Evaluation of an artificial neural network rainfall disaggregation model

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Abstract Previous research produced an artificial neural network (ANN) temporal rainfall disaggregation model. After proper training the model can disaggregate hourly rainfall records into sub-hourly time increments. In this paper we present results from continued evaluations of the performance of the ANN model specifically examining how the errors in the disaggregated rainfall hyetograph translate to errors in the prediction of the runoff hydrograph. Using a rainfall-runoff model of a hypothetical watershed we compare the runoff hydrographs produced by the ANN-predicted 15-minute increment rainfall pattern to runoff hydrographs produced by (1) the observed 15-minute increment rainfall pattern, (2) the observed hourly-increment rainfall pattern, and (3) the 15-minute increment rainfall pattern produced by a disaggregation model based on geometric similarity. For 98 test storms the peak discharges produced by the ANN model rainfall pattern had a median under-prediction of 16.6%. This relative error was less than the median under-prediction in peak discharge when using the observed 15-minute rainfall patterns aggregated to hourly increments (40.8%), and when using rainfall patterns produced by the geometric similarity rainfall disaggregation model (21.9%).

Keywords Artificial neural networks; rainfall disaggregation

Introduction

Continuous hydrologic simulation is recommended as an alternative to the traditional design event approach for the analysis and design of hydrologic and hydraulic systems, especially for the estimation of detention storage (James and Robinson, 1982; Ormsbee, 1989). The main problem with continuous hydrologic simulation is the need for long-term meteorological records (e.g. precipitation) and the management of these massive data sets. Furthermore, the precipitation data, both recorded and generated, are often not in small enough time increments nor do they have the necessary spatial resolution to accurately estimate the hydrologic response of small urban watersheds. Recommended time intervals for accurate characterization in homogeneous urban catchments are on the order of minutes, e.g. less than 15 minutes (King, 2000), while the required spatial resolution can be on the order of hundreds of metres (Faurès et al., 1995; Goodrich et al., 1995).

In locations where rainfall data are available in unacceptable temporal or spatial resolutions, disaggregation techniques can be used to perform spatial-temporal downscaling to an appropriate level. Techniques have been introduced to disaggregate annual or monthly rainfall data to daily levels, daily data to storm events (e.g. Hershenson and Woolhismer, 1987; Connoy et al., 1998), daily data to hourly values (Glasbey et al., 1995), hourly data to sub-hourly increments (e.g. Ormsbee, 1989), and other time-scale combinations (e.g. Srikanthan and McMahon, 1983). Spatial disaggregation techniques have been developed to downscale the output of mesoscale meteorological models to an appropriate scale for use in hydrological modeling (e.g. Perica and Foufoula-Georgiou, 1996). Recently, Venugopal et al. (1999) developed a coupled space-time downscaling model for rainfall. In this paper...
we focus on temporal disaggregation and do not address spatial disaggregation issues. Below we describe and evaluate an artificial neural network (ANN) rainfall disaggregation model that disaggregates long-term hourly-increment rainfall records into 15-minute increments.

**Ann rainfall disaggregation model**

ANNs are mathematical models of biological nervous systems, though much of the biological detail is neglected (Hagan et al., 1996). ANNs are massively parallel systems composed of many processing elements and trained by showing example inputs and target outputs to the network and iteratively adjusting internal parameters until the network can produce meaningful results. After the network is trained, the relationship between inputs and outputs, which may be nonlinear and extremely complicated, is encoded in the network. In general, the form of the ANN model depends on the specific problem being examined. For temporal rainfall disaggregation the logical outputs of the network would correspond to the desired disaggregated rainfall amounts or intensities, while the inputs should have a direct relationship with the disaggregated rainfall pattern.

Burian et al. (2000) introduced two ANN models for disaggregating long-term hourly rainfall records into 15-minute increments. One was a three-layer, feed-forward model trained by backpropagation (Rumelhart and McClelland, 1986) and adapted from a computer code presented in Dowla and Rogers (1995). The other model was a similar network, but based on the idea of competitive learning (Hagan et al., 1996). Both models were developed to disaggregate long-term hourly rainfall records into sub-hourly increments. In this paper we will focus the evaluation on the backpropagation model. In the backpropagation network the artificial neurons are organized into one input layer, one output layer, and one hidden layer (see Figure 1). The input layer consists of three inputs and the output layer produces four outputs. The three inputs are any three sequential hours of rainfall amounts in a long-term hourly rainfall record. The four outputs are the four 15-minute rainfall amounts corresponding to the disaggregated rainfall pattern of the central hour of the three-hour sequence.

The disaggregation increment of the ANN model is dependent on the increment of the rainfall data used for training the model. The ANN model evaluated in this paper was trained using 15-minute increment rainfall data and must be used to disaggregate hourly records into 15-minute increments, but other increment training data could be used to develop an ANN model to disaggregate to increments other than 15-minutes. We chose the disaggregation time scale ratio of one hour to 15 minutes for this study because of the availability of 15-minute rainfall data for performance evaluation. Rainfall data in the United States has traditionally been collected at 15-minute, hourly, and daily time increments by the federal agencies responsible for meteorological and hydrological data collection. The spatial coverage of hourly gauges is much greater than for the 15-minute gauges and the records have much longer durations (usually twice as long). Therefore, practitioners in the U.S. typically have access to hourly rainfall records of sufficient duration to perform adequate hydrologic analyses, but they need records of similar length in smaller time increments to improve the accuracy of their analyses. Thus, there is a need for techniques to disaggregate hourly records into sub-hourly time increments.

Although 15-minutes is the time increment of interest in this study, other applications may require different temporal resolutions. The ANN disaggregation model and other disaggregation techniques can be applied at other time increments. In essence, a single trained ANN model is time-scale dependent (e.g. the hour to 15-minute model described in this paper), but the training of several ANN models effectively makes the ANN concept time-scale independent. However, the performance of the ANN model and other disaggregation
methods is expected to decrease as the disaggregation time increment decreases. Preliminary results from a separate study have confirmed these expectations.

After the initial ANN model development was complete an investigation was conducted to establish the basic ANN model characteristics and training procedures (Burian et al., 2001). The first part of that investigation addressed perhaps the most important issue associated with developing an ANN rainfall disaggregation model, namely the need for adequate training data. Prior to the investigation there was a perceived need to use rainfall records recorded at rain gauges near to the rain gauge that produced the record to be disaggregated. However, the results of the investigation suggested that training data for the ANN model could be obtained from rainfall records several hundred kilometres from the rain gauge of interest. The investigation also established recommended ranges for the number of hidden neurons in the network, the number of training iterations and training data sets, and data standardization limits. Table 1 presents the recommended ranges for an ANN rainfall disaggregation model developed for central Alabama, located in the Southeast United States. The ranges would likely be different for models developed to represent regions with different climatic conditions.

Upon establishment of the basic model and training characteristics, the performance of the model was compared with two other disaggregation techniques, a linear technique (see Durrans et al., 1999 for a description of this simple technique) and a technique based on geometric similarity (Ormsbee, 1989). The ANN model was shown to predict the disaggregated rainfall pattern with more accuracy than the other two techniques. In that study we trained the ANN model using data sets selected from a 20-year rainfall record (1975–1995) recorded in central Alabama, USA. We then applied the model to a set of 98 storm events not included in the training data set and compared the predicted rainfall hyetograph to the observed rainfall hyetograph. Figure 2 displays the distribution of the relative error of the predicted peak 15-minute rainfall amount (DMP) for the 98 storms in the form of box plots. The median value of the distribution defines the centerline of the box, the ends of the box are the 25th and 75th percentiles and the whiskers extend to the minimum and maximum

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Recommended range or value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden neurons</td>
<td>4 neurons</td>
</tr>
<tr>
<td>Number of training iterations</td>
<td>1000–1500 iterations</td>
</tr>
<tr>
<td>Number of training data sets</td>
<td>600–800 data sets</td>
</tr>
<tr>
<td>Data standardization limits</td>
<td>Lower limit of zero and upper limit of 0.8</td>
</tr>
</tbody>
</table>

Figure 1 ANN rainfall disaggregation model network architecture

Figure 2 ANN model performance compared to linear and geometric similarity techniques

Table 1 Summary of investigation of ANN model characteristics and training procedures
values. The ANN model results are based on using 1500 training iterations, 349 data sets, and four hidden neurons, all of which are characteristics consistent with the results of the preliminary investigation of the ANN model. The results shown in Figure 2 suggest the ANN model predicts the 15-minute peak rainfall amount more accurately than the linear or geometric similarity techniques (median relative error of –0.21 for ANN model, –0.50 for linear, and –0.32 for geometric similarity). However, the significant negative bias of all three models is a reason for concern because it suggests the models under-predict peak rainfall amounts. The magnitude of prediction error was also found to increase as the magnitude of the peak rainfall amount increased. This observation suggests difficulty in predicting extreme rainfall values.

**Prediction of runoff hydrograph**

Often temporal rainfall disaggregation techniques are used to derive a shorter time-increment rainfall pattern for use in hydrologic modeling. The objective is to improve the representation of the storm event and produce a more accurate runoff response for use in engineering design or water resources analyses. Therefore, if hydrologic modeling is the ultimate use for the disaggregated rainfall pattern the evaluation of the rainfall disaggregation technique should incorporate an assessment of the relative runoff prediction accuracy. Following this line of thought a simple experiment was performed to compare temporal rainfall disaggregation techniques in terms of predicting runoff hydrographs. The disaggregated rainfall patterns and the observed rainfall pattern are used to drive a rainfall-runoff model for a hypothetical 500-acre urban watershed. The resulting runoff hydrographs are compared with the hydrograph produced by the observed rainfall record representing the desired response.

The US Environmental Protection Agency (EPA) Storm Water Management Model (SWMM) (Huber and Dickinson, 1988) was used to simulate the runoff from the hypothetical watershed. The 500-acre watershed was subdivided into ten 50-acre catchments each draining directly into an open drainage channel. SWMM uses a nonlinear reservoir runoff model that requires the estimation of several input parameters. The input parameters were selected, based on the authors’ experience, to correspond to the characteristics of a medium-density residential subdivision with 40% of the impervious surfaces directly connected to the storm drainage system. The selection of the model and parameters is expected to have some influence on the performance evaluation. The degree of that influence will be determined in future work. For the present study, we assumed that the performance evaluation of the methods would be valid if a single model with consistent parameter selections was used.

The same 98 storm events that were used in the previous evaluations of the ANN rainfall disaggregation model (see Burian et al. (2000, 2001)) were used in this study. The 20 years of rainfall data recorded at the Warrior Lock and Dam rain gauge in central Alabama were separated into individual storm events by assigning an interevent period of at least one hour of zero rainfall. From the resulting record of storm events 28 2-hour duration events, 41 4-hour duration events, and 29 6-hour duration events were selected for the evaluation. The complete set of 98 evaluation storms had an average intensity of 7.1 mm/hr and an average depth of 42.4 mm. The evaluation storm set does include events with relatively extreme (high) incremental intensities and cumulative storm depths. The ANN model and the geometric similarity technique were each used to derive a disaggregated 15-minute rainfall hyetograph for the 98 storm events based on the aggregated hourly-increment record. The disaggregated rainfall hyetographs were then used to drive the rainfall-runoff model to predict runoff hydrographs for the 98 storm events.

The peak discharge of the runoff hydrograph was selected for assessment of prediction accuracy because this characteristic is important in designing hydrologic and hydraulic
systems and evaluating the performance of those engineering designs. Figure 3 contains three scatter plots showing peak discharge produced by the rainfall-runoff model using the observed 15-minute rainfall pattern versus using the predicted rainfall pattern for (a) the observed rainfall pattern aggregated to hourly increments, (b) the ANN rainfall pattern, and (c) the rainfall pattern produced by the geometric similarity disaggregation technique. The ANN model provides predictions that align most closely with the one-to-one line representing perfect prediction. For each storm event the peak discharge produced using the hourly rainfall pattern and the two disaggregated rainfall patterns (i.e. ANN and geometric similarity) was compared to the peak discharge produced using the observed 15-minute rainfall pattern and in each case a relative error was calculated. The median relative error for the 98 storm events using the hourly rainfall patterns as input to the rainfall-runoff model was –40.8%, a significant under-prediction. Using the patterns produced by the ANN method and the geometric similarity method the median relative error was –16.6% and –21.9%, respectively. Consistent with the observation of the prediction of rainfall hyetograph peak incremental amounts, each method consistently under-predicts the peak discharge and the error of prediction increases as the magnitude of the observed peak increases. Another observation from the study is the consistent under-prediction of the peak discharge when using rainfall data at coarse time intervals (hourly in this case). Ball (1994) made a similar observation when he found variable rainfall excess intensity patterns to produce higher peak discharges than those produced by a constant rainfall excess intensity. We are currently investigating the improvement in the prediction of the peak intensity and runoff rates gained by disaggregating to smaller time increments.

Figure 3  Scatterplots of peak discharge observed versus peak discharge predicted for 98 rainfall-runoff events using the (a) observed hourly rainfall, (b) 15-minutes rainfall produced by the ANN rainfall disaggregation model, and (c) 15-minute rainfall produced by the geometric similarity rainfall disaggregation model.
Conclusions

An ANN approach for performing temporal rainfall disaggregation and a preliminary evaluation of the approach were reviewed in this paper. We then further evaluated the ANN model by determining the runoff hydrographs produced by the disaggregated rainfall patterns. The runoff hydrographs for 98 storm events produced by the ANN model rainfall patterns were compared to the runoff hydrographs produced by the observed 15-minute rainfall patterns, the observed hourly-increment rainfall patterns, and the rainfall patterns from a geometric similarity disaggregation technique. The peak discharges produced by the ANN model rainfall patterns had a median under-prediction of 16.6%. This relative error was more accurate than the median under-prediction in peak discharge when using the observed hourly increment rainfall (40.8%), and the rainfall patterns produced by the geometric similarity rainfall disaggregation model (21.9%).

References


