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REAL TIME NEURAL FUZZY SYSTEM FOR RAINFALL-RUNOFF MODELING

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The Neuro-Fuzzy Systems (NFS) are computational intelligence tools that have recently been employed in hydrological modeling. The learning algorithms used are based on batch learning where all the parameters of the fuzzy system are optimized off-line. Although these models have frequently been used, one criticism of batch learning is its inability to react to changes in the system. For example, for a rainfall-runoff model, once the model is trained in batch mode, the model would not be able to make the correct predictions of the runoff unless it is trained again. For a model to be able to react to changes in the runoff characteristics without the need for re-training, two conditions have to be satisfied. Firstly, the model must be capable of online or incremental learning. This means that learning takes place with the presentation of each input data, rather than the entire dataset. Secondly, the model should be capable of learning in real-time. To address these issues, Real Time Dynamic Evolving Neural Fuzzy Inference System (RT-DENFIS) has been developed. RT-DENFIS is a Takagi-Sugeno-type fuzzy inference system and utilizes online learning. Online or local learning evolves through local adjustments in the model as new data is introduced in sequence. RT-DENFIS utilizes an evolving, online clustering method called the Evolving Clustering Method (ECM) (Kasabov and Song, 2002) which is an online, maximum distance-based clustering method. It is a fast, one-pass algorithm for a dynamic estimation of the number of clusters in a data set and finding their current centres in the input space. For each new input data point the output will be simulated based on the available rules created from training with previous data. The observed output and the input information are then fed back to the model to update the clusters and rules. Hence, for the next incoming data, the model has been updated by the last data point. In other words there is no specific training data set in RT-DENFIS, but training is continuously in progress as each new data point is presented to the model. For example, in a discharge forecasting problem, RT-DENFIS can predict the one day ahead discharge $Q(t+1)$ by using the historical data till the present time t. One day later, the observed discharge at time $t + 1$ will be fed back to the model to update the clusters and rule nodes for predicting $Q(t + 2)$, and so on.

In the present study, updating capabilities of RT-DENFIS is compared with the Adaptive Network-based Neuro-Fuzzy Inference System (ANFIS) which is a common batch NFS model for a rainfall-runoff modeling problem in Rönne catchment, Sweden. A sub-catchment of Rönne named Klippan_2 with area of 241.3 km^2 was chosen for this study and the mean daily rainfall, runoff, and temperature time series from 1961 to 2003 was used. The following two scenarios were considered: Scenario (1): The first year of data (1961) was used to train an ANFIS model but the model was used to forecast Q(t+1) for the next year (1962) only. The model was subsequently retrained every year using all available data to date and used in the simulation phase to simulate

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Q(t+1) over the following year period. Thus, training using data from 1961 - 1962 was used to simulate Q(t+1) for 1963. This process was repeated until data for 1961 - 2002 was used for training and the model used to forecast Q(t+1) for 2003. In this scenario, the positive effects of updating a model once a year using a batch model can be investigated. Scenario (2): Using the first year of data (1961) for initialization, an RT-DENFIS model was developed to simulate Q(t+1) in real time mode from 1962 to 2003. In this scenario, RT-DENFIS uses the present day information to predict the discharge for the next day. At the end of the day, the observed discharge will be used to update the model to predict the discharge for the following day. This procedure is repeated to the last available data point. In this scenario, the effect of a local model, trained online can be investigated.

The *CE* values obtained by the ANFIS model for Scenario (1) and RT-DENFIS for Scenario (2) in simulating Q(t+1) for the time period 1962 - 2003 are presented in Fig. 1. As can be seen, the ANFIS model trained and updated under Scenario (1) is not performing well for the first few years. As shown in the figure, improvements are obtained especially for 1971 onwards. RT-DENFIS (Scenario (2)) shows significant improvements over ANFIS model, especially during the early simulation period, from 1962 – 1971.

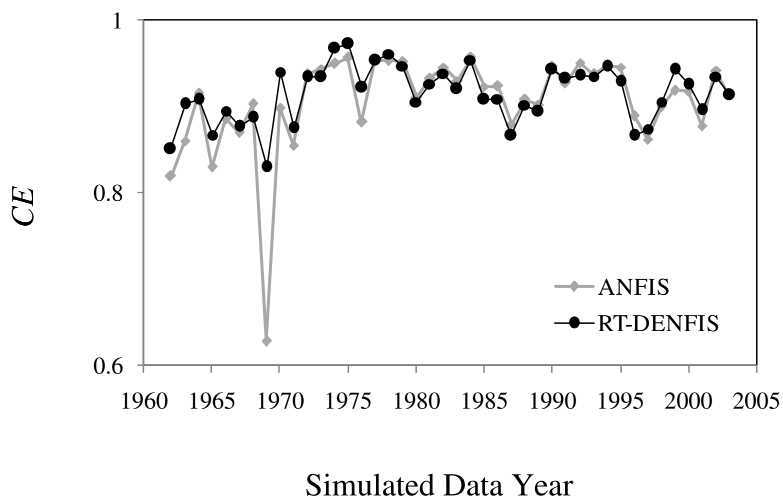

Figure 1 Performance of ANFIS model for Scenario (1) and RT-DENFIS for Scenario (2) in simulating Q(t+1) in terms of *CE*.

This indicates the strength of online models, where a shorter data length is required for training. The improvements of RT-DENFIS over ANFIS are modest for 1980 – 2003 and this is attributed to the fact that ANFIS benefits from retraining after every 1 year. However, it should be mentioned that the results for RT-DENFIS were achieved without having the need to retrain the model.

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