

Interactive comment on “Classification of hydro-meteorological conditions and multiple artificial neural networks for streamflow forecasting” by E. Toth

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General comments

The paper deals with the so-called modular models (or multi-models) where each model is calibrated (trained) on a specific subset of the calibration data representing a particular sub-process. The presented method involves using Kohonen network (self-organising feature maps, SOM) to cluster the hydrological records into groups, and then building for each of the groups an individual forecasting data-driven (ANN) rainfall-runoff model. The author correctly states that various elements of such an approach have been used during the last decade for similar problems, and refers to the

C67

relevant literature. The value of this paper is seen in that it considers the multi-step forecasts, adequately interprets the SOM-generated clusters, and uses a more flexible approach allowing for switching to a different number of clusters based on the results of the initial experiments.

The paper is well written and structured, includes relevant references. The narration is logical. The assumptions are tested by the experiments. Conclusions reflect the material covered in the paper. The paper contains the original material and can be recommended for publication in HESS, provided the comments and suggestions given below are addressed.

Specific comments

1) Typically Kohonen network is profiled as a clustering method, and not a classification one. Classification results in a learned machine that is able to attribute new data to one of the existing classes. The training data for such machine should include the known (observed) output, since this is a supervised learning method. On the contrary, clustering methods belong to the group of non-supervised learning methods since the output is not known. (Often, the clusters found by a clustering method can be interpreted as classes, data is labeled accordingly, and then a classifier is trained – but this was not done in the paper.) The task solved by Kohonen network in the paper is a clustering task. It is suggested to consider using the term “clustering” or “grouping” instead of “classification”. Interestingly, such use of terms can be found in other publications as well; for example, this reviewer has made exactly the same comment on the paper “Clustering of heterogeneous precipitation fields for the assessment and possible improvement of lumped neural network models for streamflow forecasts” by N. Lauzon, F. Anctil, and C. W. Baxter, Hydrol. Earth Syst. Sci., 10, 485–494, 2006 (which originally had “classification” in the discussion paper version).

2) The reader may ask, if SOM is a clustering method, how (page 910) it could be used to perform classification for the new data vectors to attribute them to a particular clus-

C68

ter/model. Was a separate classifier trained? What method was used for classification? The author is invited to clarify this.

3) It would have helped, if the ways the data is partitioned into the training, cross-validation (if any) and validation sets had been presented. It is not specified what is the total size of the data set.

4) The author uses the following logic: build 9 models – analyse the multi-model performance on the test (validation) set – reduce number of modules from 9 to 4 – analyse the results again. This means that the test set is used in building the model (deciding on the number of its modules) which is methodologically questionable. Indeed, sometimes, in the situations of data shortage this is done, but in the considered case, as I understand, there is no data shortage, so a separate, cross-validation set could be used. The author is invited to present the justification for this approach.

5) In data-driven rainfall-runoff (RR) modelling input selection can be performed by using “physical” approach, for example determining the lags through studying the travel time through the catchment, or by studying the correlations and mutual information between lagged rainfalls and flows. Unfortunately, it is not clear how the lags for rainfall (3) and flows (4) were chosen for the case study considered? (page 905) It is recommended at least to mention such possibilities.

6) In the model on page 905, out of 7 inputs, 4 inputs represent a very strong autocorrelation component (flow). The problem with such models is of course that the forecasted flow mainly depends on the flow of the previous day and much less on the precipitation. However, the most important use of such model is forecasting the increase of flow due to the past precipitation, and they may be tuned to react to a strong (but physically uninteresting) signal of the past flow(s). This issue is not discussed, and it would be advisable to mention this problem.

7) Clustering is performed in the same 7-variable space, which is characterized by the high (auto)correlation of flow components. It would be interesting to see if similar

C69

results can be achieved by clustering in a much simpler space – for example with the linear combinations (moving averages) of $Q(t-L)$, $L=0, \dots, 3$.

8) How the ANN topology was optimized (number of hidden nodes). Was cross-validation set used?

Technical corrections/suggestions

P 899, line 20: keep \rightarrow take; line 26: in the \rightarrow of the

P 904, line 4: an hybrid \rightarrow a hybrid

P 907, line 19: chosen an \rightarrow chosen to have an

P 909, line 26: instant \rightarrow instance (?)

P 910, line 15: second [\rightarrow]

P 911, line 18: numerousness \rightarrow size

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 6, 897, 2009.

C70