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Evaluation of the application of neural networks on real-time river flood prediction

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ABSTRACT: This study aimed to model river flow in a multi-gauging station catchment and provide real-time prediction of peak flow downstream using artificial neural networks (ANN). Three types of ANN (Multi-Layer Perceptron (MLP), Recurrent, and Time Lag Recurrent) were adapted to evaluate the applicability of this technique. The study area covers the Upper Derwent River, a tributary of the River Trent in the UK. River flow was predicted at the subject site with lead times of 3, 6, 9 and 12 hours. Tests were completed using different lengths of input data to evaluate the effect of input data size in model outputs. The number of gauging sites to be used as data sources in the model was also evaluated. According to the results of this research it can be said that for real-time forecasting of flow in gauged catchments the type of neural network is an important factor and dynamic architectures, especially general recurrent networks, show a superior ability even for longer prediction horizons.

1 INTRODUCTION

The prediction of river flow is used in different aspects of water resources planning and management as well as flood damage protection or mitigation. Reliable prediction of flow discharge and its variability along rivers is an essential part of surface water planning projects. In addition, prediction of discharge at a particular point using upstream conditions helps in designing storage plans or control measures. Moreover, it is an important part of the projects such as flood warning systems and dam release operations. For most of these applications real-time prediction of river flow is usually required.

Improvements in river peak flow forecasting have resulted partly from the global increase in stream gauging stations and partly from accelerating advances in the technology of data collection as well as in computer-based data handling and telecommunication systems. The three main parameters in real-time flood forecasting are accuracy, reliability, and timeliness. In flood warning applications there is likely to be more emphasis on timing and the reproduction of distinctive shapes on the rising limb and crest segment of the hydrograph. It is therefore important to develop forecasting models, which are relatively simple, but quick and efficient to execute. The technique of artificial neural networks is widely used as an efficient tool in different areas of water related research activities. Some completed investigations in this area are: Bhattacharya and Solomatine, 2000; Dawson and Wilby, 1998; Hsu, et al., 1995; Karunanithi, et al., 1994; Luk, et al., 1998; Minns and Hall, 1996; and Sezin, et al., 1999.

In this study it was decided to investigate the application of ANN to model river flow discharge variation between gauging stations and real-time prediction of flow in downstream points using upstream discharge. It would be a useful step to prevent damage by predicting flood flow in flood plains, where the risk of flooding is high, using the measured flow data from upstream gauging stations. The potential of artificial neural network models for simulating the hydrologic behaviour of catchments is presented in this research. The influence of the type of the neural network as well as the variation of input data in terms of record length and the number of sources (number of upstream sites used for data) on the prediction results have been the main elements to investigate in this research. Three different types of artificial neural networks (Multi-layer Perceptron, Recurrent, and Time Lag Recurrent) have been applied to evaluate the applicability of different types of the technique of ANN for this particular problem.

2 REAL-TIME FORECASTING PROCESS

Prediction of flow by the method presented in this research, is carried out for the next time step using the previous measured data. If $Q_{(t)}$ represents the discharge at subject site (Whatstandwell gauging station) at time t, and $q_{(t)}$ the discharge at an upstream gauging station at the same time (t), the prediction aim is:

$$Q_{(t+1)} = f(Q_{(t)}, Q_{(t-1)}, \ldots, Q_{(t-n)} + q_{(t)}, q_{(t-1)}, \ldots, q_{(t-n)} + e_{(t)})$$

where:

$f()$ is an unknown non-linear mapping function, $e_{(t)}$ is an unknown mapping error, n is the number of past inputs contributing to the prediction of flow at the next time-step.

$Q_{(t+1)}$ which is river flow at Whatstandwell for next time step ($t+1$), is predicted using upstream flow at time $t, t-1, \ldots, t-n$. Due to use different upstream gauging sites as sources of input data as well as data at 30 minute intervals and four different prediction horizons in this research, predictions in first three tests are as follows:

$$\begin{aligned}
\textit{For 3 hours lead time, } Q_{(t)} = f(&Q_{(t-6)}, Q_{(t-7)}, \ldots, Q_{(t-n)} + q_{(t-6)}(1), q_{(t-7)}(1), \ldots, q_{(t-n)}(1) \\
&+ q_{(t-6)}(2), q_{(t-7)}(2), \ldots, q_{(t-n)}(2) \\
&+ q_{(t-6)}(3), q_{(t-7)}(3), \ldots, q_{(t-n)}(3) + e_{(t)}) \\
\textit{For 6 hours lead time, } Q_{(t)} = f(&Q_{(t-12)}, Q_{(t-13)}, \ldots, Q_{(t-n)} + q_{(t-12)}(1), q_{(t-13)}(1), \ldots, q_{(t-n)}(1) \\
&+ q_{(t-12)}(2), q_{(t-13)}(2), \ldots, q_{(t-n)}(2) \\
&+ q_{(t-12)}(3), q_{(t-13)}(3), \ldots, q_{(t-n)}(3) + e_{(t)})
\end{aligned}$$

and so on for 9 and 12 hours.

Variables $q_{(t)}(1)$, $q_{(t)}(2)$, and $q_{(t)}(3)$ are river flow at first, second and third upstream gauging stations at time t.

For the fourth test in which different numbers of upstream sites are used as data sources in different sub-tests, along with data at 1 hour intervals predictions will be as follows:

Sub-test 1 (only one upstream gauging site as data source):

$$\begin{aligned}
&\textit{For 3 hours lead time, } Q_{(t)} = f(q_{(t-3)}(1), q_{(t-4)}(1), \ldots, q_{(t-n)}(1) + e_{(t)}) \\
&\textit{For 6 hours lead time, } Q_{(t)} = f(q_{(t-6)}(1), q_{(t-7)}(1), \ldots, q_{(t-n)}(1) + e_{(t)})
\end{aligned}$$

and so on for 9 and 12 hours.

Sub-test 2 (two upstream gauging sites as data sources):

$$\begin{aligned}
\textit{For 3 hours lead time, } Q_{(t)} = f(&q_{(t-3)}(1), q_{(t-4)}(1), \ldots, q_{(t-n)}(1) \\
&+ q_{(t-3)}(2), q_{(t-4)}(2), \ldots, q_{(t-n)}(2) + e_{(t)}) \\
\textit{For 6 hours lead time, } Q_{(t)} = f(&q_{(t-6)}(1), q_{(t-7)}(1), \ldots, q_{(t-n)}(1) \\
&+ q_{(t-6)}(2), q_{(t-7)}(2), \ldots, q_{(t-n)}(2) + e_{(t)})
\end{aligned}$$

and so on for 9 and 12 hours.

Sub-test 3 (three upstream gauging sites as data sources):

$$\begin{aligned}
\textit{For 3 hours lead time, } Q_{(t)} = f(&q_{(t-3)}(1), q_{(t-4)}(1), \ldots, q_{(t-n)}(1) + q_{(t-3)}(2), q_{(t-4)}(2), \ldots, \\
&q_{(t-n)}(2) + q_{(t-3)}(3), q_{(t-4)}(3), \ldots, q_{(t-n)}(3) + e_{(t)}) \\
\textit{For 6 hours lead time, } Q_{(t)} = f(&q_{(t-6)}(1), q_{(t-7)}(1), \ldots, q_{(t-n)}(1) + q_{(t-6)}(2), q_{(t-7)}(2), \ldots, \\
&q_{(t-n)}(2) + q_{(t-6)}(3), q_{(t-7)}(3), \ldots, q_{(t-n)}(3) + e_{(t)})
\end{aligned}$$

and so on for 9 and 12 hours.

3 STUDY AREA AND DATA AVAILABILITY

The study area covers the upper Derwent River catchment located in the River Trent basin. The site for prediction is Whatstandwell gauging station. Three gauging stations called Matlock, Chatsworth and Mytham Bridge have been selected upstream with distances of about 10, 25 and 50 kilometres from the subject site respectively (Figure 1). Measured flow data for related gauging stations were collected from the Environment Agency. The original flow time series were measured with a 30 minute interval. For the first test, flow data at a 30 minute recording interval from January 1999 (1–31) was used as input. For the second and third tests a longer period of data was used, 6 months and 3 years respectively. For each experiment the data was split into three parts; training data (50%), cross-validation data (10%) to prevent model over-training, and testing data (40%). Table 1 gives information about the data used in different tests.

Figure 1. An index plan of the upper Derwent river catchment showing discharge measuring stations.

Table 1. Data has been used in training, testing and cross validation phases of each test.

Test	Length	Data set	% of data	No. of obs.
1	1 month	Training	50	734
		Cross val.	10	146
		Testing	40	588
		Total	100	1468
2	6 months	Training	50	4347
		Cross val.	10	869
		Testing	40	3477
		Total	100	8693
3	3 years	Training	50	26380
		Cross val.	10	8653
		Testing	40	17503
		Total	100	52536
4	1 month	Training	60	441
		Cross val.	10	73
		Testing	30	220
		Total	100	734

4 PREPARATION OF DATA

As there are different distances between the subject site and each upstream gauging station, the travel time for flow will be different from one to the other. In this research, a correlation coefficient analysis procedure was used to determine the lag time between upstream gauging sites and the subject site. According to the results of this analysis the lag time was estimated at 5.5, 3.5 and 1.5 hours respectively for Mytham bridge, Chatsworth and Matlock to the subject site (Whatstandwell). According to the distances between the upstream stations and the subject site, the mean velocity of the water flow is determined about 2.52 m/s, 1.98 m/s and 1.85 m/s for the distances between the Mytham bridge and Whatstandwell, Chatsworth and Whatstandwell, and Matlock and Whatstandwell respectively.

5 ARTIFICIAL NEURAL NETWOKS

Neural networks must be trained with a set of typical input/output pairs of data called the training set. The final weight vector of a successfully trained neural network represents its knowledge about the problem. As different types of neural network deal with the problems in different ways, their ability varies depending on the nature of the problem in hand. Therefore, three types of ANN were used in this study. Multi-layer perceptron, which is a static architecture of neural networks as well as Recurrent and Time Lagged Recurrent neural networks, which are dynamic networks.

5.1 *Multi-layer perceptron neural network (MLP)*

In this network a connection is allowed from a node in layer i only to nodes in layer $i + 1$, and not vice versa (Figure 2). An advantage of MLP in terms of mapping abilities is its capability of approximating arbitrary functions. This is an important point in the study of non-linear dynamics, and other function mapping problems. In this study different types of transfer and output functions for hidden and output layers as well as different numbers of hidden layers were used to find the best structure of MLP for this application. From these trials it was found that the tangent hyperbolic function was the most compatible one for the hidden layer. However, for the output layer the sigmoid function was the most suitable one. One hidden layer was most suited number to the model.

5.2 *Recurrent neural networks*

This type of network can be divided into fully and partially recurrent. Having a memory element distinguishes this network from the previous one (Figure 3). Although recurrent networks are more powerful than feedforward networks, they are more difficult to train and their properties are not as well understood. The training of a recurrent network is much more sensitive to divergence. To construct the best architecture for this study, many structures were tested and the results were considered. The number of hidden layers, number of processing elements in hidden layers, type of transfer and output functions and type of learning rule and its parameters have been considered and evaluated. After using different types of transfer and output functions for hidden and output layers, it was realized that a tangent hyperbolic function was the

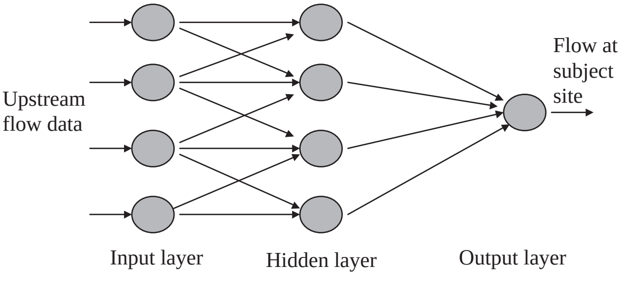

Figure 2. A typical 3 layer feedforward neural network.

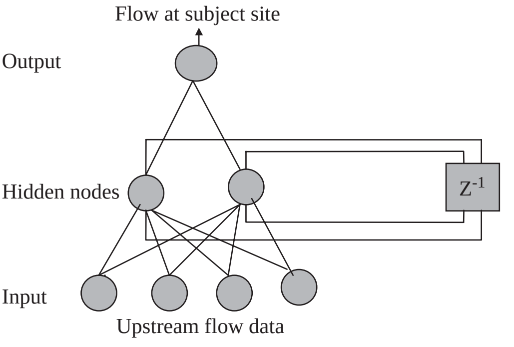

Figure 3. A typical recurrent neural network.

most suitable one for the hidden layer. However, for output layer the sigmoid function is a more compatible function. Between the dynamic processing elements of Gamma, Laguarre and Time delay, the Laguarre and Time delay gave better results. The number of hidden layers differed from one in tests with a shorter length of input data to two for a longer length of input data. For the tests of this research, the partially recurrent network showed better adaption than fully recurrent one.

5.3 *Time lag recurrent neural networks*

This type of network contains locally recurrent layers with a single adaptable weight. As opposed to the Recurrent networks stability in Time Lag Recurrent networks is guaranteed. It usually suits temporal problems with short temporal dependency however it does not seem appropriate for more difficult temporal problems. For this type of neural network it was found that the tangent hyperbolic function and in few cases the sigmoid function was the best one for hidden layer. However, for output layer the sigmoid function suited better for all tests. Between the dynamic processing elements of Gamma, Laguarre and Time delay, the Gamma was found to be the most compatible. Networks with only one hidden layer presented the best performance.

6 PREDICTION OF FLOW

The amount and type of input data is always an important factor when using artificial neural networks. Therefore, in evaluating the performance of this technique for a particular application, using data with different characteristics as input would seem necessary. For flow data the length of the record period seems to be an important factor in terms of evaluation of the applicability of the models for real-time flow prediction. Another important variable to investigate is the number of input pattern to the neural network, which corresponds to the number of upstream gauging sites as data sources of data in present study. Therefore, the tests 1, 2 and 3 were carried out using three different lengths of data, while test 4 uses different upstream gauging sites as data sources.

6.1 *Prediction with a short data period*

In this test input data covers only one month (January 1999). After consideration of the flow at the gauging stations it was found that January 1999 is a good representative of the flow conditions in this catchment. During these months high and low flow discharges are seen and several flood waves occurred, which provides appropriate data for this test. Flow data with a 30-minute increment from upstream gauging stations and the subject site are entered to the model. Predicted hydrographs with different lead-times produced by recurrent network are seen in Figure 4 (it is not possible to show the results of all networks due to space limitation). The horizontal axis shows the time with 30 minutes intervals. Flow at any specific time step on this axis is predicted using flow at a previous time step, which one will depend on the lead-time.

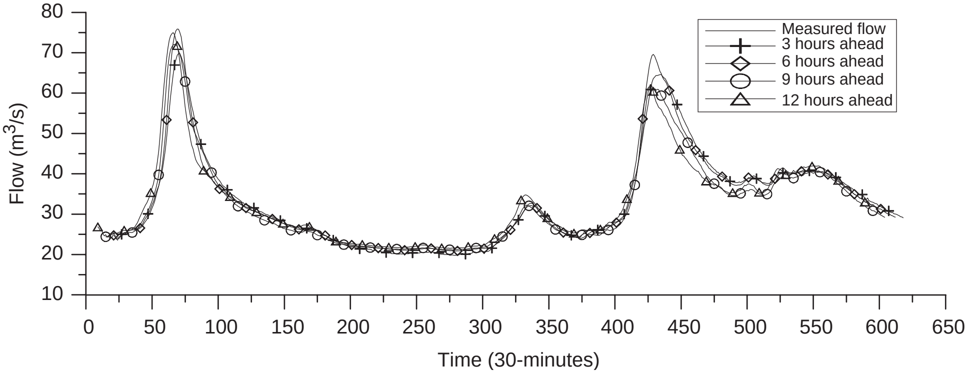

Figure 4. Hydrograph of the flow in Whatstandwell and the corresponding predicted hydrographs 3, 6, 9 and 12 hours ahead by Recurrent neural network with shorter length of input data (testing phase).

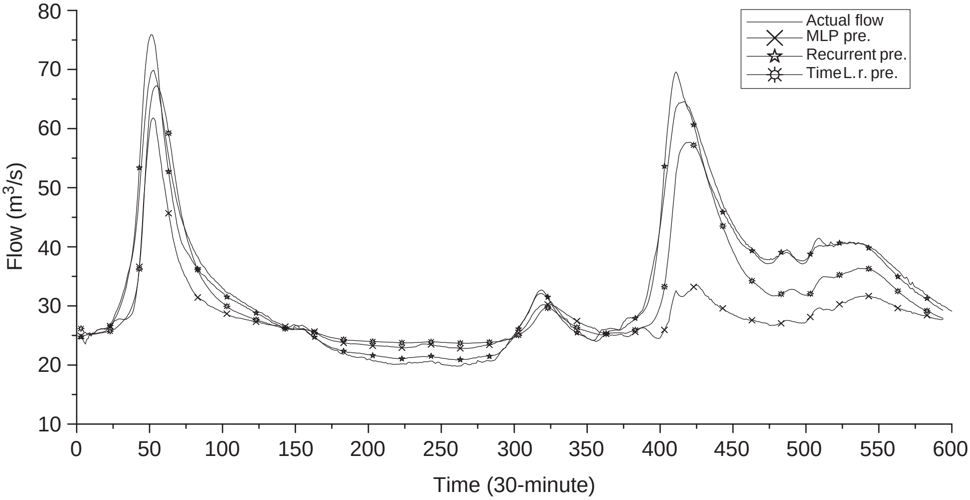

Figure 5. Actual hydrograph against the 3 hours ahead predicted hydographs by different types of the neural networks and short length of input data (testing phase).

Figures 5 and 6 show the predicted hydrographs respectively 3 and 12 hours ahead produced by different networks. These figures facilitate the comparison of the outputs of different networks for the specific prediction horizon.

6.2 *Prediction with a medium length of data*

In this test the length of input data was increased to 6 months. Flow data measured with a 30-minute increment provided 8693 observations during the 6 months. Due to space limitation it is not possible to show the hydrographs but the results is discussed later.

6.3 *Prediction with a long data period*

In this test data with a longer period is used. River flow data for 3 years and with a 30-minute increment was prepared to train and test the models. This length of data record provided 52536 observations, which were divided into three sets for training, cross-validation and testing phases.

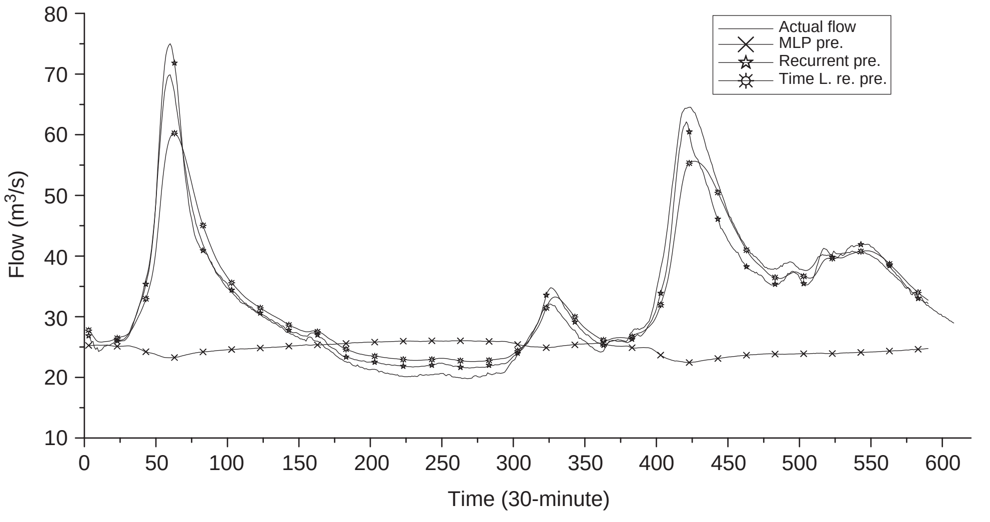

Figure 6. Actual hydrograph against the 12 hours ahead predicted hydographs by different types of the neural networks and short length of input data (testing phase).

6.4 *Prediction of flow using different numbers of upstream gauges*

To evaluate the effects of the number of input patterns in the accuracy of the prediction results, three sub-tests were carried out by using input data from one, two and three upstream gauging sites respectively. In each sub-test all three types of neural network were employed to see the effects of different number of input patterns on the output of each type separately. These sub-tests are as follows:

- Sub-test 1 (using 1 upstream gauging station): In this sub-test river flow was predicted at Whatstandwell gauging station using previous flow data only from Chatsworth gauging station. Predictions are carried out for 3 hours, 6 hours, 9 hours and 12 hours ahead.
- Sub-test 2 (using 2 upstream gauging station): In this sub-test the length of data used as input was the same as the previous test but the number of gauging stations used was increased. Networks were trained and tested using two input patterns and one output pattern. Similar to sub-test 1, flow has been predicted 3, 6, 9 and 12 hours ahead by three types of neural networks.
- Sub-test 3 (using 3 upstream gauging station): In this sub-test, the prediction of flow has been carried out at the subject site using data from three upstream gauging stations. There were three input patterns and one output pattern for each neurone. In terms of the number of upstream gauging stations and the length of data, this test is similar to test 1. However, there are two differences; the first one is the measured data interval, which is 1 hour in this test while it is 30 minutes in test 1. The second difference is the mode of training. In this test the network was trained using default mode but in test1 prediction mode was used to train the network. Lead-times were the same as in the previous sub-tests (3, 6, 9 and 12 hours).

6.5 *Prediction using a naive method*

In addition to three types of neural networks, prediction of flow at Whatstandwell was made with a simple naive method. In this method prediction of the future condition is made using only the historic time series of data at the subject site.

7 RESULTS AND DISCUSSION

Suitable statistical parameters of comparison were used to consider the accuracy of the output in different tests and sub-tests. To make a reliable comparison and judgment about the capabilities of

Table 2. The values of root mean square error (rmse) of the predicted flow with different type of the neural networks, input data length and lead-time in training and testing phases.

			Training phase			Testing phase		
Test	Sub-test	Lead-time	MLP	Rec.	T.L.R.	MLP	Rec.	T.L.R.
1	–	3 hr	1.727	2.125	5.374	9.484	1.646	2.982
		6 hr	3.480	3.012	4.604	11.485	1.818	3.006
		9 hr	4.379	3.625	4.932	15.505	2.185	3.243
		12 hr	6.164	4.899	5.706	15.766	4.313	3.897
2	–	3 hr	2.567	2.315	3.878	4.551	2.168	3.153
		6 hr	3.842	3.267	5.290	6.772	2.185	3.344
		9 hr	4.418	4.234	3.690	7.472	3.159	3.388
		12 hr	6.562	5.207	4.769	11.230	3.182	4.298
3	–	3 hr	3.352	5.664	12.171	9.298	10.456	12.647
		6 hr	6.237	6.990	14.976	14.958	10.783	13.084
		9 hr	8.689	9.813	18.329	21.367	11.539	18.736
		12 hr	10.727	11.637	21.504	24.342	11.734	19.930
4	1	3 hr	1.930	2.464	2.800	2.094	1.897	1.692
		6 hr	1.939	3.217	3.669	3.325	1.923	1.937
		9 hr	2.714	3.573	4.443	6.093	2.044	2.405
		12 hr	3.650	3.825	7.572	7.040	2.084	4.361
	2	3 hr	1.434	3.325	2.472	1.984	2.696	2.097
		6 hr	2.804	3.355	3.561	4.784	2.375	1.930
		9 hr	3.791	3.803	4.010	6.029	2.164	1.841
		12 hr	4.865	3.929	4.489	6.162	2.157	1.807
	3	3 hr	1.164	2.390	2.977	1.653	1.417	1.591
		6 hr	2.555	2.357	3.215	5.267	1.656	1.593
		9 hr	3.878	4.225	3.593	8.002	1.808	1.745
		12 hr	5.105	4.038	4.207	8.282	2.001	1.882

the different networks for real-time flow prediction RMSE (root mean square error) as well as R^2 (coefficient of efficiency) were used. Values of the root mean square error for the results of the tests 1, 2, 3 and 4 are shown in Table 2.

In tests 1, 2 and 3 all aspects were the same except the size of data used to train and test the models. Data were used from all three upstream gauging stations as well as the subject site. However, the nature of test 4 is different as the size of data for training and testing was the same in all three subtests but the number of input patterns was different i.e. a different number of upstream gauging sites were used as data sources in different sub-tests. In addition, no data from the subject site (Whatstandwell gauging station) was used in sub-tests of test 4. Another difference between the first three tests and test 4 is the mode of training. First three tests were trained using "Prediction Mode", where data from the subject site is automatically used as input but all sub-tests of the test 4 were trained in a default way. The interval of the measured data used in test 4 was different from the first three tests. This was 30 minutes in tests 1, 2 and 3 and 1 hour in test 4. Because of these differences the results of networks will be discussed in the first three tests together, and then followed by sub-tests of the test 4.

The first thing that seems quite clear from the results of all tests is that MLP network does not perform well. In fact the results of this network are quite poor in the testing phases, and even the hydrograph for a 3 hours ahead prediction is not close to the actual hydrograph. Also the accuracy of the outputs decreases dramatically with the increase of prediction horizon. The values of RMSE in Table 2 clearly indicate that the outputs are poor in the testing phase. However, for the training phase the results of this network seem quite close to the measured value. It seems that a form of over training has occurred during the training of this network despite employing a set of data as cross-validation. In general, the results of this network in test 2 are almost similar to those in test 1. Increasing the amount of input data has not helped the MLP. The only difference is with the predicted hydrograph 9 hours ahead, which shows improvement in test 2 comparison to the previous test, although it is still far from the actual hydrograph. In test 3 despite using a large number of data, there is no improvement in the results over first two tests. In this test the MLP has produced results that are considerably over estimated in contrast with its outputs in previous tests. The results of the MLP are still quite poor as in previous tests, and the main problem with MLP to produce appropriate results seems to be the lead-time. It gives good results when prediction is made with very short lead-time.

In contrast with the MLP, the results produced by the dynamic networks (recurrent and time lag recurrent) are quite close to the actual values, showing a very good performance in test 1. This is probably due to the memory unit in dynamic networks. This unit, which exists in dynamic networks such as Recurrent and Time Lag Recurrent, provides the network with a feedback and reminder of the previous iterations during the training. This helps the networks to be able to cope with a time series better than MLP, which is a static network and has no memory unit. The Recurrent network has presented the best results although the results of the Time Lag Recurrent network are also encouraging. Another important point about the outputs of the dynamic networks is the variation of the accuracy between different prediction horizons. Reduction of the prediction accuracy is quite gradual against the increase in prediction horizon. A final point to mention here is the variation of network performance in training and testing phases of these two types of networks. In some cases RMSE in the testing phase is even smaller than training phase, which shows superior ability of these networks to learn the process and establish a relationship between inputs and outputs and especially generalization to the new set of data. In test 2 the Recurrent network performed well except for the 12 hour horizon, which is slightly over estimated in some parts of the hydrograph. The main point about outputs of this network is the over estimation of the peak flows. As opposed to the Recurrent network, the Time Lag Recurrent network has produced results that are mostly underestimated. For the results of the Recurrent network and especially Time Lag Recurrent networks the effects of the prediction horizon on accuracy of the results is very small. In test 3 the dynamic networks have again produced quite good results but they do not seem as accurate as the outputs produced by these networks in previous tests. The accuracy of the predictions has even slightly declined for these despite using a large number of input data to train the models. In real-time prediction the time is very important, and fast prediction leads to more time for mitigating actions to be taken. Using a large number of data in test 3 required a long time for training to be completed.

The results produced in test 4 are slightly different from tests 1, 2 and 3. The first important thing is the improvement of the results produced by MLP in all 3 sub-tests of this test in comparison to those of previous three tests. This is a result of the training mode. In tests 1, 2 and 3 the “prediction training mode” was used to train the models in which the data of the subject site is also automatically used as input but with delta time step delay. In this mode of training manual preparation of the data to suit a specific lead-time is not needed. However, in test 4 this mode of training was not used and the training was carried out with normal mode in which the data of the subject site is not automatically used as input. To define the lead-times of predictions for the model input data were entered to the model with a delay equal to each lead-time, as no delta is used to do this in this mode.

In the testing phase of sub-test 1 although the outputs of MLP shows a considerable improvement from first three tests for short prediction horizons, but prediction accuracy decreases sharply when the lead-time increases. In sub-test 2 there is an improvement over sub-test 1 for all lead times given by MLP as well as the Time Lag Recurrent network. In addition, the rate of decrease in accuracy caused by the lead-time increase for these types of networks is smaller in sub-test 2 than sub-test 1. As the only change in the models used in sub-tests 1 and 2 is the number of input patterns (has been increased from one in sub-test 1 to two in sub-test 2), it can be said that the number of input patterns shows a clear influence on the results of MLP and Time Lag Recurrent networks. In sub-test 3 the output of the MLP for a 3 hour lead-time is quite close to the measured values but this closeness decreases considerably when the prediction lead-time increases to 6, 9 and 12 hours.

In Recurrent and Time Lag Recurrent neural networks the accuracy of the predictions decreases quite gradually when the lead-time of the predictions increases. The difference between the outputs of the Recurrent and Time Lag Recurrent networks is also considerable, and the results of the Recurrent network show accuracy much better than those of the Time Lag Recurrent network. In sub-test 2 as mentioned earlier the results of the Time Lag Recurrent network show an improvement over sub-test 1. However, there is no considerable difference between the outputs of the Recurrent network from sub-test1 to sub-test 2. In sub-test 3 the outputs of the Recurrent and Time Lag Recurrent networks are also quite satisfactory even for 12 hours lead-time. However, the effect of additional gauging site on the results of this sub-test over sub-test 2 is negligible.

In real-time prediction, a decrease in the accuracy with increasing lead-time is usually assumed but the quality and quantity of this variation is important and case dependent. The maximum lead-time for satisfactory results is different from case to case and should be considered for any specific problem. Despite all three types of ANN presenting acceptable results for short prediction horizon, dynamic architectures (Recurrent and Time Lag Recurrent) have shown superior performance for this application even for 12 hours lead-time. Results produced by the naïve method is almost comparable to those produced by MLP in accuracy but considerably poorer than the results of the dynamic networks.

8 CONCLUSIONS

Results obtained from this study show good performance of the ANN in predicting river flow using hydrological time series. All three types of ANN presented acceptable results for a short prediction horizon, but dynamic architectures (Recurrent and Time Lag Recurrent) have shown superior performance even for a 12 hour lead-time. MLP could not produce acceptable results for a prediction horizon longer than 3 hours. Using too long a period of data, which produces a large number of examplars does not give any improvement in the outputs. In addition, it makes the training time too long which is a disadvantage in the process of real-time prediction. The number of upstream gauging stations for input data does not show an important influence on the accuracy of prediction for Recurrent networks. However, for MLP and Time Lag Recurrent networks, using two upstream gauging stations produced results better than using one gauging station. In this test, in which data from the subject site was not entered to the model (training was carried out without using the prediction mode), the results produced by the MLP are considerably improved in comparison to the first three tests. It is concluded that appropriate prediction of flow with appropriate lead-time can be made using only flow data of the upstream gauging sites in headwater, steep catchments. In this regard appropriate selection of the neural network architecture has an important effect on quality of predictions.

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