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Interactive Comment

Interactive comment on “A time delay artificial neural network approach for flow routing in a river system” *by* M. J. Diamantopoulou et al.

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RESPONSE TO REFEREES

We are very grateful to ANONYMOUS REFEREES for expending considerable time and effort in reviewing the original manuscript as well as for their constructive comments and suggestions.

An item-by-item response to the comments and suggestions of REFEREES can be summarized as following:

REFEREE #2

1. “__ the paper doesn’t appear to provide any new significant scientific contributions. In fact ___ presentation of novel concepts”

After a detailed study of the references suggested by the Referee #2, we would like to give our comments as follows:

- Sajikumar and Thandaveswara (1999) have been used a temporal back-propagation neural network (TBP-NN) for monthly rainfall - runoff modeling in scarce data conditions.

- ANN concepts and applications in hydrology have been discussed by the ASCE Task Committee on Application of ANN in Hydrology (2000), which concludes that ANNs may be perceived as alternative modeling tools worthy of further exploration.

- Thirumalaiah and Deo (2000) have been demonstrated the application of Neural Network models to real - time forecasting of hourly flood runoff and daily river stage, as well as to the prediction of the sufficiency or deficiency of monsoon rainfall.

- Coulibary et al. (2001) have been provided an informative comparison of dynamic neural network models and static multilayer perceptron (MLP) models within the context of short - term hydropower reservoir inflow forecasting.

- Kneale et al. (2001) have been developed back propagation and Time Delay Neural Networks to forecast stage on the River Tyne, for lead times ranging from 2 to 6 hours.

- Luk et al. (2001) have been developed three alternative types of ANNs to forecast rainfall depth one time step (15 minutes) ahead for 16 gauges concurrently.

In most of the above papers the ANNs are considered to be back propagation neural networks. Moreover, the Cascade Correlation algorithm in which Kalman's learning rule is embedded, in none of the above suggested papers has been used. In a revised version we could be reformulated the introduction to highlight the new contribution provided by our paper compared to these of the above References.

The new significant scientific contributions of our paper to the field of flow routing in a river system, are: the architecture of the ANN and the type of the learning rule. Specifically, the novel concept is the use of a new type of learning rule: the Kalman's

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learning rule (Grewal and Andrews, 1993; Demuth and Beale, 2001). Kalman filter theory (Grewal and Andrews, 1993) is used to obtain the best estimate of the weights based on the stream of training data. The Kalman learning rule seems to be a key feature of the ANN. This learning rule is acceptable to forecasting type problems where the number of inputs is not too large. A Kalman filter is an optimal recursive data processing rule. It includes two phases: Predict and Update. The predict phase uses the estimate from the previous time step in order to produce an estimate of the current state. In the update phase measurement information from the current time step is used so as to refine this prediction and arrive at a new, more accurate estimate. The architecture used is the Cascade method of training, based on the Cascade Correlation (Fahlman and Lebiere, 1990). In our paper, this architecture in which the Kalman's learning rule is embedded has been used. Although none of these aforementioned methods are new itself, the novelty of this work is the fact, that this type of TDANN approach has not been used so far, for flow routing in a river system.

Specific comments

2. Sec 1. Pag. 2737, lines 11-20: "the authors ___and applications"

The response has been covered in the previous step. In a revised version we could be reformulated the introduction to highlight the new contribution provided by our paper.

3. Sec 2. Pag. 2739, lines 2-8: "the same symbol ___be changed"

The authors agree with the suggestion and this remark will be considered in a revised version of our paper.

4. Sec 2. Pag. 2739, lines 14-20: "this paragraph ___to better understand Section 2"

The authors agree with the suggestion and a schematic representation could be added in a revised version of our paper.

5. Sec 3. Pag. 2742, lines 7-8: "The authors state ___should be developed and presented."

By contacting a few trials around the values obtained from the correlograms, it was found that the delayed memory of 10 days was the optimum.

6. Sec 3. Pag. 2742, lines 13-15: “The authors use the notation___i.e. Q I(t+1). Moreover,___in the conclusions.”

a. The authors agree with the suggestion about the notation and this remark will be considered in a revised version of our paper.

b. Two different TDANN models have been developed to forecast the daily flow values at 2 and 3 days ahead (QI(t+2) and QI(t+3)), as suggested by Referee #2. It may be noted that the input to the above two models were kept as the same as in case of 1 day ahead. It was observed that the performance of any model may be good for smaller lead times but may become worse as the lead time increases. The performance of the models in terms of R, MAE, RMSE and RMSE (%) for 1, 2 and 3 days ahead could be included in a revised version of our paper.

7. Sec 3. Pag. 2744, lines 8-11: “the results ___to the conclusions”

a. The focus of our paper is to develop a new approach for flow routing in a river system. We agree that the utility of ANNs in the hydrology field has already been estamblished by others but space for research still exists. For example, flow routing in a river system with the approach of cascade correlation in which Kalman filter is embedded has not been used. This approach seems to be a key feature of the ANN modeling.

The motivation for developing the above approach is to overcome difficulties of other ANN algorithms such as the back propagation algorithm which has been described and used widely. It is well-known that the back propagation training algorithm has some basic disadvantages. The main are that the convergence progress slowly and the network architecture is required to be prefixed.

In our approach, cascade correlation in which Kalman filter theory (Grewal and Andrews, 1993) is used to obtain the best estimate of the weights based on the stream of training data, builds hidden units into the neural network as it goes, the neural network designer is relieved of the task of having to guess at the configuration of hidden units for a particular problem. Furthermore, studies have shown cascade correlation to be a faster algorithm and better able to converge (Fahlman and Lebiere, 1990, Drago and Ridella, 1994). Also, shows very good generalization characteristics.

b. With respect to rigour of analysis, for the sake of brevity, comparisons with other ANN models were not included in this paper. The results showed that this particular TDANN approach of Cascade Correlation algorithm in which Kalman's learning rule is embedded performed better than the backpropagation ANNs. The performance of the backpropagation ANN models in terms of R, MAE, RMSE and RMSE (%) for 1 day ahead could be included in a revised version of our paper.

REFEREE #3

1. "___However, the authors ___understanding (or usage) of TD-ANN"

This consideration pointed out by the REFEREE #3 has been answered in our response to the REFEREE #2.

2. "choice of data for developing ___ data for validation"

We agree with the comment that there are historical records until present day. The data we used were available only by the Public Power Corporation of Greece and they are referred to the daily flow data for the period 1977-1987. The recent time series of the daily flow data, as the REFERREE #3 suggested, are available neither by the Public Power Corporation of Greece nor by the Web.

The preliminary investigation of the daily flow time series indicates that the most significant events (i.e. very high values and significant variations in the series) fall within the calibration and validation periods which have been used in our study. Consequently, there is nothing to be gained in the training of ANNs from the inclusion of the recent data.

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3. “the choice of forecasting horizon ___1 day seems too long”

The reason for choosing the one day ahead as forecasting horizon is that the available data are measurements for only one day time step and this makes it not possible for choosing shorter forecasting horizons, as the REFEREE #3 suggested.

Three multipurpose reservoirs, downstream of the Ilarion station, Polyfyto, Sfikia, and Assomata, are currently in operation along the Aliakmon river route in order to satisfy irrigation, water supply and power generation needs. The capability to make forecasts one day ahead is useful in decision making for the operation and the management of the three reservoirs.

4. “comparison of methodology ___ANN”

This consideration pointed out by the REFEREE #3 has been answered in our response to the REFEREE #2.

Minor and specific points

1. ___ felt that the authors ___ learning rule”

In our point of view, all references have important and complement issues to give. So, it is very difficult to us to exclude any of them but this suggestion will be considered in a revised version.

2. “In Table 3, ___ explanations to this?”

The performance of TDANN model in terms of errors is consistent as it is concluded from the corresponding errors given by using other ANN models (see Sudheer et al., 2003; Shrestha et al., 2005). The underestimation or overestimation of peak flows could be due to a lack of information provided to the network, such as the lateral inflow from smaller tributaries.

REFEREE #1

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In the summary of the review, REFEREE #1 criticizes the lack of novelty of our paper. The novelty of our work has been detailed analyzed in our responses to the REFEREES #2 and #3.

Other points

1. It is accepted that the discussion on overfitting to be revised as suggested by REFEREE #1. In this regard is appreciated and more relevant references will be added in a revised version of our paper.

2. It is worth mentioning that the correlograms were not used in ANN modelling but as a tool for the delayed memory determination.

3. To address the concerns of the REFEREE #1, information on pages 2739-2740 and Figure 3 can be removed from a revised version, if required.

4. It is also accepted that all other suggestions by the REFEREE #1 will be considered in a revised version of our paper.

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