International Conference on Hydroinformatics

2014

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11th International Conference on Hydroinformatics
HIC 2014, New York City, USA

AN ARTIFICIAL NEURAL NETWORK-BASED RAINFALL RUNOFF MODEL FOR IMPROVED DRAINAGE NETWORK MODELLING

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Urban drainage catchment modelling is an important hydrological problem that necessitates accurate runoff prediction. This paper presents a model, based on an artificial neural network and trained with an evolutionary algorithm, which makes accurate predictions of sewerage flow in urban catchments where the runoff is dominated by infiltration problems. A range of input sets are examined, the best of which is found to be a linear aggregation of antecedent rainfall and air temperatures over a period of three months.

INTRODUCTION

Accurately modelling rainfall runoff is an important issue in hydrology. In order to be able to properly plan how to respond to extreme rainfall events and prevent flooding, organisations must be able to predict the runoff that will result from forecast events. Urban drainage catchment modelling requires rainfall runoff models as a prerequisite and a variety of different runoff models can be used. These include the Wallingford Procedure Runoff [1] (i.e., PR Equation), the New UK Runoff Model [2], and the SCS Method [3]. These methods are based on relatively simple procedures which have been shown to be reasonably robust in predicting runoff. This paper takes an alternative approach to constructing a practical runoff model that will allow for the complex inter-relation of runoff that actually occurs from impermeable areas, local surface storage and variation in rainfall induced infiltration due to wet weather responses.

As an alternative to constructing physical models, various computational intelligence approaches have been used to predict model output, including artificial neural networks (ANNs) [4]. Apart from the uncertainties associated with the actual measurement of connected surfaces to an urban drainage system, the process by which runoff occurs is known to be non-linear, and ANNs are adept at predicting such processes. They have been used to predict runoff in a number of natural catchments (e.g., [5]) and in studies for predicting the performance of urban drainage systems (e.g., [6]). This paper proposes a model that uses an ANN trained to predict runoff in a system dominated by infiltration. The ANN is a data-driven approach, in this case using information about various meteorological conditions (e.g., rainfall and air temperature over time) as inputs and flow data as a single output to be predicted. The basic procedure for making predictions with an ANN is as follows. The network is trained on inputs for which the corresponding outputs (in this case, the amount of runoff caused by the meteorological conditions at a given time) are known and validated on a further set of known examples that were not used during training. The resulting model is called a black box model, as the inner workings of the ANN cannot be equated to the physical processes driving runoff. The goal of the study is to determine a set of inputs that produces sewerage flow predictions in urban catchments where the runoff is dominated by infiltration problems (due to high groundwater table and sewer condition), a major issue for the water industry. As demonstrated by the results presented later in this paper, given an appropriate set of inputs an ANN is capable of predicting runoff, thus avoiding many of the uncertainties involved in traditional runoff modelling.

The results presented in this paper are for a site in the UK in which runoff is dominated by infiltration. The goal of the study is to demonstrate that an ANN is capable of modelling runoff in such an environment. The available data relating to the case study site comprises of rainfall data, air temperature and sewer flow data. All data has been aggregated from their native frequencies to the hourly level, and is available over a period covering January 2010 to October 2012. There are periods within this range where measurements were not recorded.

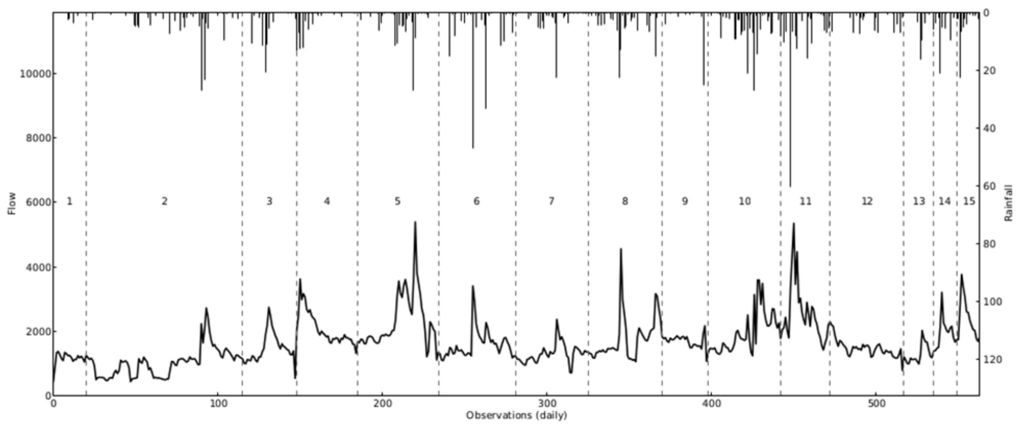


Figure 2: Rainfall events; rainfall is shown from the top and flow runs along the bottom. The separation of the data into events is shown, and the numbers running along the centre of the plot show the event IDs.

The inputs used in this study are rainfall and air temperature data. This data is separated into a set of 15 rainfall events that have been identified such that they contain contiguous measurements (i.e. they have no missing data) and any intervening periods with missing data are excluded from study. Figure 1 illustrates the data, subdivided into rainfall events.

MODELLING RUNOFF WITH ANNS

The model proposed in this study is called RAPIDSLite, and is based on an earlier ANN model, RAPIDS [7]; it was specifically developed for modelling rainfall runoff. It consists of an ANN model which is trained by an evolutionary algorithm (EA).

Neural Network Model

An ANN is a computational model based on the way in which the human brain processes information [4]. It is a collection of neurons which are arranged into layers. Neurons in adjacent layers are connected by weighted edges. The model consists of an input layer, a hidden layer, and an output layer. The neurons in the hidden and output layer produce a signal that is calculated by taking a weighted sum of the inputs to the neuron:

$$y_k = \left(\sum_{d=1}^{D} x_d w_{kd} + w_{k0} \right). \tag{1}$$

Here, x_d is an input to the node, and w_{kd} is the edge between that input and the node. The bias term is w_{k0}. The output y_k is then passed through an activation function:

$$a(x) = \frac{1}{1 + e^{-x}}. \tag{2}$$

RAPIDSLite employs the sigmoid function (Eq. 2) and, in this study, uses a single hidden layer of size H = 10. Various studies have used this architecture [5]. Since the aim is to predict total daily flow, the network consists of a single output.

Network Training

The network weights were trained with an EA. An EA is a population-based algorithm in which each candidate solution is an ANN model. The training process seeks a set of weights that maximises the predictive quality of the model. Edge weights are constrained to lie between -1 and 1, and are mutated with probability $1/P$ (P is the number of solution parameters, for P edges in the ANN) using an additive Gaussian mutation. The predictive quality of a network is evaluated with the mean absolute error (MAE) of the predictions for the training data and the best solutions from the combined parent and child populations are retained as the parent population in the next generation. The EA is executed for sufficient generations to allow it to converge; this period was determined experimentally.

In order to prevent *over training* [8], whereby the model cannot generalise to new observations, a cross validation scheme is used. Given the set of E rainfall events, leave-one-out cross validation was used such that the model was trained E times on the full set of training data with one of the events omitted. This event was then used to test the data by using it as a set of previously unseen inputs.

EXPERIMENTAL SETUP AND RESULTS

One of the principal motivations behind this study is to identify a set of inputs that can be used to predict runoff. To this end, RAPIDSLite has been tested on a range of different inputs (varying the form of antecedent rainfall incorporated into the model). In the case of each experiment, the optimisation parameters remain fixed. The standard deviation σ of the mutation was 0.1 (computed from the Gaussian distribution from which the mutations were drawn). The EA operated with a population size $\mu = 5$ and its runtime, determined experimentally, was 2,000 generations for daily inputs and 10,000 generations for sub-daily inputs. In order to study the sensitivity of the model to different sets of inputs, each experiment was repeated 10 times so that the distribution of results could be evaluated. Experimental results were evaluated using Nash-Sutcliffe Efficiency Coefficient (NSEC) [9], where the best possible score is 1 and would indicate that the model has perfectly matched the target values. NSEC scores of 0.5 or higher are generally accepted in the water industry, and in this paper scores of 0.8 or higher are sought.

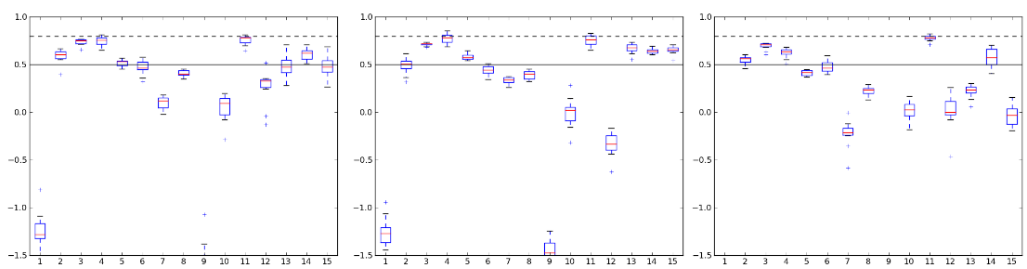
Initial Results

Initial experiments were conducted at the daily level with inputs describing rainfall and air temperature. The inputs for rainfall consisted of the current day value, as well as for the previous seven days, and aggregated inputs covering the 30 and 90 days prior to the current observation. Matching air temperatures were used, making a total of 20 inputs.

Table 1: The parameters used in the three configurations of the initial experiments conducted. A mark indicates that a given input was included in the model tested under a specific option.

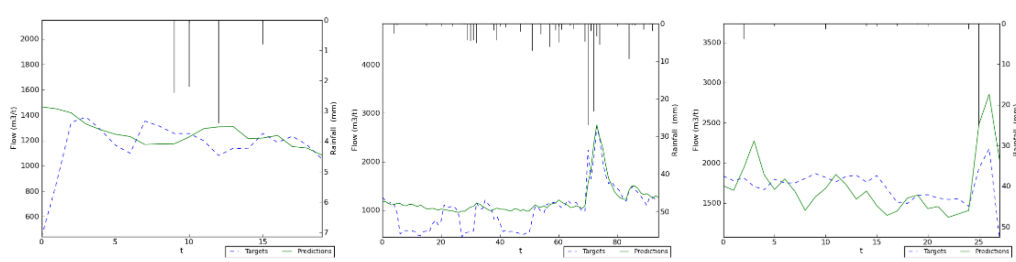
	Current rainfall	Previous 7 days' rainfall (7 inputs)	30 days antecedent rainfall (1 input)	90 days antecedent rainfall (1 input)	Current air temperature	Previous 7 days' air temperature (7 inputs)	30 days air temperature (1 input)	90 days air temperature (1 input)
Option 1	●	●	●	●	●	●	●	●
Option 2	●	●		●	●	●		●
Option 3	●	●	●		●	●	●	

Table 1 lists the inputs that were included in each of the three initial configurations of the model. The first contains all of the inputs, while the subsequent two options omit the 30 and 90 day antecedent information, in order to study the difference in quality caused by long periods of antecedent rainfall and air temperature data.



(a) Option 1 (b) Option 2 (c) Option 3

Figure 3: Boxplots showing the distribution of NSEC results for the initial set of experiments. The results show that the model is reasonably insensitive to the length of antecedent rainfall, although results for option 3 are marginally worse than those for options 1 and 2. A preliminary experiment omitting 30 and 90 days antecedent information entirely produced considerably poorer results.



(a) Event 1 (b) Event 2 (c) Event 9

Figure 4: Hydrographs for exemplar test events evaluated with a model developed under the set of inputs described by option 2.

Figure 3 illustrates the distribution of NSEC results of the 15 rainfall events for each of the first three model configurations examined. Each of the 15 boxes in each experiment represents a single event, each of which was used as the training event 10 times in order to evaluate the distribution of results. NSEC results below -1.5 are omitted from these plots. The configuration that yielded the most events with a mean NSEC of 0.5 or greater was option 2 (with 8 events), however it is difficult to say that there is a clear winner between the three options as the results are fairly similar. Option 3 has the worst performance; the fewest events of the three options achieved a mean NSEC of 0.5 or greater, and two of the events are completely omitted as they are completely below the lower bound of -1.5. Exemplar hydrographs for option 2 are shown in Figure 3.

In the case of option 3, the model evaluated on event 2 again showed the best results; the model identifies the shape of the main peak in the flow data, and its prediction of the peak's magnitude is only slightly below that of option 2. As in Figure 3, the period of low flow in the first half of the event, where the model has over-predicted the amount of flow, is likely to be indicative of inaccuracies in the target data. In both events 1 and 9, the predicted flow values are much worse than those for event 2, with the model failing to match the shape, and in some case the magnitude, of the peaks. The significantly poorer predictions in these events, characterised by a lack of rainfall and compared to events with more rainfall on which predictions were much better, indicates that these events are affected by a dry weather flow; results for these two events were systematically poor for all experiments conducted in this study. This demonstrates the importance of selecting a set of inputs that completely represents the complete runoff generation process. In fact, the NSEC performance for these events throws into question its suitability as a performance measure for this type of analysis; for low flows it tends to heavily penalise the algorithm, resulting in the values shown for events 1 and 9.

Sub-Daily Timesteps

Rainfall can occur within the daily frequency discussed so far. To demonstrate that the model can make predictions at sub-daily timesteps, we perform a similar experiment to the daily simulations described above, for 6-hourly inputs. The input set is as follows:

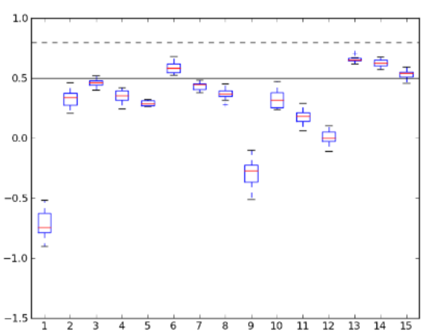
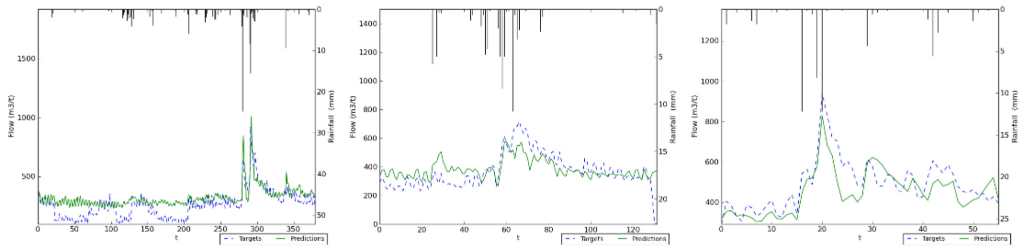


Figure 5: NSEC results for the sub-daily experiment.



(a) Event 2 (b) Event 3 (c) Event 14

Figure 6: Event hydrographs for the sub-daily experiments.

1. Rainfall and air temperature for the current timestep (2 inputs).
2. Rainfall and air temperature for the previous 24 hours at 6-hourly intervals (8 inputs).
3. Rainfall and air temperature for the three days preceding the 6-hourly inputs in (2) at 24-hourly intervals (6 inputs).
4. Summed rainfall and average air temperature for the previous 90 days (2 inputs).

The input set therefore has a total of 20 inputs. The parameterisation of the optimiser and the ANN configuration remains unchanged from the previous set of experiments, however, to cope with the increased number of observations the model was trained for 10,000 generations.

Figure 4 shows the distribution of NSEC values for the sub-daily experiments. As before, the model is capable of making predictions with mean NSECs of 0.5 or more, however perhaps the more interesting result is for events 1 and 9. As can be seen, the events (which the model failed to predict accurately in the daily experiments) show an improvement. Although they still represent poor results, the error is less severe indicating that the model is able to better predict events containing little flow using sub-daily timesteps; optimising the ANN for longer may further improve the results. Figure 5 illustrates the hydrographs predicted by the sub-daily configuration. The quality of the predictions in this case is poorer; this is to be expected, as the target hydrographs themselves are less smooth. That said, the general trend has been identified, implying that further training may result in a better fit of the noisy target data.

Alternative Antecedent Precipitation as a Network Input

The previous section's experiments incorporated the notion of antecedent rainfall into the model by means of aggregated rainfall values, for 30 and 90 days. An alternative is to use the normalised antecedent precipitation index (NAPI) [10], formulated as follows:

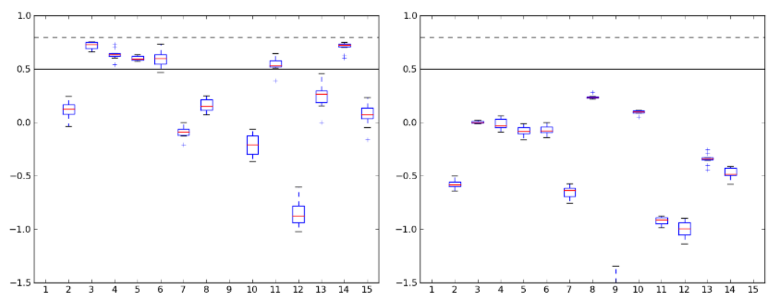
$$NAPI = \frac{\sum_{t=0}^{-i} P_t \, k^{-1}}{\bar{P} \sum_{t=-1}^{-i} k^{-t}}. \tag{3}$$

NAPI is incorporated into the set of inputs, replacing the summed antecedent rainfall inputs used in the previous experiments. Two sets of inputs are examined. Both of which include the current day's rainfall and NAPI for the preceding 30 days. One of the options also contains an input describing rainfall for each of the 7 days leading up to the current observation, as was the case in options 1–3. The air temperature inputs remain the same as used in the previous experiment; the structure of the ANN and the parametrisation of the EA is unchanged from options 1–3 (running for 2000 generations). The NAPI decay coefficient k is set to 0.8.

Table 2 shows the inputs used in the two NAPI experiments and Figure 6 illustrates the corresponding distribution of NSEC results for the two experiments. The results for option 5 are comparable to those of options 1–3, however are of slightly lower quality (the mean NSEC is 0.5 or greater for fewer events than it is for those of option 2). Option 6, which omitted the inputs relating to the previous 7 days rainfall, resulted in noticeably poorer results than for any of the input sets tested so far, with the model output simply peaking on days of peak rainfall. None of the events achieved predictions with NSEC scores greater than 0.5, indicating that the increased resolution close to the event is important, as was shown for the sub-daily input set. Figure 7 illustrates flow hydrographs for option 5. In each case, the predictions are a poorer match than those shown for earlier daily input sets. In particular, this configuration is unable to properly match the peaks of the true target signal, under or over predicting in each case.

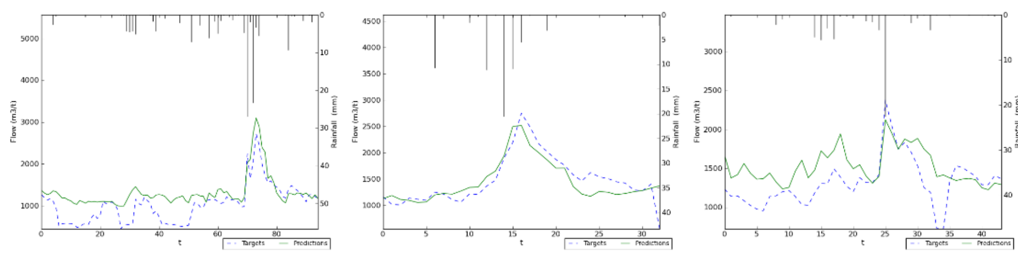
Table 2: The parameters used in the two configurations of the NAPI experiments.

	Current rainfall	Previous 7 days' rainfall (7 inputs)	NAPI	Current air temperature	Previous 7 days' air temperature (7 inputs)	30 days air temperature
Option 5	●	●	●	●	●	●
Option 6	●	●		●	●	



(a) Option 5 (b) Option 6

Figure 7: NSEC results for the NAPI experiments.



(a) Event 2 (b) Event 3 (c) Event 7

Figure 8: Event hydrographs for option 5, the first of the NAPI experiments.

Summary of Results

Comparing the three types of configuration tested in this section, the best result is for the initial configuration (under option 2, 8/15 events have NSEC greater than 0.5, compared to option 4 with 4/15 and option 5 with 6/15) in which antecedent rainfall information is incorporated in the form of aggregated values (summed for rainfall and averaged for air temperature) over a significant period, such as the 90 days used in this study. Such an input set is capable of producing a model with comparable predictive ability in other catchments, providing that the physical drivers of the runoff process itself are not drastically different to that of the case study site used as an example in this paper.

CONCLUSION

This paper has demonstrated an ANN model for predicting runoff in a system dominated by sewer infiltration. The study compared various sets of inputs with the aim of determining a sensible input configuration, and, while they cannot be said to be a general set of inputs, those based on summed antecedent rainfall and averaged air temperature produced the best results, with the majority of the predictions resulting in NSEC scores greater than 0.5. Models for other case study sites using such an input set should theoretically produce runoff predictions of a similar quality to those shown for the case study used in this paper. Subsequent experiments with sub-daily inputs produced the interesting result that the prediction error of the model in the worst case was significantly reduced. Other input sets included NAPI values in the place of summed antecedent rainfall, and this was shown to be less effective for this case study.

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