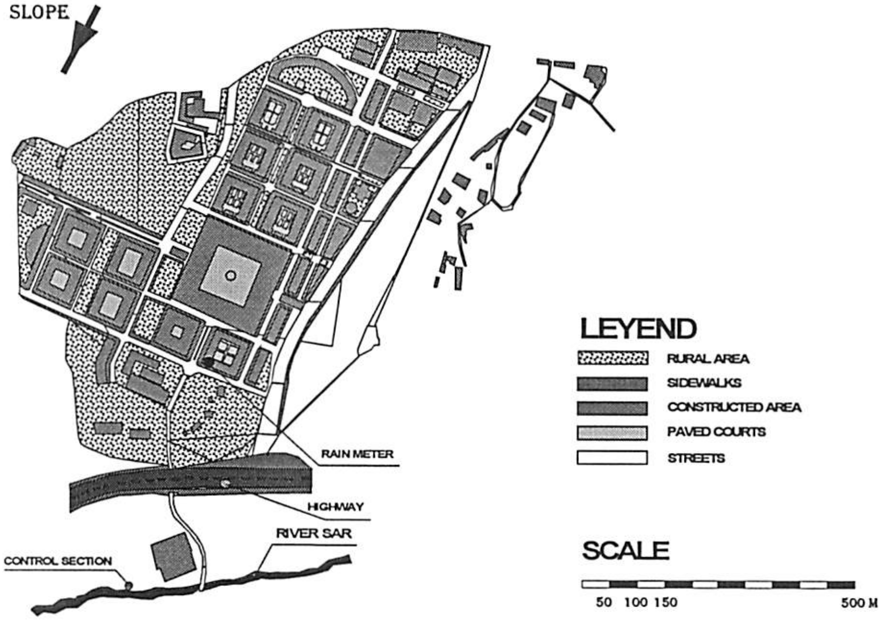


Figure 1.- "Fontiñas" catchment. Land uses.

METHODOLOGY: USE OF SWMM AND PEST MODELS

Modeling with the SWMM

The drainage basin has been conceptually represented by a network of hydraulic elements: subcatchments (discretization of the catchment), channels and pipes. The first two first elements have been used to simulate the quantity of urban storm water runoff (RUNOFF BLOCK) for different rain events, while pipes and manholes represent the closed conduit system that routes inflow hydrographs of runoff down to the outfall of the catchment (EXTRAN BLOCK).

The data collected were:

(1) topographic information on the urban catchment and pluviometry information in the form of rainfall hyetographs for the runoff simulation;
(2) information on the sewer network for the unsteady flow routing model.
(3) recorded hydrographs at the control section for the calibration process.

The RUNOFF Block generates surface runoff in response to precipitation and the key to applying RUNOFF is the division of the catchment into a number of subcatchments. Each subcatchment should be relatively homogeneous (i.e.,the physical characteristics such as slope, roughness, imperviousness,...should be consistent). In accordance with this, we divided our catchment into a total of 189 subcatchments (streets, roofs and rural areas). The representation of the discretization of the catchment is shown in Figure 2.

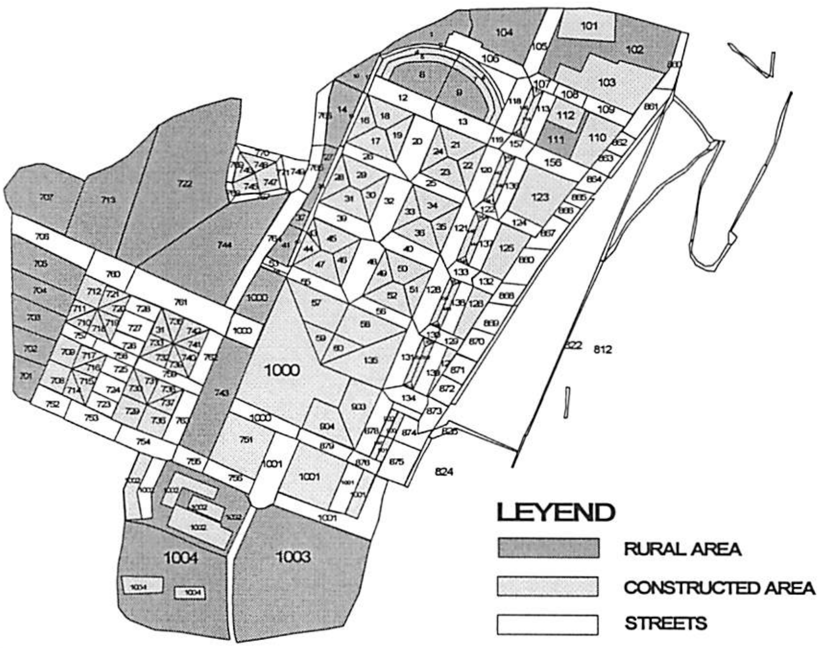


Figure 2.- Discretization of "Fontiñas" catchment.

The conceptual view of surface runoff used by the Runoff block holds that each subcatchment surface is treated as a nonlinear reservoir with a single inflow, precipitation. There are several discharges including infiltration, evaporation and of course runoff. The capacity of this reservoir is the maximum depression storage, which is the maximum surface storage provided by ponding, surface wetting and interception. Surface runoff occurs only when the depth of water in the reservoir exceeds the maximum depression storage. So, the precipitation intensity minus the evaporation rate is the net inflow to the resorvoir. The entire process is repeated for each subcatchment and is modelled by two equations: (1) continuity equation, which keeps track of the volume or depth of water on the surface of the subcatchment; (2) Manning´s equation to model the rate of surface runoff as a function of the depth of flow above the maximum depression storage depth (Nix,1994).

The roofs drain to what we call channels, which represent the drainage conduits that carry the generated runoff to an inlet of the sewer network or main net. Streets drain directly to an inlet of the sewer network located at intersections. This is an effective approach because a very high rate of storm water does not enter into street inlets due to the steep slopes; instead, it goes into inlets at intersections because they are flat. We have introduced 53 channels which are called the secondary net. The secondary net is simulated in RUNOFF, while the main one is simulated in EXTRAN (Figure 3).

The extended transport block (EXTRAN) is a dynamic flow routing model that routes inflow hydrographs through an open channel and/or closed conduit system, computing the time history of flows and heads throughout the system (Roesner et al.,1992). The program uses the complete Saint-Venant equations with an explicit solution technique to step foward in time.
The conceptual representation of the sewer network is based on the "link-node" concept so that links (pipes) transmit flow from node to node. Nodes are the storage elements of the system and correspond to manholes or pipe junctions in the physical system. We have modelled 158 pipes and 158 manholes.
So the result is a simulated hydrograph at the outfall of the catchment for the rainfall history that has been registered and introduced to the model. The next step is to calibrate de model by comparing simulated hydrographs to those that have been recorded at the control section.

Calibration with PEST

The simulated hydrographs from the Stormwater Management Model are compared to measured hydrographs at the outfall point of the catchment. This second phase has been developed with a numerical model called PEST 98 which stands for Parameter Estimation.

This involved the installation of a control section at the outfall of the catchment. Water level and velocity are recorded in order to calculate the output hydrographs, which are entered into PEST 98 as the "*observations*" in an observation file, together with the template file where the "*parameters*" to be

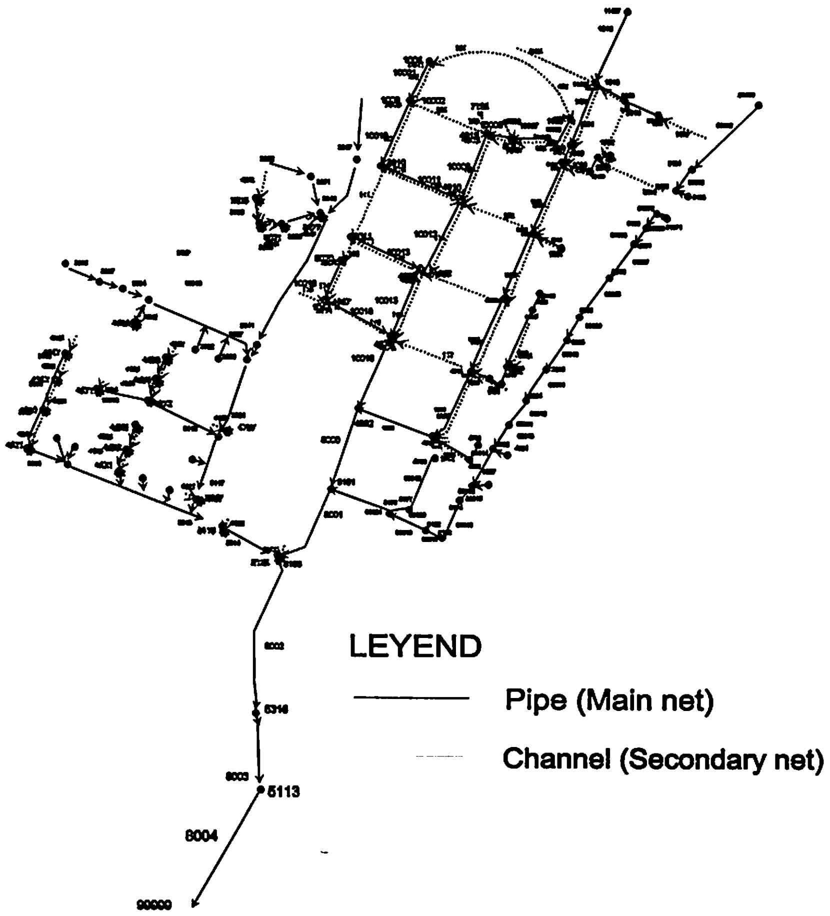


Figure 3.- Main and Secondary Net of "Fontiñas" catchment.

calibrated are set, and the instruction file where PEST 98 is linked to the physical model SWMM as well as the place where certain variables are set to ensure the success of the calibration process.

An automatic parameter estimation procedure consists of four major elements: (1) an objective function; (2) the optimization algorithm; (3) the termination criteria, and (4) calibration data.

An objective function is an equation that is used to compute a numerical measure of the difference between the model-simulated output (hydrograph at the outfall) and the observed watershed output. The aim of the autocalibration process is to find those values of the selected model parameters that optimize (minimize) the numerical value of the objective function.

PEST uses the Weighted Least Squares (WLS) function:

$$\boxed{F(\theta)=\sum_{t=1}^{n}\omega_t\cdot\left[q_t^{obs}-q_t(\theta)\right]^2}$$

where:

q_t^{obs} = observed (measured) flow value at time t
$q_t(\theta)$ = model simulated flow value at time t
θ = vector of model parameters
ω_t = weight at time t
n = the number of data points to match

PEST uses the "Gauss-Marquardt-Levenberg algorithm". The purpose of this paper is not to discuss this algorithm, but rather we will comment briefly on how the optimisation process is developed. For nonlinear problems, parameter estimation is an iterative process. At the beginning of each iteration the relationship between model parameters and model-generated observations is linearised by formulating it as a Taylor expansion around the currently best parameter set; hence the derivatives of all observations with respect to all parameters must be calculated. This linearised problem is then solved for a better parameter set, and the new parameters tested by running the model again. By comparing parameter changes and objective function improvement achieved through the current iteration with those achieved in previous iterations, the program can tell whether it is worth undertaking another optimisation iteration. If so, the whole process is repeated. Derivatives of observations with respect to parameters are calculated using finite differences with the method of "foward differences".

Figure 4 shows the recorded hydrograph that has been used to calibrate the model together with the hyetograph that causes it.

This hydrograph corresponds to a continuous simulation of two storm events occurring between the 8th and the 10th of January 1999. The total length of simulation is 53 hours.

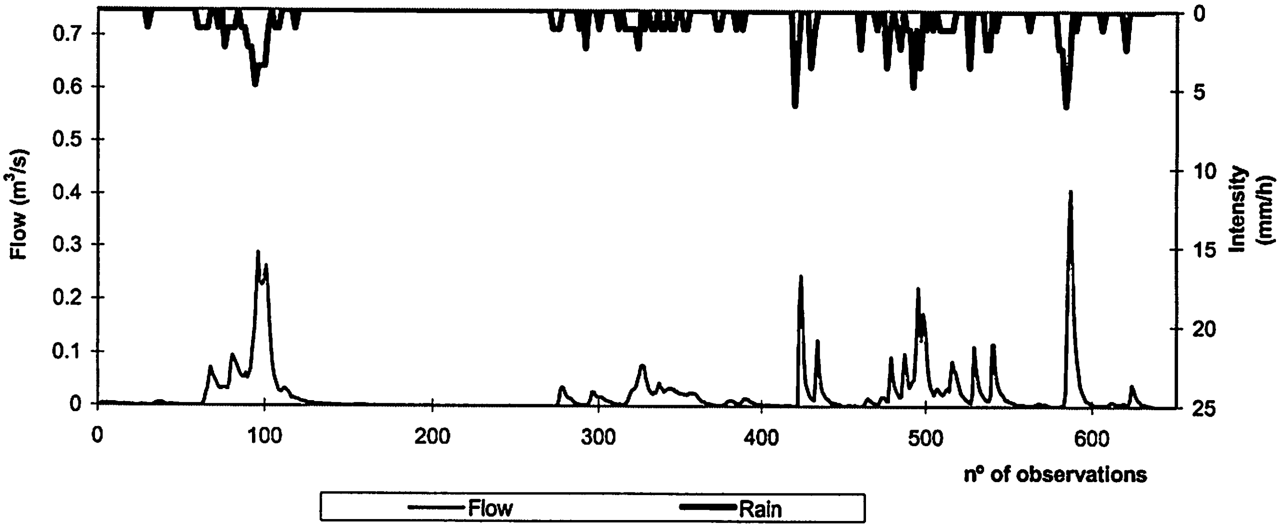


Figure 4.- Hyetograph and hydrograph for the calibration process.

The criteria used in the selection of the parameters to be calibrated were based on the combination of:

(0) the most influential parameters in the form of the simulated hydrographs as a result of a sensitivity analysis.
(1) parameters with no site-information.
(2) a high degree of difficulty and/or a great amount of time-consuming work for their estimation in the real watershed.
(3) parameters that are not bound to be correlated in order to increase the reliability of the predictions of a successful calibration process.

According to points (0) and (2), the most sensitive parameter, and, at the same time, the most difficult one to obtain is the slope of the sub-catchments "roof" (*ptej*). It is a necessary to explain that the "equivalent slope of roof surfaces" (*ptej*) is a fictitious parameter. By this we mean that the physical process that we are modelling includes the runoff over the roof surface and the drainage alongside the gutters of the roof before it enters the rainwater pipe that leads down to the conduit under the street. The conceptualisation of this same process in the model is much simpler, as explained in the conceptualisation of the catchment.

According to the third statement, a first set of four parameters (1.- Manning's roughness coefficient of impervious surfaces *nimp* ; 2.- Equivalent slope of roof surfaces, *ptej* ; 3.- Depression storage of pervious surfaces *reteper* ; 4.- Depression storage of impervious surfaces *reteimp*) was selected for calibration. On analysing the Covariance and Correlation Coefficient Matrixes, a high correlation between certain combinations of parameters was found. These combinations correspond to: 1-2, 2-4 and 1-4; therefore, they should not remain together in the same calibration performance. According to this, we selected the following set of non-correlated parameters for calibration, as shown in Table 1 :

Table 1

Parameter	Seed	Lower bound	Upper bound
ptej	1E-4	1E-10	1E-1
reteper	2(mm)	0.1(mm)	5(mm)

The rest of the parameters were fixed with commonly accepted values, as compared in the international scientific literature and adapted to the watershed under study.

Results of the calibration

The calibration results are shown in Table 2:

Table 2

Parameter	Estimated value	95% percent confidence limits	
		Lower value	Upper value
ptej	4.25E-04	4.04E-04	4.45E-04
reteper	2.25(mm)	1.4(mm)	3.1(mm)

As can be observed from Table 2, 95% percent confidence limits are quite good for the adjusted parameters (especially for *ptej*) which implies the following that there is a high level of certainty in the estimation of parameter values.

We are aware that the calibration results for this set of parameters depends on the values established for the fixed parameters. Therefore, the physical sense is partially lost in order to reproduce the recorded hydrograph at our control section (Figure 5).

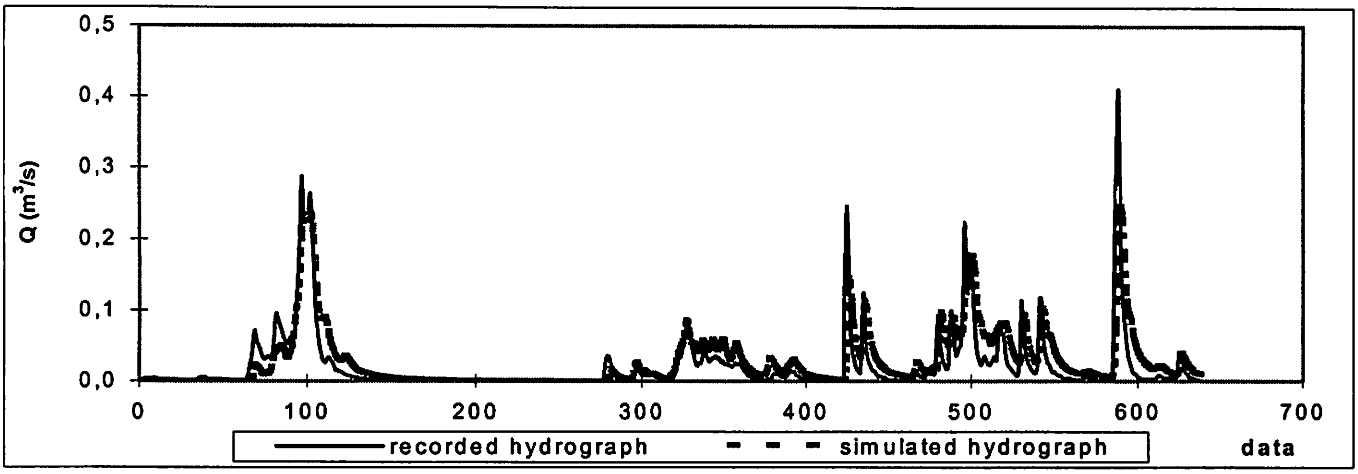
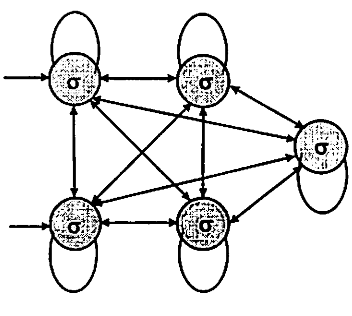


Figure 5.- Recorded vs calibrated hydrograph.

Model of the drainage network of Fontiñas using an Artificial Neural Network (ANN)



For the study of the rain-runoff transformation in the drainage network of Santiago de Compostela, we proposed the use of a totally recursive artificial neural network, consisting of two layers and five neurons (in order to obtain a good model of the hydrograph tails when the rainfall has ceased) and two entry cells where rain data is entered (the number of effective cycles for one entry data is increased).

The network being fed with rain data at a specific instant, provides the flow at the same instant in its exit neuron –the need to store historical information justifies its recursiveness- after a two-cycle calculation. (trials with one and three-cycle processes led us to the conclusion that the value obtained in two cycles is stable, which is not the case with the one-cycle process.)

We used a sigmoid function in the neurons and the identity in the conections; the training process used 450 records of rainfall-runoff, which were adjusted using the mean square error measurement of the differences between the value measured and the value that was obtained, through Newton optimisation algorithms and a conjugated gradient.
Shown below is the result of the application of the test archive using the 450 preliminary data as training and the following data as a prediction stage:

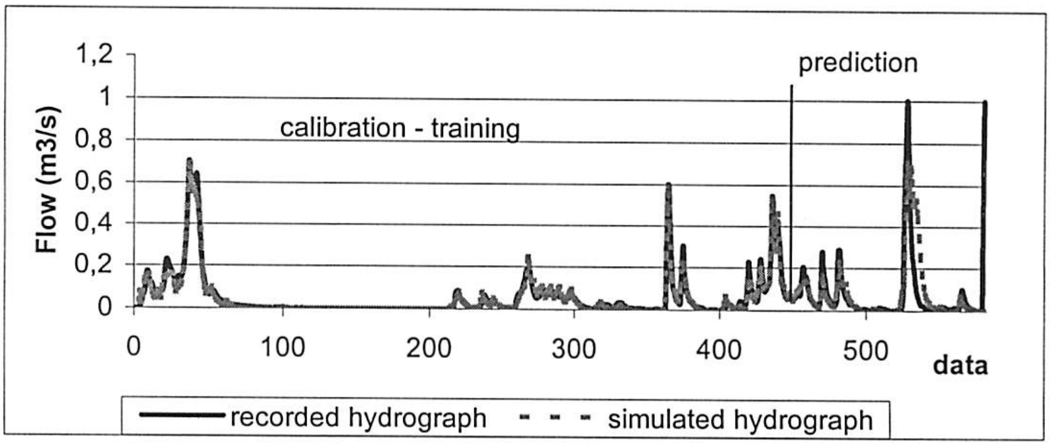


Figure 7.- Fit obtained using the artificial neural network (standardised variables).

We studied networks having a lower degree of recurisiveness and others with a greater number of neurons (3 and 4) in the hidden layer. The first case did not have satisfactory results, while the second did not show signs of any significant improvement.

Rainfall and runoff data were standardised dividing them by the highest record obtained in each of the two series. In this way both series were within the (0-1) interval. This standardisation is considered to be adequate for the study presented in this paper, whose aim is to asses the efficiency of the method. If we consider the proposed network as a predictive element, the standardisation should be carried out foreseeing higher rainfall and runoff values, otherwise, it would be saturated for a wider range of values.

Figure 8 shows the degree of adjustment of the SWMM and the neural network models with the data expressed in the same variables (rainfall and actual flow).

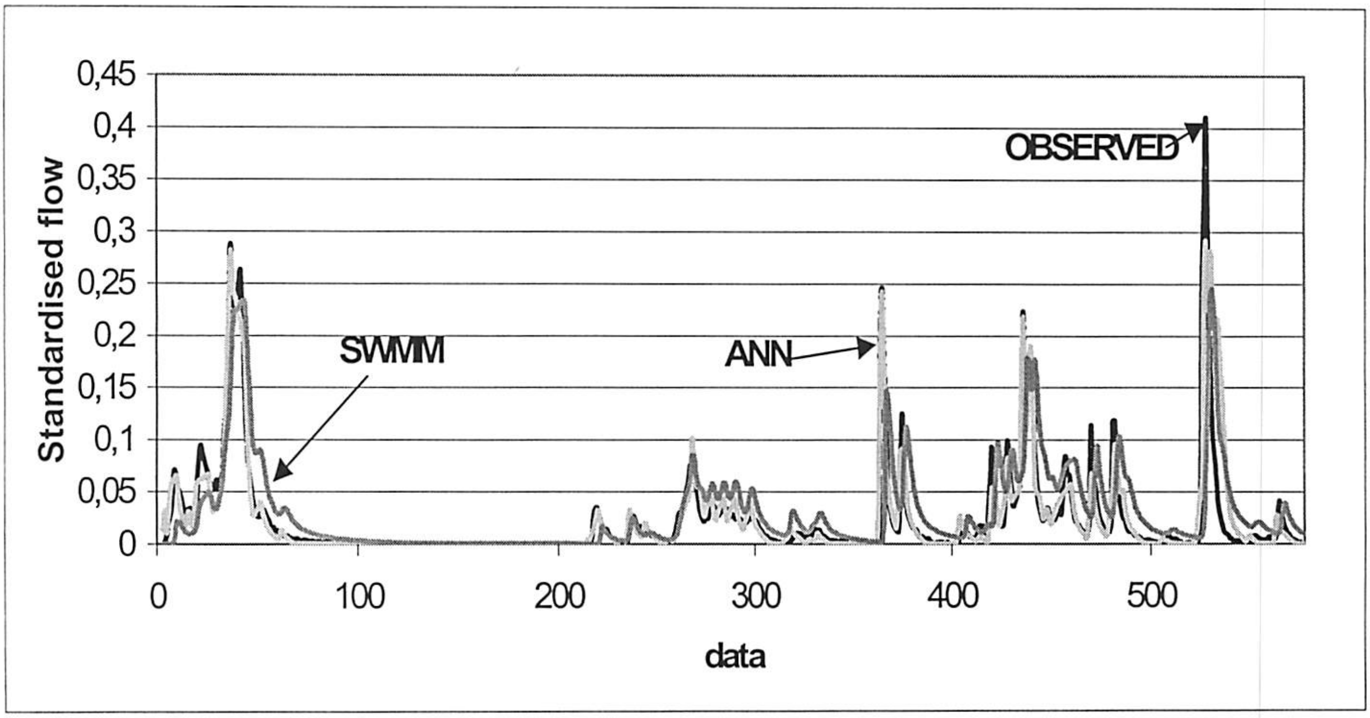


Figure 8.- Comparison of SWMM and ANN (Artificial Neural Network) methodologies.

CONCLUSIONS

The main conclusions of this study are:

- A general methodology for the hydrological study of a catchment based on simulation and further parameter autocalibration processes were developed and particularised for the catchment "Fontiñas"of Santiago de Compostela, attaining considerably good results in the simulation of its behaviour.
- The autocalibration process was developed using a non-linear parameter estimation tool called PEST98, which stands for Parameter Estimation. This process showed that certain parameters are highly correlated and cannot be considered in the same calibration performance. Therefore, calibration results depend on the values of fixed parameters and as a result, physical sense is partially lost in order to reproduce the recorded hydrograph at the control section of the catchment studied.
- We were able to reproduce the behaviour of runoff generated in an urban watershed with a limited number of parameters (2) comparing the results with a "black box" methodology (artificial neural network). The results of the two models area comparable, which would imply that the neural networks are a very useful tool in predicting the behaviour of a previously calibrated watershed.
- Parameter estimation in a model like SWMM is a complex process. By choosing a certain number of parameters among the many that are influential, their optimisation causes them to loose their physical sense, since they must answer to all the uncertainties in the model. If "reasonable" values are chosen for all the parameters included in the model, major errors could be made, given that the parameters included do not use up the degree of freedom of the problem.

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