River Water Level Prediction Using Physically Based and Data Driven Models

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Keywords: *Artificial neural network, data driven model, flood prediction, hydrodynamic model, Muskingum-Cunge model, neuro-fuzzy system*

EXTENDED ABSTRACT

The ability to simulate the propagation of flood waves is of crucial importance for planning and operational management of river floods. Hydrodynamic and hydrologic numerical models provide such capabilities and represent conventional approaches to river flood modelling. In the recent years, data driven models such as artificial neural networks (ANNs), and neuro-fuzzy systems have also emerged as viable tools for this purpose.

An objective comparison of these models is necessary to evaluate their individual performances and assess strengths and limitations. This paper considers four different modelling approaches for water level simulation, using the same flood event data for model calibration and testing. The models include a full dynamic one dimensional hydrodynamic numerical (HN) model, a Muskingum-Cunge (MC) hydrological routing model, and two data driven models: artificial neural network (ANN) and adaptive network based fuzzy inference system (ANFIS). Four flood event datasets from the years 1988, 1990, 1993 and 1994 for a reach of about 100 km from the rivers Rhine and Neckar in Germany are used in this study. The statistical performance of the models is assessed using the criteria of coefficient of efficiency, root mean square error, peak error and maximum absolute error.

The results of this study indicate that carefully set up HN, MC, and data driven models are all capable of producing good results. All four models performed similarly for the same datasets. For example all four models overpredicted the peak of the 1990 flood event, while each of these models are able to reproduce the 1993 and the 1994 flood events quite well. The ranges of root mean square errors for the HN, MC, ANN and ANFIS models are obtained as 0.17–0.38 m, 0.08–0.15 m, 0.07–0.22 m and 0.08–0.24 m, respectively. Similarly, the ranges of coefficient of efficiency for the HN, MC, ANN and ANFIS models are obtained as 0.942–0.975, 0.981–0.989, 0.979–0.991 and 0.976–0.990, respectively. The results also show that the MC, ANN and ANFIS models performed better compared to the HN model. Figure 1 shows a comparison of the results of all four models with the observations for the 1993 flood event.

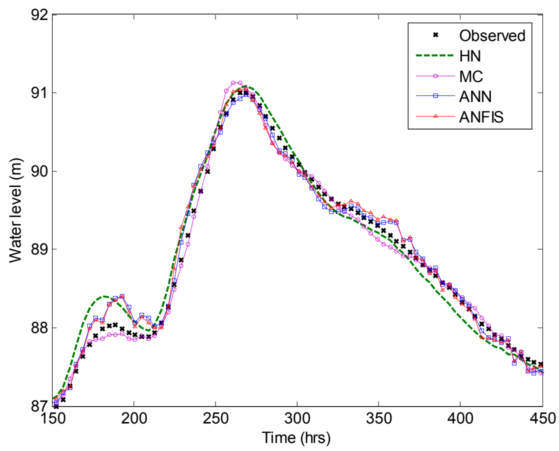

Figure 1. Observed, HN, MC, ANN and ANFIS results and errors for 1993 flood event

A number of factors need to be considered for selecting the appropriate model for river flood prediction. The physically based HN models require detailed topographical data and are able to make predictions at every cross section. The simplified hydrological routing and the data driven models require little or no topographical data but are only capable of making predictions at the model output boundaries. These strengths and limitations can be a basis for complementary modelling. The HN model can be applied in the critical locations where water surface profiles are of specific interest. The simplified distributed or data driven models are more efficient for flood routing purposes. It may also be more reliable to use more that one model for flood forecasting purposes, so that the results can be cross validated and different scenarios tested.

1. INTRODUCTION

River floods are complex dynamic processes characterised by spatial and temporal variations. The understanding of these processes and the capabilities to encapsulate them in terms of numerical models are of crucial importance for planning and operational management of river floods. Hydrodynamic and hydrologic numerical models provide such capabilities and represent conventional approaches to river flood modelling. In recent years, several researchers have used data driven models such as artificial neural networks (ANNs) and fuzzy systems for river flood modelling. (eg. Thirumalaiah and Deo 1998; Imrie *et al.* 2000; Liong *et al.* 2000; Bazartseren *et al.* 2003; Shrestha *et al.* 2005).

The fundamental notions and hypotheses of each of these models are entirely different with major differences in model structure, data requirements and capabilities. For the scientific and engineering communities to benefit more from these different modelling approaches, it is important to bring them to a common platform and analyse their capabilities. Khatibi and Haywood (2002) categorised different models for river flood forecasting based on the representation of physical systems. Abebe and Price (2004) illustrated the relative position of physically based and data driven models in the spectra of physical insights and data needs. A one to one comparison of these modelling approaches will facilitate further assessment of these models according to their individual strengths and limitations.

A number of researchers have made a comparative study of different data driven modelling approaches (eg. Lekkas *et al.* 2001, Shivakumar *et al.* 2002, Bazartseren *et al.* 2003). However, studies that compare physically based hydrodynamic models with hydrological routing models and data driven models are not available. This paper addresses this need with a detailed comparison of four different models in the context of river flood prediction. Two conventional flood routing models: a full dynamic one dimensional HN model and a hydrological routing model based on the Muskingum-Cunge formulations are used. Similarly, artificial neural network (ANN), and adaptive network based fuzzy inference system (ANFIS) based data driven models are trained for the same study reach. For an objective comparison of these modelling tools, the same flood event data are used in each of these models for calibration and validation.

2. STUDY AREA AND DATA

The study is conducted in the section of the rivers Rhine and Neckar in South - Western Germany in the region of Heidelberg, Karlsruhe, Mannheim and Ludwigshafen (Figure 2. The study area consists of a reach of about 80 km in length between the gauging stations Maxau and Worms in the River Rhine and a 26 km reach from the gauging station Heidelberg to the confluence in the River Neckar. The catchment area of the River Rhine at the Worms station and the River Neckar at the Heidelberg station are 68827 km^2 and 13783 km^2, respectively. There are no major tributaries in either of the reaches.

The time series of flow and water level data at one hour intervals are available from the gauging stations located at Maxau, Worms and Heidelberg for the 1988, 1990, 1993 and 1994 flood events. The obtained discharge time series are derived from a single value stage discharge rating curve. The water levels are directly measured values and are more accurate compared to discharges. Hence, water levels from the Worms station are used for the calibration of the hydrodynamic and hydrological routing models and as targets for the training and validation of the data driven models.

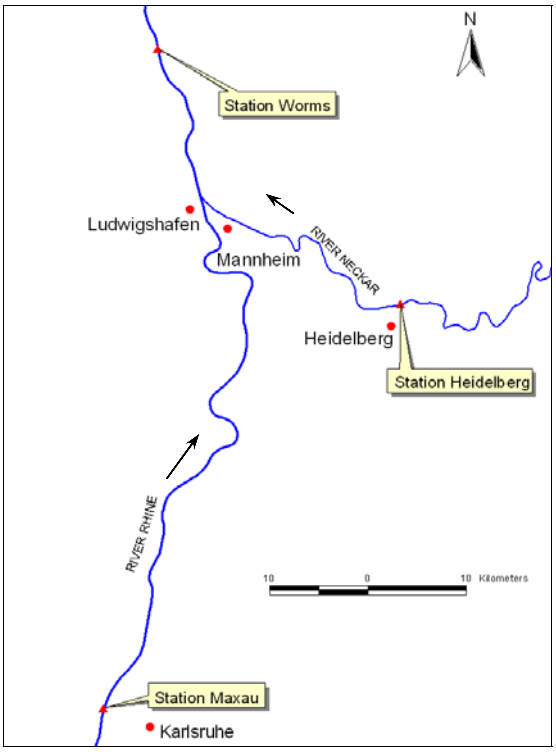

Figure 2. Study reach of the River Rhine and River Neckar

3. HYDRODYNAMIC NUMERIC MODEL

The one dimensional (1D) hydrodynamic numerical (HN) model is the first model considered for the study area. The HN model is based on the conservation principles of mass and momentum, also known as the Saint-Venant equations and expressed in terms of the continuity (equation 1) and the momentum equations (equation 2):

$$\frac{\partial y}{\partial t}+\frac{1}{b}\frac{\partial Q}{\partial x}=0 \tag{1}$$

$$\frac{\partial Q}{\partial t}+\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right)+gA\frac{\partial h}{\partial x}+gA\left(S_f-S_o\right)=0 \tag{2}$$

where, y = water surface elevation [m], h = depth of flow [m], Q = discharge [m^3/s], b = top width of flow [m], A = active cross sectional area of flow [m^2], g = gravitational acceleration [m/s^2], S_f = friction slope, S_0 = bed slope, x = distances along the channel [m] and t = time [s].

The HN model is set up using the 1D modelling system CARIMA from SOGREAH (Cunge *et al.* 1980). CARIMA is a generalised hydrodynamic numerical modelling system based on the full one-dimensional Saint-Venant equations. The solution of these equations is based on the Preissmann implicit finite difference method, which is generally considered unconditionally stable for all Courant numbers (Cunge *et al.* 1980). As the system is based on the full Saint Venant equations, it is also capable of representing the backwater influence of tributaries, such as in the Rhine - Neckar confluence.

The HN model is constructed as shown in Figure 3 with cross sections at 100 m intervals in both the Rhine and the Neckar sub-reaches. The number of cross sections is 811 in the Rhine sub-reach from Maxau to Worms and 298 in the Neckar sub-reach from Heidelberg to the confluence. The flow hydrographs *Q(t)* from the gauging stations at Maxau (Rhine) and Heidelberg (Neckar) are used as upstream boundary conditions. A stage discharge relationship *Q(y)* is used as the downstream boundary condition, located at a distance of 36.6 km downstream of the Worms station. The initial conditions of the model are set up using a steady flow calculation.

The unsteady flow calibration is done by adjusting the model parameter (Manning-Strickler coefficient) in such a way that a good match can be obtained between the observed and simulated time dependent hydrographs. The stage hydrograph from the Worms station from the 1988 flood event is used for the calibration of the model. The 1990, 1993 and 1994 flood event data are used as test datasets.

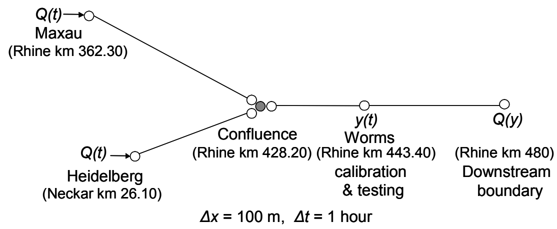

Figure 3. Schematisation of the reaches in the HN model

4. MUSKINGUM CUNGE MODEL

The hydrologic flood routing basically constitutes a reach by reach prediction of discharge hydrographs based on the response of the river reach to inflow and storage. Amongst different hydrological flood routing methods, the Muskingum-Cunge formulation (Cunge, 1969) is one of the most popular methods. The model is based on the continuity (equation 3) and storage equations (equation 4):

$$\frac{dS}{dt}=Q_{in}(t)-Q_{out}(t) \tag{3}$$

$$S_j^n=K\{XQ_{in}^n+(1-X)Q_{out}^n\} \tag{4}$$

where, S = storage in the channel [m^2], K = storage time coefficient [s] and X = weighing factor. The parameters K and X are obtained by forcing the numerical diffusion to match the hydraulic diffusion (Cunge 1969), such that the model parameters can be obtained in terms of the Manning-Strickler coefficient.

The MC model is set up for three sub-reaches: Maxau – confluence, Heidelberg – confluence and confluence – Worms, as shown in Figure 4. The selection of the space time grid discretisation is based upon the criteria given by Ponce (1994). Accordingly, model reaches are further divided into seven sub-reaches (*j*) between the Maxau – confluence, three between the Heidelberg – confluence and two between the confluence – Worms. A simple algebraic summation is used for the addition of flows at the confluence.

The MC based routing model is developed using the interactive MATLAB/Simulink environment, with the river sub-reaches represented by subsystem blocks. The river cross sections at Maxau, Heidelberg and Worms are used to define the river geometry. Rating curves are used for the relationship between discharge and water levels. Lookup tables are used to calculate time varying cross section parameters: flow area, flow width and wetted perimeter.

The MC model does not require a downstream boundary condition and the available downstream water levels can be used for model calibration. In this case also, the water level time series are used in preference to the flow time series for the calibration. The water levels at the Worms station are obtained by transforming the output discharge time series using a depth discharge lookup table (rating curve). The MC model calibration is done by adjusting the model parameter (Manning-Strickler coefficient). In this case too, the 1988 datasets are used for model calibration and the 1990, 1993 and 1994 for model testing.

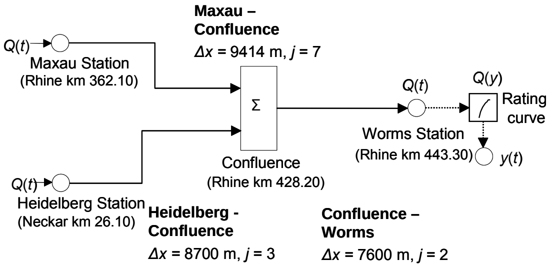

Figure 4. Schematisation of the reaches in the Muskingum Cunge based model

5. DATA DRIVEN MODELS

The third part of this study considers data driven methods for the study reach. In contrast to the HN and MC models, the data driven models do not explicitly follow physical principles inside a system. They constitute a universal approximation of the input and output signals and are able to make abstractions and generalization of the processes. The prediction of downstream water levels based on the upstream discharges using a data driven model may be represented by the following relationship.

$$y(t) = f\{Q_1(t - a_1), Q_2(t - a_2)\} \qquad (5)$$

where, $y(t)$ = downstream water level and $Q_i(t)$ = upstream discharge and a_i = travel time.

Two different data driven models: artificial neural network (ANN) and a special neuro-fuzzy system, known as adaptive network based fuzzy inference system (ANFIS) are considered in this study. More details on ANNs and ANFIS are available in Haykin (1994) and Jang (1993), respectively. Since both the modelling approaches are quite similar, they are considered together.

The first step in developing the ANN and the ANFIS based models is the selection of an appropriate model architecture and the model inputs and outputs. The ANN architecture selected consists of a recurrent network consisting of one input layer, two hidden layers and one output layer. The architecture of ANFIS consists of a five layered special network topology, with the domains of the antecedent variables partitioned into a specified number of membership functions.

The inputs to both data driven models consist of flow time series from the Maxau station in the River Rhine and the Heidelberg station in the River Neckar. The water level time series from the Worms station is taken as the targets. The training sets for both the data driven models are taken as the 1988 flood event data, which consist of the highest range of data. The flood event data from 1990 are used as validation, and 1993 and 1994 as test datasets. The inputs and outputs are normalised between –1 and 1. The 24 hours lag time from Maxau to Worms and 8 hours lag time from Heidelberg to Worms are considered. The inputs and outputs of the data driven models are shown in Figure 5.

The structure of the ANN consists of 2 neurons in the input layer, 16 neurons in the first hidden layer, 10 neurons in the second hidden layer and 1 neuron in the output layer. It is observed during the preliminary trials that the use of recurrent feedback in the output layer enhances the performance of the ANN. Hence, recurrent networks are used, although this slowed down the training process considerably. The network consists of hyperbolic tangent activation functions in the hidden layers and linear activation function in the output layer. The ANN model is developed using the procedure of the MATLAB Neural Network Toolbox (Demuth and Beale, 2004). The backpropagation algorithm with Bayesian regularisation of the Levenberg-Marquardt approximation is used for ANN training. Early stopping criteria provided by the validation datasets are used to prevent overtraining. The test datasets are used independently for the evaluation of model performance.

The ANFIS model is developed using the procedures of the MATLAB Fuzzy logic toolbox (The MathWorks Inc., 2004). The structure of the ANFIS model consists of a Sugeno type fuzzy system with generalised bell input membership functions and a linear output membership function. The network consists of 2 inputs, each with 3 input membership functions, 9 rules and 1 output membership function. The training algorithm consists of a backpropagation and least squares estimation for the adjustment of premise and consequent parameters of the ANFIS, respectively. In this case too, early stopping criteria provided by the validation datasets are used to prevent overtraining and the test datasets are used for the independent evaluation of model performance.

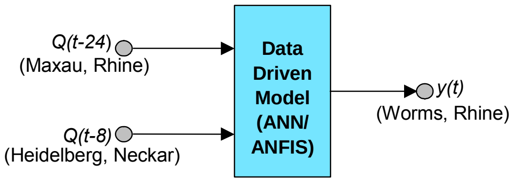

Figure 5. Input and output of the data driven models

6. RESULTS

The comparison of the observed and simulated results of the HN, MC, ANN and ANFIS models for the 1990, 1993 and 1994 flood events are depicted in Figures 6, 7 and 8. The performance of the models is assessed using the statistical criteria of the coefficient of efficiency (CE) and the root mean square error (RMSE). In addition, the peak error (PE) and the maximum absolute error (MAE) in water levels are also considered. The results of the statistical analysis are summarised in Table 1. It is to be noted that the 1990 flood event represents the validation dataset and the 1993 and 1994 flood events represent the test datasets for the ANN and ANFIS models. All three flood event datasets are used as the test datasets for the HN and MC models.

The comparison of performances generally demonstrated reasonable results for each of these models and all four models performed similarly for the same datasets. There are some problems in reproducing the 1990 flood event, with all the models showing overprediction. The overprediction is higher in the ANN and ANFIS models compared to the MC and HN models. There are also phase errors in the model results, particularly in the case of the HN and MC models. The MC model produced the best overall statistical performance of the four models considered.

In the case of the 1993 flood event, the flood peaks are predicted quite well by all of the models. There are some problems in the reproduction of the secondary peak where the HN, ANN and ANFIS models show overprediction. The phases are well reproduced by these models, except for the MC model, which shows some phase shift. The statistical performance of the MC, ANN and ANFIS models are quite close to each other with the MC model performing slightly better in terms of RMSE and the ANN and ANFIS models performing slightly better in terms of CE.

The performance of all four models for the 1994 flood event is found to be very good, considering reproduction of both the phase and amplitude portraits of the flood wave. In this case, the statistical performance of the MC, ANN and ANFIS models is similar.

The overall results of the model show that the approximate MC and ANN and ANFIS models performed better compared to the HN model. Between the data driven models, the statistical performance of the ANN is found to be slightly better in comparison to the ANFIS model. It is to be noted that the performance of the HN model may be affected by a number of factors, such as inadequate description of the floodplain - river channel interaction, which need not be considered in the MC, ANN and ANFIS models.

Table 1. Statistical performance of the model results for 1993 datasets

Flood event	Model	CE	RMSE (m)	PE (m)	MAE (m)
1990	HN	0.9416	0.38	-0.32	0.46
	MC	0.9810	0.15	-0.30	0.48
	ANN	0.9791	0.22	-0.62	0.74
	ANFIS	0.9755	0.24	-0.68	0.77
1993	HN	0.9747	0.21	0.08	0.22
	MC	0.9857	0.08	0.14	0.22
	ANN	0.9909	0.10	0.04	0.43
	ANFIS	0.9902	0.10	-0.04	0.50
1994	HN	0.9696	0.17	0.14	0.41
	MC	0.9885	0.09	0.09	0.26
	ANN	0.9871	0.07	-0.11	0.40
	ANFIS	0.9814	0.08	-0.02	0.52

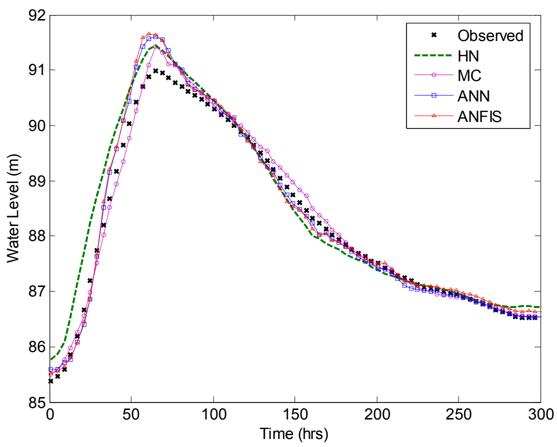

Figure 6. Observed, HN, MC, ANN and ANFIS results and errors for 1990 flood event

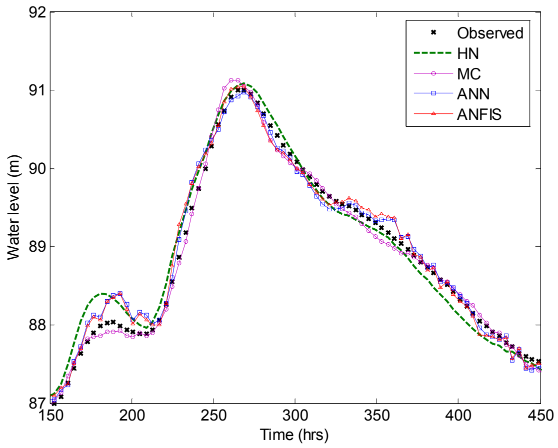

Figure 7. Observed, HN, MC, ANN and ANFIS results and errors for 1993 flood event

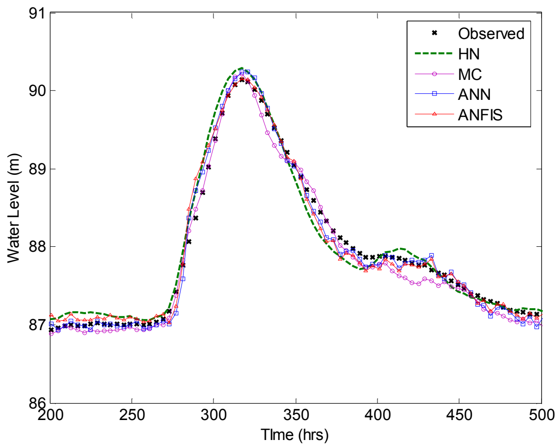

Figure 8. Observed, HN, MC, ANN and ANFIS results and errors for 1994 flood event

7. CONCLUSIONS

This paper has provided an objective comparison of the hydrodynamic, hydrologic and data driven models for river flood prediction. The results of this study indicate that carefully set up HN, MC, and data driven models are all capable of producing good results. Generally, the MC, ANN and ANFIS models performed better compared to the HN model. However, it is also important to consider that each of these models is based on entirely different philosophies, with different strengths and limitations. Important considerations in this context include data requirements and forecasting capabilities.

In the context of data requirements, the HN model requires detailed topographical data in the river channel and floodplains. In contrast, the hydrological routing and data driven models require little or no topographical data. However, the HN model is capable of making predictions at every cross section, while the hydrological routing and data driven models are only capable of making predictions at the model output boundaries. On the other hand, the hydrological routing and data driven models can extend the forecast horizon based on the travel time of the flood wave from upstream to downstream. This gives the possibilities of making short term flood forecasts, only based on upstream flows.

The strengths and limitations of these models can be a basis for complementary modelling. As an example, hydrological routing and data driven models can be used to predict flows at the gauging stations. The HN model can be applied at the critical locations where water surface profiles and inundation extents are of specific interest. It may also be more reliable to use more that one model for flood forecasting purposes, so that the results can be cross validated and different scenarios tested. It is hence argued that these models should be viewed as complementary rather than competitive.

8. REFERENCES

Abebe, A.J. and Price, R.K. (2004). Information theory and neural networks for managing model uncertainty in flood routing, *Journal of Computing in Civil Engineering ASCE*, 18(4), 373-380.

Bazartseren, B., Hildebrandt, G. and Holz, K.-P. (2003). Short-term water level prediction using neural networks and neuro-fuzzy approach, *Neurocomputing*, 55(3-4), 439-450.

Cunge, J.A. (1969). On the subject of a flood propagation computation method (Muskingum method), *Journal of Hydraulic Research*, 7(2), 205-230.

Cunge, J.A., Holly, F.M., and Verway, A. (1980). *Practical Aspects of Computational River Hydraulics*, Pitman, London.

Demuth, H. and Beale, M. (2004). *Neural Network Toolbox User's Guide*, The MathWorks Inc., Online documentation: http://www.mathworks.com/access/helpdesk/help/toolbox/nnet/.

Haykin, S. (1994). *Neural Networks a Comprehensive Foundation*, 1st Edition, Macmillan College Publishing Company Inc., New York.

Imrie, C.E., Durucan, S. and Korre, A. (2000). River flow prediction using artificial neural network: generalisation beyond calibration range, *Journal of Hydrology*, 233, 138-153.

Jang, J.-S.R. (1993). ANFIS: Adaptive network based fuzzy inference system, *IEEE Transactions on Systems, Man and Cybernetics*, 23(3), 665-685.

Khatibi R. and Haywood J. (2002). The role of flood forecasting and warning in sustainability of flood defence, *Proceedings of the Institution of Civil Engineers-Municipal Engineer* 151 (4), 313-320.

Lekkas, D.F., Imrie, C.E. and Lees, M.J. (2001). Improved nonlinear transfer function and neural network methods for flow routing for real-time flood forecasting, *Journal of Hydroinformatics*, 3, 153-164.

Liong, S.-Y., Lim, W.-H., and Paudyal, G. (2000). River stage forecasting in Bangladesh: neural network approach, *Journal of Computing in Civil Engineering ASCE*, 4(1), 1-8.

Ponce, V.M. (1994). *Engineering Hydrology*, Principles and Practice, Prentice Hall, New Jersey.

Sivakumar, B., Jayawardena, A.W. and Fernando, T.M.K.G. (2002). River flow forecasting: use of phase-space reconstruction and artificial neural networks approaches, *Journal of Hydrology*, 265, 225-245.

Shrestha, R.R., Theobald, S. and Nestmann, F. (2005). Simulation of flood flow in a river system using artificial neural networks, *Hydrology and Earth System Sciences*, Special Issue on Advances in Flood Forecasting in Europe (In Press).

The MathWorks Inc. (2004). *Fuzzy Logic Toolbox for Use with MATLAB*, The Mathworks Inc., Online documentation: http://www.mathworks.com/access/helpdesk/help/toolbox/fuzzy/.

Thirumalaiah, K. and Deo, M.C. (1998). River stage forecasting using artificial neural networks, *Journal of Hydrological Engineering, ASCE*, 3 (1), 26-31.