RAINFALL-RUNOFF MODELING FOR FLOOD FORECASTING: APPLICATION OF GLOBAL METHODOLOGIES TO A MEDIUM-SIZE BASIN IN BRAZIL

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INTRODUCTION

Due to the difficulty in the calibration of the large number of parameters that conceptual models generally require, global empirical methods are currently used in studies and technological applications. The use of the DPFT (First Differences of the Transfer Function) methodology to identify the Unit Hydrograph and effective precipitation, by means of sets of total precipitation and observed runoff, makes it possible for us to obtain the loss function model which best fits the characteristics of the hydrographic basin under study. The DPFT method was applied to Honório Bicalho, a cross section of the hydrographic basin of the Rio das Velhas, with a drainage area of 1655 km^2. Two simple models of loss function were studied and calibrated: the reservoir model (with three parameters) and the GR3 model (with one parameter). The results were analyzed and compared with regards to their efficiency. Additionally, Artificial Neural Networks are currently being presented as an alternative approach to traditional methods in the solution of problems in predicting temporal runoff series. In the case in question, the use of this technique is attractive as, in order to use it, it is not necessary to have a prior knowledge of the mathematical relationships that describe the nonlinear complex relationships between the input variables (precipitations) and the output variables (run-off). Here this type of black box model is compared to the Unit Hydrograph Method (DPFT methodology,) regarding it as a semi-conceptual model.

RAINFALL-RUNOFF MODELING

The Unit Hydrograph and the DPFT methodology

Basically, this classical Unit Hydrograph method (UH) proposes that, for a given hydrographic basin, runoff is the result of a loss function (LF) and of a linear Transfer Function (H). The linear Transfer Function (H) increases over time the effective rainfall Pe, so as to obtain the surface runoff, as in Figure 1.

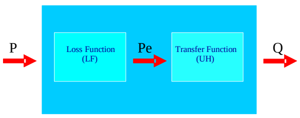

Figure 1

As opposed to this classic approach, the DPFT method, proceeding iteratively from an array of episodes of total rainfall – runoff, establishes the Transfer Function (H) and the effective rainfall (Pe) for each event, and the relation P-Pe (Duband et al.,1993; Nalbantis et al. 1995). This distinctiveness permits a comparison and choice of the best Loss Function for a given hydrographic basin (Versiani, 1983; Sempere-Torres et al., 1992).

The Loss Function Models

➢ GR3 model - is a global empirical model developed by Edijatno and Michel (1989) with 3 parameters with a daily time step (Nascimento, 1995). The parameters to be calibrated are *A* which characterize the basin and *S1*, which simulates the initial condition of average humidity of the basin lands for each event considered, which will supply us with the relation *S1/A*.

➢ Rerservoir Model - proposed by Lorent (1975). In this model, α and β are two parameters characterizing the basin and should be calibrated with respect to the condition $0 < (\alpha,\beta) < 1$. *D(0)* is a parameter which characterizes the initial conditions for each event, taking into account the previous hydrologic state (conditions of humidity prior to the beginning of the event). These parameters relate the reservoir deficit behavior with the reservoir retention or loss.

The choice of the best parameters for each model is made through the minimization of the Root Mean Square Error (RMSE) between the effective rainfall calculated by the DPFT methodology and the effective rainfall generated by the loss function models. To compare the observed and the calculated floods, the Nash coeficient was used.

The Artificial Neural Networks approach in Rainfall-Runoff modeling

The second global method, compared to the DPFT method, is based on a class of black-box models, which used Artificial Neural Networks, applied to hydrological modeling since the 1990's. The architecture of the network employed (NSRBN) proved to be very effective, dealing directly with the nonlinearity inherent in the rainfall-runoff process in the hydrographic basin. In the study of the case shown, where the worked data are only data for rainfall and runoff, this technique is advantageous, in the sense that, as with all black-box models, it is not necessary to know details of the basin studied (basin physiography, state and constitution of the soil, previous humidity) and how they interfere in the extent of the runoff.

In training the multi-layer network, the problem consists of estimating the weight adjustment for the intermediary layers, which do not have the desired outputs, contrary to the single layer networks, where there is a difference between the desired output and the output flow of the networks. The solution to this problem was discovered in the 1980´s, with the description of the *backpropagation* algorithm, which consists of a retropropagation of errors (Braga et al, 2006). Figure 2 illustrates a typical MLP network, with an intermediary layer ('hidden layer').

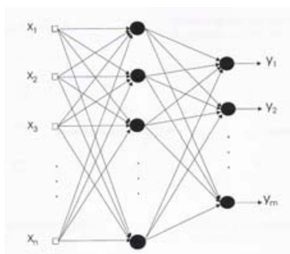

Figure 2

RESULTS AND DISCUSSION

The Figure 3 shows the Rio das Velhas basin, located in the State of Minas Gerais, Brazil. Two samples of rainfall-runoff events were selected for this study case: the first sample, using 8 events for calibration and the second, with 7 events, for validation. Figure 4 shows the two adimensional Transfer Functions (Unit Hydrographs) obtained by the DPFT methodology for these two samples.

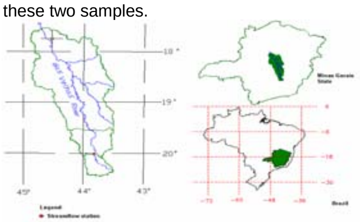

Figure 3

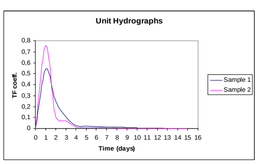

Figure 4

➢ Calibrated paremeters for GR3 and Reservoir model (Sample 1) and Nash coefficients

Sample 1				
	GR3	Reservoir		
Event	S_1/A	alfa (α)	beta (β)	*D(0)* (mm)
1	0.33	0.92	0.99	333
2	0.29	0.8	0.99	246
4	0.24	0.92	0.99	132
6	0.38	0.92	0.99	40
7	0.41	0.8	0.99	121
9	0.19	0.92	0.99	236
10	0.40	0.8	0.99	215
11	0.17	0.92	0.99	419

GR3		Reservoir	
Event	NASH	Event	NASH
1	**0.9303**	1	**0.9136**
2	**0.2860**	2	**0.3942**
4	**0.8952**	4	**0.8325**
6	**0.6140**	6	**0.6911**
7	**0.4164**	7	**0.0207**
9	**0.8781**	9	**0.7534**
10	**0.8174**	10	**0.8744**
11	**0.6722**	11	**0.4646**

➢ The validation for sample 2 was carried out using the calibrated average values of the parameters of the respective LF models of sample 1. Figure 5 shows the hydrographs corresponding to the observed and calculated discharges, generated by the respective LF models, for event 13 (chosen at random), in the validation phase for sample 2 and a table (Nash Coefficients for Sample 2).

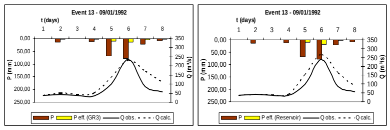

Figure 5

GR3		Reservoir	
Event	NASH	Event	NASH
12	**0.7474**	12	**0.9187**
13	**0.6108**	13	**0.6617**
14	**0.8104**	14	**0.4297**
16	**-1.8113**	16	**-9.6056**
17	**0.7989**	17	**0.4087**
18	**0.4782**	18	**0.2862**
19	**0.2415**	19	**-0.3488**

➢ The 15 events (samples 1 and 2) were divided in 9 greater events for training of ANN models (named events 1N, 2N,…,9N). For each of the 9 events a model of Neural Network was trained. The table shows the results obtained by the Nash coefficient for the prediction, using the three RNA models for sample 2 (validation). It can be seen that the best result is that obtained by model 3.

Events	**10 neuron**	**6 neuron**	**4 neuron**
	Model 1	**Model 2**	**Model 3**
	Calibration: event 6N	Calibration: event 5N	Calibration: event 6N
13	-0.0076	0.6747	0.7228
14	0.4526	0.5604	0.7479
16	0.6153	0.6142	0.3425
17	0.7554	0.6779	0.7967
18	-0.6427	0.2084	0.1414
19	0.1273	0.4950	0.4890

➢ The table shows the results obtained by the Nash coefficient for the prediction, using the three RNA models for sample 2 (validation). Figure 6 shows the observed and predicted hydrographs, using the DPFT methodology with the GR3 model and the neural networks model (with 4 neurons), for sample 2 (events 13, 14 and 17).

Events	ANN	DPFT
13	0.7228	0.6108
14	0.7479	0.8104
16	0.3425	-1.8113
17	0.7967	0.7989
18	0.1414	0.4782
19	0.4890	0.2415

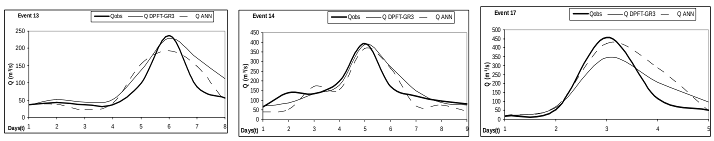

Figure 6

CONCLUSION

➢ The tests made reveal that, initially (calibration phase), the DPFT methodology performs very satisfactorily in the reconstitution of the runoff observed by means of the effective rainfall estimated by the DPFT.

➢ For the two calibrated Production Function models, the variation of the parameters with respect to the initial state of the humidity of the soil of the hydrographic basin, event by event, given by the sum of the precipitation in the 5 days prior to the event was shown to be coherent.

➢ When analyzing the performance of the Reservoir and GR3 models in the calibration phase of the data, it was established that the loss function models produced similar results. However, in the validation stage (with the calibrated average parameters), a superior performance of the GR3 model was observed.

➢ Among the Neural Networks models analyzed, it was established that a parsimonious model of 4 neurons (3 input and 1 output) demonstrated better performance, with the condition that the events in the calibration phase are prolonged, in such a way as to have a sufficient number of training examples. In accord with the tests made, it was established that the Neural Network models shown here made a more precise prediction for rainy periods that are neither very short, nor excessively long, of a form that does not include periods of drought.

➢ Finally, the analysis of figures and tables above allows us to conclude that, in this case study, both global methods demonstrate very satisfactory results in prediction, taking into consideration the hydrographic information available for each basin, and that the Neural Networks model exhibits a greater efficiency than the DPFT method, even though no physical analysis of the behavior of the basin was possible.

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