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A HYDRODYNAMIC/NEURAL NETWORK APPROACH FOR ENHANCED RIVER FLOW PREDICTION

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Abstract: *In this study, an artificial neural networks (ANN) was used to optimise the results obtained from a hydrodynamic model of river flow prediction. The study area is Reynolds Creek Experimental Watershed in southwest Idaho, USA. First a hydrodynamic model was constructed to predict flow at the outlet using time series data from upstream gauging sites as boundary conditions. The model, then was replaced with an ANN model using the same inputs. Finally a hybrid model was employed in which the error of the hydrodynamic model is predicted using an ANN model to optimise the outputs. Simulations were carried out for two different conditions (with and without data from a recently suspended gauging site) to evaluate the effect of this suspension in hydrodynamic, ANN and the hybrid model. Using ANN in this way, the error produced by the hydrodynamic model was predicted and thereby, the results of the model were improved.*

Keywords: *Hydrodynamic modelling, flow prediction, flow forecasting, river flow, artificial neural networks, hybrid model, ANN, optimisation, error prediction.*

1. INTRODUCTION

Prediction of river flow generally requires the collection of rainfall data, river level and other meteorological data and catchment characteristics, and an assessment of that information. A main criterion is the size of the catchment. In a flood prediction system, especially for large river catchments, a combination of rainfall-runoff and routing models may be used. A rainfall-runoff model is normally used for tributaries while a hydrodynamic or routing model for the main river reaches. The computational models used to predict river floods are in most cases one-dimensional. River floods are normally gradually varied unsteady flows and so a time-dependent simulation is required. Different software packages have been developed to carry out this type of simulation.

Machine learning techniques such as artificial neural networks, genetic programming and fuzzy logic have been widely applied to different aspects of water engineering during the last decade [1]. Despite some similarities, each of these techniques works with its own procedure, which of course is different from the others. The main type of neural networks, which are supervised networks operate on the principle of learning from a training set. They 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. In general, it is assumed that the network does not have any a priori knowledge about the problem before it is trained. At the beginning of training, the network weights are usually initialised with a set of random values. There are a variety of neural network models and learning procedures.

This research uses a combination of the two above mentioned tools in a new approach to river modelling where the artificial neural networks (ANN) are used to improve the accuracy of the results obtained from a hydrodynamic model of river flow. After consideration of the study area and the most important factors such as climate conditions, precipitation characteristics, flow regime and the data gauging network in the RCEW, modelling works are explained. Models were developed using hydrodynamic and artificial neural networks separately to predict flow at the outlet of the catchment, and their performances were evaluated. An MLP neural network model was adopted to optimise the outputs of the hydrodynamic modelling procedure by predicting the error produced by the hydrodynamic model.

2. REYNOLDS CREEK EXPERIMENTAL WATERSHED (RCEW)

This research was completed using data from the Reynolds Creeks Experimental Watershed (RCEW), a typical intermountain region of the western United States. It is located in Owyhee Mountains of south-western Idaho, about 80 km south-west of Boise, Idaho with a 239km2 drainage area. The main stream flows from south to north in the Owyhee mountains at an elevation exceeding 2200 m. The topography of the study area is generally rugged except in the broad valley floor in the north-central part of the watershed. It ranges from a broad, flat alluvial valley to steep, rugged mountain slopes. The elevation ranges over 1100 m through the catchment, resulting in a strong climatic gradient. The lower boundary of the catchment is determined by the outlet weir location, which is near the head of a small canyon through which Reynolds Creek flows before entering the Snake River about 12 km to the north. The lowest elevation on the watershed is 1101 m above the sea level and the highest elevation is 2241 m at the southern boundary of the catchment. The eastern boundary rises to about 1525m and the western to 830 m above sea level. The climate of the RCEW and more localised distribution of soils and vegetation are largely controlled by the elevation and local topography. The catchment's main perennial stream flow is generated at the highest elevations in the south and northwest where deep and late lying snow packs are the main source for water. Local slope and aspect strongly influence the hydrology of the catchment by controlling the incoming solar radiation and snow deposition patterns [2].

Annual Precipitation varies considerably from low elevations to high elevations. At the northern low elevation near the outlet it is about 230 mm while in the southern part it is over 1100mm of which more than 75% occurs as snowfall [3]. Annual water yield varies over the watershed from a few mm in small sub-drainages in lower portions of RCEW to over 583 mm in the higher elevation at the south western edge of RCEW [4]. For the catchment outlet the average annual water yield has been measured at 0.564 m^3/s or 77 mm p.a. The variation of runoff is considerable from year to year. The largest recorded flow at the outlet gauging site is over 107 m^3/s. This occurred on December 23, 1964, due to a rain-on-snow event with a frozen soil surface.

2.1. RCEW main reach

The RCEW main river reach between the Tollgate weir upstream and the Outlet weir downstream has been modeled in this study. This reach is a perennial stream with 14.082 kilometers length of stream course (the detailed surveyed thalweg length has been calculated as 17.073 kilometers). The downstream end of the reach (the Outlet weir) is also the outlet point of the RCEW. It is a self-cleaning overflow V-Notch (SCOV) weir draining all 239 km^2 of the catchment area, and located in a narrow canyon at low elevation of the catchment (1108 meters above sea level), and about 12 kilometers south of the confluence of Reynolds Creek and the Snake River. The upstream end of the reach is limited to the Tollgate weir. It is a gauging station with a Drop-Box V-Notch located at an elevation of 1410 m above sea level. The drainage area above this weir is 54.57km^2, ranging from 1410m to 2241m elevation with precipitation mostly in the form of snow. Fig. 1 gives more detail about the reach.

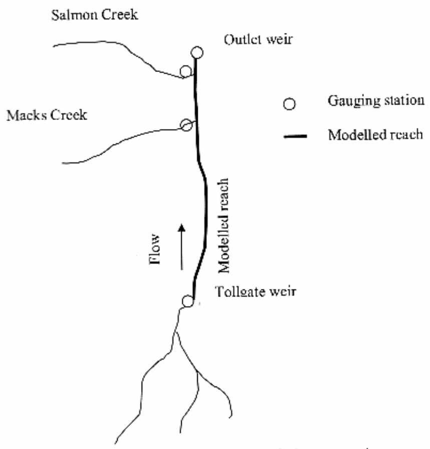


Fig. 1. Modelled river reach and the gauging stations used to collect data for this research.

The longitudinal slope of the modeled waterway in upper parts of the reach is relatively greater than in lower parts. A total of 53 cross sections have been drawn by surveying the distance between two weirs to provide the data required for calibration of the models.

3. DEVELOPING A 1D NUMERICAL MODEL

A 1D model was constructed for the reach between the Tollgate and Outlet weirs using MIKE 11 and was used to predict flow at the Outlet for a flood wave occurring in the period of February-April 1982. Flow data were entered into the model from Tollgate, Macks Creek and Salmon Creek located upstream of the outlet weir as the boundary conditions. These three gauging sites, which drain three main sub-catchments can be used to model the main river reach, while all other gauging sites are located in headwater tributaries of the sub-catchments and not delivering flow directly to the main river. 53 cross sections with associated photographs of the main channel and flood plain in each cross section location were used to define geometry and roughness (Manning's n) to the model. A Q-H relationship at the outlet weir section was used as the downstream boundary condition of the model.

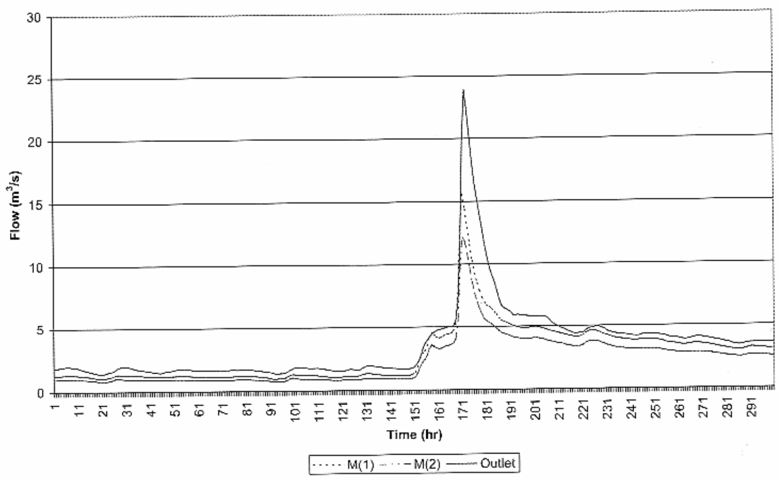


Fig. 2. Estimated flow for the outlet of the RCEW using MIKE 11 versus the measured values (with and without data from Macks Creek).

In the first stage this model was just used to predict flow at the Outlet using data from the three sites mentioned above. Fig. 2 shows the related hydrograph predicted by the model against the measured values. As the figure shows, the estimated values are not close enough to the measured values especially for the peak flow, which is mostly underestimated. As a result the output of the model at this stage may not be accurate enough for practical applications.

As the operation of Macks Greek has been suspended since 1991, the second stage in this part was to evaluate how this gauging site suspension affects the hydrodynamic modelling and how ANN might be able to bridge this gap in order to improve the results of the hydrodynamic model affected by this shortage of measured data. Therefore, another simulation was carried out but this time using data from only two stations where gauging has been continued (Tollgate and Salmon Greek). The estimated flow hydrographs at the outlet for this simulation are also compared to the measured values in Fig. 2. As can be seen from the figure results are not satisfactory and much worse than the first simulation. This clearly shows the effect of the absence of the Macks Creek as a source of data for the model. In the other word, suspension of the operation of this gauging site causes problems for the model.

4. DEVELOPING A NEURAL NETWORKS MODEL

A neural network model was developed and used to predict flow at the outlet point of the RCEW using the same input data as the hydrodynamic model. In this way the hydrodynamic model was replaced by a neural network model. The artificial neural network architecture used was a three-layer perceptron feedforward (MLP) network. This type of network is normally trained with the backpropagation algorithm. The backpropagation rule, propagates the errors through the network and allows adoption of hidden processing elements. One hidden layer with a tangent hyperbolic transfer function was used, while the output layer function was a logistic one. To prevent the model from over training, a small part of data (10 percent of the measurements) was specified and entered as a cross-validation data set. In the first simulation all three upstream gauging sites (Tollgate, Macks Creek and Salmon Creek) were used as sources of data to the model. The data was divided into three parts to use as training, testing and cross validation data sets. February 1 to March 10 was used to train the model to establish the relationship between input and output patterns, while the data of March 11 to April 16 was used as a testing set to evaluate the performance of the model. Each set covers at least a peak flow period. The remaining data (April 17-30) was used as cross validation data set. The period of data specified for testing phase was similar to the period of data used in MIKE 11 in previous section to be able to compare the results produced by these two models for a specific flood. As in the hydrodynamic modelling, the simulation was repeated here without data from the suspended gauging site (Macks Creek) to see how this technique deals with the problem of data source reduction. Fig. 3 shows the outputs of the model in testing phase in both first and second simulations. It must be mentioned that in testing phase, trained model has been evaluated by using new data, which had not been used in training or cross-validation.

Fig. 3 shows that removal of the Macks Creek data from the ANN model actually caused a significant improvement in the predictions. In addition to the figure the values of R^2 and RMSE indicate this improvement quite clearly. R^2 increases from 0.54 for the result of the first test (using all three sites) to 0.80 for the results of the second test (without data from suspended

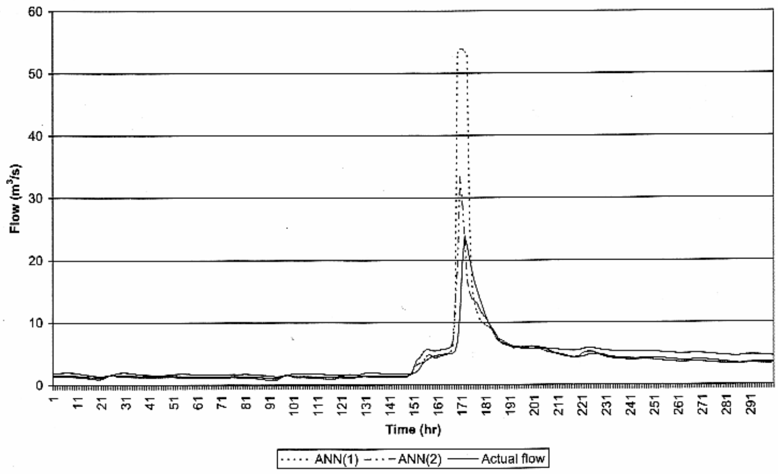


Fig. 3. Estimated flow for the outlet of the RCEW using ANN versus the measured values (with and without data from Macks Creek).

site). RMSE also decreases from 2.814 in first test outputs to 1.081 in the second test outputs. This behaviour was not what was expected. In view of the above it was decided to carry out a simulation after removing a second source of data (Salmon Creek) and therefore use data only from Tollgate, which is located across the main stream and for which the data shows more correlation to those of the outlet. Results of this simulation however showed that removing Salmon Creek data from the model has affected the results by decreasing the accuracy. R^2 and RMSE were calculated as 0.788 and 1.327 for the outputs of this simulation. Therefore the neural network model has produced its best possible results in the second simulation (using data from Tollgate and Salmon Creek).

5. DEVELOPING A HYBRID MODEL

In this part a combination of two techniques (hydrodynamic and ANN) was used to predict flow at the outlet of the RCEW. To improve the accuracy of the hydrodynamic model, an artificial neural network was employed to estimate the errors of hydrodynamic modelling results. Different architectures such as Radial Basis Function, Recurrent Network, Time Lag Recurrent Network and Multi-layer Perceptron (MLP) were used and the predicted errors were compared to the actual errors. The MLP gave the most accurate results and therefore it was selected as the neural network architecture to be combined with the hydrodynamic model. The error of the hydrodynamic model estimations was calculated using the following formula:

$$E_p = X_{obs} - X_{est}$$

where E_p is the error of the estimated pattern, X_{obs} is the observed value and X_{est} is the estimated value. The ANN model was trained using Tollgate measured flow data and MIKE 11 outputs for the outlets as input to the ANN model and the difference between MIKE 11 outputs and the measured values for outlet (error of MIKE 11 estimation, EP) as output of the neural network model. Hourly flow data for the period of February 1 to April 30, 1982 was used for this simulation (similar to that used in hydrodynamic and ANN models in previous sections). The prediction of error

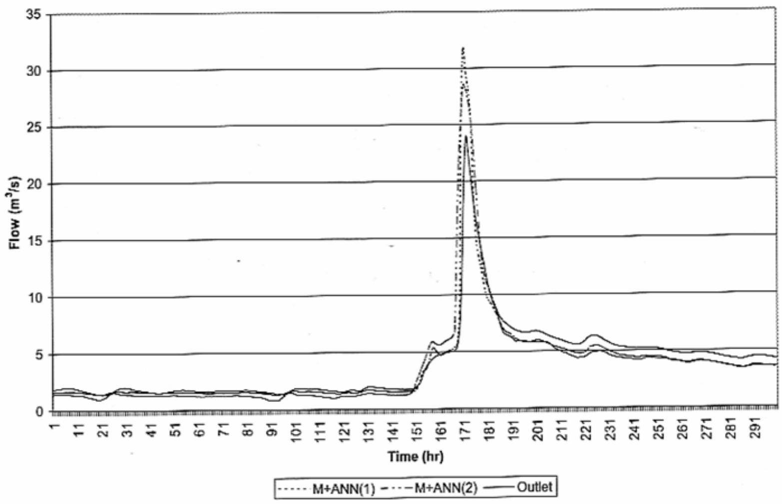
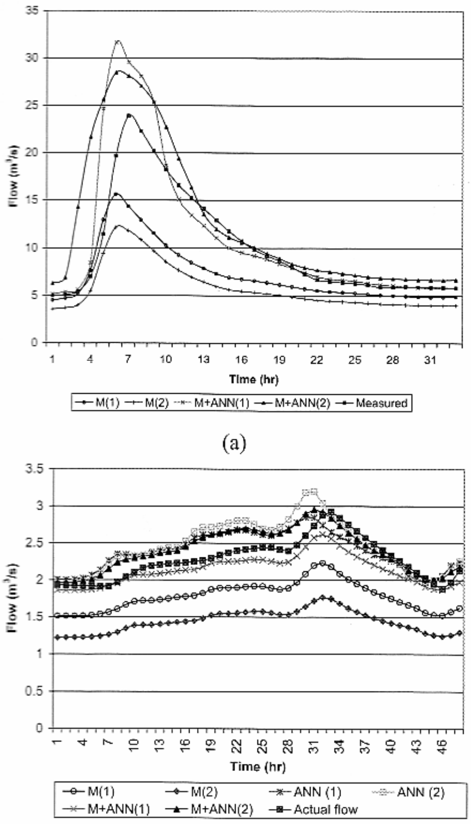


Fig. 4. Optimised results of the MIKE11 for the outlet of the RCEW using ANN versus measured values (with and without data from Macks Creek).

for the first (using all three stations) and second (without Macks Creek) hydrodynamic simulations was carried out separately. The data sets for training, testing and cross validation were the same as in the previous ANN modelling. By consideration of the predicted errors, the results of MIKE11 were improved (Fig. 4). This improvement was obtained by addition of the amount predicted as the error of MIKE11 (by ANN model) to the outputs of MIKE 11. The combination of a hydrodynamic model and ANN caused a clear improvement in the results. It would appear that the combination of these two techniques for this specific application uses the potential of both methods (Fig. 4). The optimised flow hydrograph of the MIKE11 model for the outlet of the RCEW using ANN after suspension of the Macks Creek gauging site (without using data from this site) is also shown in Figure 4. The results have been improved considerably in comparison to Fig. 2, which shows the results of the hydrodynamic model for the same conditions (with and without data from Macks Creek). The results shown in figure 4 also indicate an improvement in prediction of the peak flow in comparison to the results of the ANN model (Fig. 3). In general, the predicted values for the low flow period seems closer to the actual values compared to the high flow period predictions (the peak flow period of the hydrographs). For example the ANN model using all three gauging sites (Fig. 3) performed very well on prediction of the low flow but its output for peak flow period is overestimated. To view the performance of the models for peak flow prediction with greater clarity, the hydrographs produced by the hydrodynamic model together with optimised hydrographs for both first and second simulations have been shown in Fig. 5.

For the hydrodynamic model alone, the outputs are generally underestimated. This is mostly due to the absence of a part of the catchment runoff as a boundary condition of the model. The south sector of the catchment has the most precipitation and runoff and most of this flow is measured at the Tollgate site. The flow measured in two other main tributaries (Macks Creek and Salmon Creek) are also considered to the model but there are still several small tributaries draining about 40% of the catchment that have no data to enter in the model. Underestimation of predictions from the hydrodynamic model is to be expected as part of the catchment is not contributing to the model. The unsatisfactory results produced by the ANN model alone is in fact a complicated task, which needs to be explained here. Neural network modelling is a black box method and establishment of an efficient input-output relationship is strongly the case and data dependent.



(b)

Figure 5 Output of the models for (a) a period of high flow (b) a period of low flow

The reliability of the outputs is mostly dependent on these relationship established between the inputs and outputs. A strong relationship in the training phase normally gives the most accurate output in the testing phase (as long as the testing data set is in the range of training data and the model is not over trained). The strength of this relationship depends on the correlation between the data series used as inputs and outputs. In most cases this correlation depends on the range, order and nature of data sets rather than closeness of the values or the number of input patterns. Removing the data of a gauging site in the present case removes the flow data of a part of catchment from the hydrodynamic model boundary and causes underestimation of the outputs. However, in the neural network model removing the Macks Creek data caused better correlation between the combination of Tollgate and Salmon Creek data and the outlet data, and finally leads to better performance of ANN model. Even simulation with only one input pattern (Tollgate data) produced results better than the simulation with three input patterns due to the facts came in previous sentences. In modeling with this technique there are no certain rules to set all the required parameters to reach desirable results, and trial and error is the only way to improve the output accuracy. Replacement of the hydrodynamic model by a neural network model with the same input data produced results completely different from the hydrodynamic model. For the low and normal flow discharge, ANN produced results which are quite close to the measured values. However, in prediction of the high flow discharge (flood wave) the outputs are considerably over estimated in contrast to the hydrodynamic model. A combination of these two techniques produced outputs that were more accurate than the results of the models individually. To evaluate the accuracy of the results statistically, two criteria were used: coefficient of efficiency, R^2, and root mean square error, RMSE. For the first simulation (before suspension of a gauging site in the catchment), the coefficient of efficiency, R^2, increased from 0.643 for the results of the hydrodynamic model to 0.915 for the results of the combined model. The root mean square error (RMSE) also decreased from 0.936 m^3/s to 0.718 m^3/s. For the second simulation (after suspension), neural networks improved the results by increasing R^2 from 0.237 to 0.872 and decreasing RMSE from 1.324 to 0.980.

6. CONCLUSIONS

This study, which investigated the role of the ANN technique as an output corrector of the hydrodynamic modelling procedure, shows that artificial neural networks can play a very effective role in obtaining more accurate results from hydrodynamic modelling. This clearly indicates that new machine learning techniques like neural networks can be coupled with existing hydrodynamic approaches to produce more sophisticated results, which will be practically helpful. In addition to usefulness of this combination in practical water related projects and plans, it opens up new research opportunities to enhance ability of the existing methods.

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