FORECASTING PERENNIAL RIVER RUNOFF USING ARTIFICIAL NEURAL NETWORK (A REVIEW)

Manish Dubey[1], Sudhir Nigam[2,] Rashmi Nigam[3]

[1](Research Scholar, Mewar University, Rajsthan, India)

[2](Professor, Civil Engineering, TIT, Bhopal,M.P. India)

[3](Assistant Professor, UIT, RGPV, Bhopal, M.P., India)

ABSTRACT: Floods are among the most destructive natural disasters, which are highly complex to model. Rainfall runoff models are found highly useful for water resources planning and development. The research on the advancement of flood prediction models contributed to risk reduction, policy suggestion, minimization of the loss of human life, and reduction of the property damage associated with floods. Forecasts of water inflow are needed for flood forecasting during peak discharge season and for determining reservoir capacity during the operationalplanning over periods ranging from a few hours to several months ahead throughout the year.

Medium-range forecasts of the order of a few days to two weeks have usually been obtained by simple ARIMA-type models, which do not utilize information on observed or forecast precipitation, nor stream flow observations from upstream gauging stations. Recently, several different hydrological models have been tested to assess the potential improvements in forecasts that could be obtained by using observed and forecast precipitation as additional inputs.

To mimic the complex mathematical expressions of physical processes offloods, during the past two decades, machine learning (ML) methods particularly artificial neural network method contributed highly in theadvancement of prediction systems providing better performance and cost-effective solutions.Therefore, the use of artificial neural networks (ANNs) is becoming increasingly common in the analysis of hydrology and water resources problems. In this paper we have carried out a review of different ANN techniques used for forecasting the water flow for various purposes including development of flood warning system and regulatory procedures.

KEYWORDS: ARIMA , Runoff, Capacity, hydrology, forecasting, Model

Introduction: Flood is the inundation of land by the rise and overflow of water resulting from from heavy rainfall or sudden rush of water when exceeds the carrying capacity of the river system (Web Resource, 2011a). Frequent flood all over the world have made river flow forecasting as one of the earliest forecasting problems that involves the important measurements, characterizing the degree of mean reversion of a time series (Hurst, 1951). Flood forecasting represents not only a very complex nonlinear problem, but also one that is extremely difficult to model. Flood forecast modeling is a complex mathematical outcome, which is the representation of the various natural processes involved during inundation over catchments. Flood intricacy includes the numerous factors that affect river water levels such as the location, rainfall, soil types and size and shape of catchments. The relationship between these factors yet not had been fully understood (Dooge, 1977; Zhang and Govindaraju, 2000). In recent years, numerous studies from varied fields of hydrodynamics, civil engineering, statistics and data mining have contributed to the area of flood prediction. The importance of estimating river flows to the livelihoods of the inhabitants around rivers made them to study and record the levels since earliest history. In fact, there are available records for the flow level of the River Nile dating back to around 3000 B.C. For example, in the Palermo Stone, 2480 B.C., available at Palermo Historical Museum, Palermo, Italy and were also discussed in literature ("The River Nile" by R. Said, Oxford, U.K.: Pergamon, 1993). The ancient Egyptians recorded the annual peak river levels for the years from 3050 B.C. until 2500 B.C. (Atiya et al., 1999).

Flood Modeling

Rainfall-runoff modeling is the process of transforming a rainfall hyetograph into a runoff hydrograph. It play an important role in water resource management planning and flood forecasting system. Different types of models with various degrees of complexity have been developed to exhibit hydrological rainfall-runoff-routing processes in terms of water levels and their variations over the time. These models, regardless to their structural diversity generally fall into the following categories (Dooge, 1977; Porporato and Ridolfi, 2001); namely,

1. Theoretical or Conceptual models
2. Physical or Deterministic models
3. Mathematical and Numerical models
4. Data-Driven (statistical and stochastic) models,
5. Black Box systems or artificial intelligent based models (ANN, GA, SOM etc.) and
6. The various combinations of these models in the sphere of the rainfall-runoff process.

Historical Modeling Approaches

First three classes of models (namely conceptual, physical and mathematical) are important in understanding hydrological processes and are reliable in forecasting the most important features of the hydrograph (Kokkonen and Jakeman, 2001).

Conceptual rainfall-runoff models usually incorporate interconnected physical elements with simplified forms and each element is used to represent a significant or dominant constituent hydrologic process of the rainfall-runoff transformation. Many of the rainfall–runoff models rely on the fact that the dynamic effects of various factors mentioned above are embedded in the rainfall and runoff data (Srinivasulu and Jain, 2006). The models under these categories use the conceptual description and mathematical formulation of the physics of the underlying process. The main research in these conventional models includes Sherman, 1932; Ishihara and Takasao, 1963; and Ramírez, 2000. For decades, great deals of research in describing the rainfall–runoff processes were based on either deterministic/ conceptual models (e.g. Stanford Watershed Model, Soil Moisture Accounting and Routing, Sacramento Soil Moisture Accounting, HEC, Xinanjiang, Mod-hydrolog, IHACRES, InHM, Tank, HEC-HMS models etc.). These models describe the natural system of rainfall and runoff using the basic fluid-flows concepts derived from the energy and water budgets. These models consist of a set of mathematical formulae / equations describing various influencing parameters that could be evaluated through independent measurements (O'Connell, et al., 1970; Burnash et al., 1973; Sugawara, (1995); Zhao et al., 1980; Jakeman et al., 1990; Chiew and McMahon, 1994; Hogue et al., 2006; and Pukdeboon et al., 2006). The characteristics parameters affecting the runoff response and flood forecast of a catchment include:

- Flow Characteristics: Discharge, velocity and extent of inundation (channel & floodplain)
- Storm Characteristics: intensity, duration and frequency of rainfall event,
- Catchment Characteristics: size, shape, slope, elevations, stream length, storage capacity
- Geomorphological Characteristics: topography, land use patterns, vegetation, soil type
- Subsurface Characteristics: infiltration rate, permeability, ground water flow
- Climatic Characteristics: temperature, humidity, wind characteristics, etc.

The influence of these factors and many of their combinations in generating runoff is an extremely complex scientific process and is not understood clearly (Zhang and Govindaraju, 2000). These conceptual models are enviable since theyresemble to the natural internal sub-processes of mean rainfall-runoff event. Conceptual models are least oriented to give wild or unrealistic predictions, even when modeling rare or extreme flood event. The implementation and calibration of these models can typically present various difficulties, requiring sophisticated mathematical tools, a large number of parameters for modelling and some degree of experience with the model (Grayson et al., 1992). Conceptual models have potential for evaluating land-use impact on hydrological processes based on relationships of the model parameters to measurable physical characteristics. The problem with conceptual models is that empirical regularities are not always evident and the consequential mathematical relationships are not easily available. Damle (2005) discussed the following input resources to obtain the input data for the rainfall runoff modeling:

- Stream and Rain-Gauge Networks and Hydrograph Analysis
- Radar and Information Systems
- Linear Statistical Analysis and
- Nonlinear Analysis and Predictions

Neural Network Modeling in Rainfall Runoff Forecasting

Artificial Neural Networks (ANNs) have been considered as systems or mathematical models that work in such a way that imitates the human brain (Lin and Lee, 1996; Thurston, 2002). They work in a way that resembles human intelligence in order to solve problems. ANNs learn by example to extract information within a data set. The model of the neural network is like synapses in the human brain which consists of a series of processing units which are collectively connected (Thurston, 2002).

Recently there are increasing number of research attempts to apply the neural network method for solving various problems in different branches of science and engineering. It is a tool to provide hydraulic engineers with sufficient details for design purposes and management practices (Nagy et. al., 2002). While ANN models do not assume any functional relationship and let the data define the functional form. Thus ANNs is extremely useful when there is no idea of the functional relationship between the dependent and independent variables. In effect, a neural network remains a "black box" that may produce useful results, but cannot be precisely understood.

ANN is being routed as the future wave in the computing paradigm (Anderson and McNeill, 1992).ANN is a unique system that is different from other systems. For example, some traditional artificial intelligent solutions and statistical solutions rely on and require a priori information to be able to solve problems. While ANNs work is based on self learning mechanisms, which do not need any a priori assumptions to solve a problem. ANN do not require the traditional skills of a programmer. ANNs may well learn any regularities or patterns that may possiblybe exist in the available data set to form a relationship.

One of the aspects that differentiate a neural network from others is its architecture. This architecture represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function (Haykin, 1999). Two ways of determining neural networks architecture are the number of layers (includes single layer, bi-layers, and multi-layers), and the direction of information flow and processing (includes feed-forward and recurrent). One network that provides good performance with regard to input-output function approximation such as forecasting is multi-layer perceptrons (MLPs). This network is a multi-layer feed-forward networks, which is trained with a back-propagation learning algorithm. A typical multi-layer feed-forward network has input layers, hidden layers, and output layers (Lin and Lee, 1996). The input layers have the main function of receiving inputs and then buffering the input signals. The signals from the input layers are then transmitted to hidden layers, particularly hidden neurons or hidden units. The function of hidden neurons is to intervene between the external input and the network output in some useful manner.

Artificial Neural Network Structure and Modeling Process

An ANN is a massively parallel-distributed information processing system which consists of many nonlinear and densely interconnected processing units. An ANN has certain performance characteristics resembling biological neural networks of the human brain (Haykin 1994). Large numbers of hidden layer neurons not only require a large computational time for accurate training, but may also result in 'overtraining' (Brion et al., 1999). ANNs offer valuable characteristics unavailable together elsewhere (Zealand et al., 1999). A sensitivity analysis can be used to determine the relative importance of a variable (Maier and Dandy 1996) when sufficient data is available. The input variables that do not have a significant effect on the performance of an ANN can be trimmed from the input vector resulting in a more compact network. (Liong et al., 2000). With this parallel-distributed processing architecture, ANNs have been proven to be an efficient alternative to traditional methods for hydrological modelling, such as rainfall forecasting (Hsu et al., 1999; Luk et al., 2000; Toth et al., 2000), streamflow forecasting (Dawson & Wilby, 1998; Atiya et al., 1999; Zealand et al., 1999; Chang & Chen, 2001; Coulibaly et al., 2001; Sivakumar et al., 2002; Cigizoglu, 2003; Hu et al., 2005) and groundwater modelling (Lallahem & Mania, 2003).

Artificial Neural Networks represent input output "connectionist models" where the formation of ANN model inputs usually consists of meteorological variables, such as rainfall, evaporation, temperatures and snowmelt; and geomorphological properties of the catchment, such as topography, vegetation cover and antecedent soil moisture conditions. A number of researchers have used ANN in a variety of natural phenomena from predicting currents in sea to flood prediction (Boogard et al., 1998; Coulibaly et al., 2000; Deo and Thirumalaiah, 2000; Hsu et al., 1995; Imrie et al., 2000; Zaldivar et al., 2000; Zealand et al., 1999). The frequently used input to ANN includes observed runoff at nearby sites or neighboring catchments. There is however, no set algorithm that can be applied to ensure that the network will always yield an optimal solution as opposed to a local minimum value, and the nonlinear nature of the ANN often results in multiple predicted values (Kingston et al., 2003). In many cases, network inputs with or without time lags is also considered in scenario analysis. A comprehensive review of the application of ANNs to hydrology can be found in the ASCE Task Committee report (2000a and 2000b) and in a specialized publication (Govindaraju & Rao, 2000).

The Hydrological Applications of Neural Network Method

Trying to get around the inconveniences (e.g. simulation duration, data requirements etc.) of highly sophisticated mathematical and physical approaches, a considerable amount of research have been invested for adapting the theory of the neural nets to flood modelling and forecasting in the last two decades. This is mainly motivated by the principal advantage of neural nets that is "once they are trained they are extremely easy to use and outperform classical models by far in terms of simulation speed". It could not be believed that the first approach towards using artificial neural networks in hydrology has directly yielded practical benefit for flood forecasting. Nevertheless the results pointed out the promising potential of the neural network approach andhave inspired to harness the ANN for hydrological modelling and forecasting purposes.

General aspects concerning artificial neural networks and their role in hydrology are concisely reviewed in (ASCE 2000a and 2000b). Apart from this basic work, a number of publicationsare available to describe the advances in the field of ANN to hydrological modelling.Daniel (1991) has reported some of the earliest application of ANN in hydrology. Kothyari and Garde (1991) developed a regression model for predicting the annual runoff volume from the annual rainfall, basin area, average temperature, and vegetation cover.French et al., (1992) have forecasted the rainfall with varying duration and rain gauge catchment area using ANN. Till the time forecasting was made one-step-ahead only which was not able to provide enough information, especially to understand the future behaviour. Su et al. (1992) were the earliest researchers who developed ANN architecture based on the back-propagation through time for long-term predictions of chemical processes.

Hjelmfelt and Wang (1993a; 1993b and 1993c) developed a neural network based on the unit hydrograph theory. Using linear superposition, a composite runoff hydrograph for a watershed was developed by the appropriate summation of a unit hydrograph ordinate and the corresponding runoff excesses. The numbers of neurons in the input and hidden layers were kept constant. Rainfall and runoff data from 24 large storm events were chosen from Goodwater creek Watershed in central Missouri to train and test their neural network with promising results. Kang et al. (1993) used ANNs and autoregressive moving average (ARMA) models to predict daily and hourly streamflows in the Pyung Chang River basin in Korea. Using different three-layered ANN architectures they concluded that ANNs are useful tools for forecasting streamflows.

Bonafe et al (1994) assessed the performance of a neural network in forecasting daily mean flow of the upper Tiber river, Italy. The previous day discharge, daily precipitation, daily mean temperature, total rainfall of the previous five days and mean temperature of the previous ten days were selected for net input. They concluded that the multi layer nets were able to yield much better performance than ARMA models. Karunanithi et al. (1994) estimated streamflows at an ungauged site on the Huron River in Michigan, based on data from USGS stream gauging stations located 30 km upstream and 20 km downstream of the sampling site. The authors stated that ANNs are capable of adapting complexity to accommodate temporal changes in historical streamflow records. They also identified the importance of lag time in predicting streamflows due to the longer memory association. Zhu et al (1994) predicted the flood hydrograph in Butter Creek, New York. Online predictions with neural nets outside the range of training data lead to poor results. With increasing forecast lead-time, neural network performance further deteriorated. The nets were found able to perform better than the ARMA models.

Hsu et al (1995) lead the way to single step predictions of stream flow employing a 3-layer network. They tried to enhancing the training speed using a three-layer network. Lorrai & Sechi (1995) utilized Neural Nets for Modelling Rainfall-Runoff process. They attempted to predict the possible transformations of the hydrological phenomenon. Smith and Eli (1995) applied a back propagation neural network model to predict peak discharge and peak time for a hypothetical watershed. Linear or non-linear reservoir models generate data sets for training and validation. By representing the watershed as a grid of cells, it was possible for the authors to incorporate the spatial and temporal distribution of rainfall into the neural net model. They trained the neural network to map a time series rainfall patterns. Discharge series are modeled using a discrete Fourier series fit of the rainfall hydrograph with 21 coefficients, rather than just two attributes as in single-storm events. The ANN output layer now consisted of 21 nodes corresponding to the Fourier coefficients. Using this method, the authors found the prediction of the entire hydrograph to be very accurate for multiple storm events. Smith (2005) used a feed-forward network to estimate the runoff and the time of uppermost spatially distributed rainfall using simulated data.

Hjelmfelt and Wang (1996) compared composite runoff hydrograph method with a regular three layered artificial network with back-propagation and concluded that a regular network could not reproduce the unit hydrograph very well and was more susceptible to noise than a network whose architecture was more suited for unit hydrograph computations. Jayawardena and Lai (1994) used while radial basis function (RBF) methods for flood forecast and concluded that RBF networks provided for faster training. Such networks required the solution of a linear system of equations that may become ill conditioned, especially if a large number of cluster centers are chosen (ASCE, 2000b). Minns and Hall (1996) developed ANN model for rainfall and runoff prediction and concluded that “artificial neural networks are a prisoner of their training data”. As observations practically never cover the full range of possible flood peaks, such a completely empirical approach is doomed to failure as regards reliable flood forecasting. Sajikumar and Thandaveswara (1999) demonstrated the supremacy of the multilayer feed forward neural network (MLFN) over the regression model in terms of predictive power for the same data. Their results thus supported the statement of Minns and Hall (1996): “artificial neural networks are a prisoner of their training data”. Warner and Misra (1996) matched up to the similarities between an ANN and statistical methods. They reported that both approaches could be used to model a relationship between the dependent and independent variables as well as any generalized linear model be mapped onto an equivalent single-layer neural network.

Hsu et al (1997) used a three-layer feedforward ANN and recurrent neural approaches in the context of hydrological modelling including rainfall forecast in the Leaf River Basin. They found the feedforward ANN was not suitable to distributed watershed modeling while the recurrent ANN provided a representation of the dynamic internal feedback loops in the system, eliminating the need for lagged inputs and resulting in a compact weight space. Shamseldin (1997), examined the effectiveness of rainfall-runoff modeling with ANNs by comparing their results with the Simple Linear Model (SLM), the seasonally based Linear Perturbation Model (LPM) and the Nearest Neighbor Linear Perturbation Model (NNLPM) and concluded that ANNs could provide more accurate discharge forecasts than some of the traditional models. Gupta et al., (1997) applied the linear least squares simplex (LLSSIM) algorithm, for training strategies in ANN to daily rainfall runoff modeling of the Leaf River Beam near Collins, Mississippi. The performance of neural networks was compared with the linear ARMAX and the conceptual SACSMA model and concluded that the LLSSIM is a better training algorithm than back-propagation or conjugate gradient techniques. Muttiah et al. (1997) used the cascade-correlation algorithm to predict two-year peak discharge from watersheds all over the continental United States. They investigated the possibility of a single model to predict peak discharges from local to regional-sized watersheds using GIS databases. Tawfik et al. (1997) used ANNs, with a saturating linear transfer function, to predict flow discharges at two locations over the Nile River using the stage and the rate of change of stage as input.

Dawson and Wilby (1998) used a three-layer back propagation network to determine runoff from the catchments of the rivers Ambers and Mole (England). The two catchments are of nearly equal size (about 140 km²). Observed flow data and mean historical rainfall data serve as inputs in their study. Their results showed that neural nets perform similar to an existing model on less input information. Vladan and Christian (1998) emphasized the role of ANN for hydrological modeling and assessed the potential in the mapping of non-linear systems

Camoplo et al.(1999) used neural networks for analyzing and predicting Taglimanto River responses. The inputs included data from seven (7) rainfall recording gauges, the output being monthly runoff. This model possesses the suitable accuracy for hour time steps, but the error, increases with increment in time steps. Drecourt (1999) used a model of neural networks for rainfall-runoff modeling and indicated that this kind of black box is capable of decreasing errors.Foka (1999) uses polynomial neural networks (PoNN) for discharge modelling. Tokar and Johnson (1999) reported that an artificial neural net model yields higher training and testing accuracy when compared with regression and simple conceptual models. Zealand et al. (1999) described the potential of neural nets for the short term forecasting of stream flow with back propagation algorithm in one week-ahead streamflow forecasting. They have compared ANN performance to conventional approaches used to forecast stream flow.

Anmala et al., (2000); Elshorbagy et al., (2000); and Zhang and Govindaraju, (2000); have made comparison studies between ANNs against traditional linear and non-linear regression methods in rainfall-runoff processes. Coulibaly et al. (2000) proposed a neural network-based long-term hydropower forecasting system. Govindaraju (2000) and Govindaraju and Rao (2000) specified the prevailing details of the ANN with reference to the Hydrological modeling. They presented a brief review of non linear modeling applied in rainfall runoff system. Imrie et al., (2000) attempted to overcome the limited extrapolation capacity of neural networks. They used different activation functions for the output layer of their multi layer net and compared the cascade correlation and backpropagation algorithm in hourly river flow prediction. Jagadeesh et al. (2000) evaluated different neural networks for monthly runoff estimation in three basins in Kanzas State. They compared the results with those found through empirical methods. Their results indicated a more capability of neural networks than the empirical methods. Maier and Dandy(2000) used ANN for predicting and forecasting water resource variables using feed-forward network applied on simulated data to approximate the duration and quantity of maximum rainfall and runoff. They also reviewed the rainfall runoff modeling practices and their relative applications. Parlos et al. (2000) developed dynamic recurrent neural networks for multi-step prediction in complex processes.

Tokar and Markus (2000) compared neural network models with traditional conceptual models for predicting watershed runoff as a function of rainfall, snow water equivalent and temperature. Zhang and Govindaraju (2000) had presented a similar approach for rainfall runoff prediction on the monthly time step. They have trained various expert networks, to portray a certain range of stream flows.

Luk et al. (2001) studied the rainfall-forecasting problem by using various ANNs and discussed the accuracies and discrepancies among these networks.

Bazartseren et al., (2002) effectively used ANN for modeling systems on a real-time basis and applied in rainfall and runoff forecasting systems. They viewed that ANN Performance is related to accurate real-time data inputs, the quality of the knowledge used to specify, build and operate the models as well as the ability of the models to respond to dynamic and sometimes rapidly changing events. Hsu et al., (2002) carried out a comparative research on various neural net types in view of their respective abilities to predict discharge time series. Rajurkar et al., (2002) attempted at improving the potential forecast performance of neural networks by combining different net types with methods of time series analysis or fuzzy logic clustering. Singh and Woolhiser (2002) developed ANN model to forecast river discharge using different activation function for describing the watershed characteristics.

Bhattacharya et al., (2003) applied ANN giving different learning in order to have an effective control over the river water forecast. Cigizoglu (2003) used ARMA models to generate synthetic series. These data then incorporated into the training database of neural networks to increase the predictive ability in the monthly mean river flow data of Turkey. Kingstone et al., (2003) developed runoff prediction model using historical stochastic time series of river runoff using Artificial Neural Network. They discussed the difficulties to the users of the MLP and FFBP algorithms of an ANN during the transferability of process to other geographic locations. They emphasized upon the requirement of stochastic training, convergence of data (e.g., trapped in local minima during training), and conceptual applicability of black-box approaches to hydrological modeling. Laio et al. (2003) have performed a comparison of ANN and NLP approaches for multivariate forecasting in daily water stage of Tanaro river discharge in Italy. The results have shown that the NLP method provides better forecasts over a shorter prediction period (1-6 hours), but over prediction periods exceeding 24 hours, the ANN approach is more accurate. Wilby et al., (2003) have tried ANN forecasting for rainfall and river runoff using different physical parameter affecting the hydrological system of the river and tried to resemble the conceptual model for rainfall–runoff processes via ANN applications.

Castellano–Mendez (2004) compared a forecast algorithm on the basis of the ARMA concept (Box-Jenkins 1976) with a multi-layer net based forecast strategy. For daily single step runoff predictions he found that the non-linear multilayer net performing better than the linear ARMA approach. Chang et al. (2004) developed a two-step-ahead recurrent neural network for streamflow forecasting. Huang et al. (2004) used backpropagation and conjugate gradient algorithm for short and long-term flow forecasting. Kisi (2004) demonstrated standard backpropagation ANN algorithm in predicting monthly mean streamflow. Ruhurkar et al., (2004) based on his research work concluded that the ANNs can be applied in hydrologic processes by coupling with a simple linear regression model to predict daily rainfall runoff. Kumar et al. (2004) used two models of neural networks namely feedforward and recurrent neural networks for a prediction of monthly flow of a river in India.

Bowden et al., (2005a and 2005b) discussed about the impact of many characteristics input parameter used in ANN design. According to them, the most correlated variables dominate the model and therefore it was not practically helpful to use all the physical knowledge or measurements available.Bruen and Yang (2005) used functional networks, which were recently introduced as an alternative for real time flood forecasting. Hettiarachchi et al.(2005) tried to improve the forecast ability of multi-layer net by incorporating an estimated maximum flood (EMF) in the training data set. Giustolisi and Laucelli (2005) attempted to improve the performance of ANN prediction in rainfall runoff modeling in order to avoid most probable cases of under- and over-fitting. Kingston et al., (2005) discussed about the role of calibration and validation techniques most suitable to apply in rainfall and runoff modeling. Schmitz et al. (2005) applied catchment specific topographic and soil hydraulic properties to conduct detailed hydrological catchment modelling. They realized the intricacy in multi-layer net approach to work stably under all conditions. However, they achieve promising results regarding flood forecasting in a small catchment. Valenca et al.(2005) used a constructive neural network model (NSRBN) to forecast daily river flows for the Boa Esperanca Hydroelectrict powerplant. Hu et al (2005) have tried to enhance their multi layer neural net based river stage modelling approach by training various nets for different parts of the observed flow. They divided the flow spectrum in low, medium and high flows.

Antar et al. (2006) used ANN model with backpropagation algorithm in daily runoff estimation in catchment of Blue Nile river (Egypt). Cullmann et al., (2006) tried to forecast the rainfall and runoff in a given catchment incorporating site specific and geomorphological characteristics in ANN input. Diamantopoulou et al., (2006) used Time Delay Artificial Neural Network (TDANN) models, to forecast the daily inflow into a planned Reservoir (Almopeos River basin) in Northern Greece. Kang et al. (2006) compare the performance of several different multi-layer feed forward neural networks with the Grey-model. However, the nets in their study were exclusively trained with historical data, rendering the extrapolation beyond observed events. Further, the forecast horizon is restricted to 6 hours. Lin et al. (2006) discussed problems being faced while designing ANN for a big river basin with many number of variables and the convenience with the an ANN model to deal with the small river basins with less variables. They further have shown with their work about the potential of ANN to model to large-scale hydrological systems and phenomenon for prediction. Srinivasulu and Jain (2006) compared three training methods namely back propagation algorithm (BPA), real-coded genetic algorithm (RGA) and a self-organizing map (SOM) for training multi-layer perceptron (MLP) type of artificial neural networks (ANNs) for modelling the rainfall–runoff process.

Dawson et al., (2007) provided a good review regarding neural networks and their application with respect to rainfall runoff modelling. Bustami et al., (2007) predicted water level at Bedup River with estimations made to absent precipitation data, using ANN. Back propagation properties of ANN were used to predict both missing precipitation and water level. The study results showed that ANN is an effective tool in forecasting both missing precipitation and water level data, which are utmost essential to hydrologists around the globe. Chang et al., (2007) presented a systematic investigation of three common types of ANN(namely multi-input multi-output (MIMO), multi-input single-output (MISO) and serial-propagated structure) for multi-step ahead (MSA) flood forecasting for two watersheds in Taiwan. Corzo and Solomatine (2007a and 2007b) have explored different pre-processing approaches for inclusion of additional hydrological knowledge as input to ANN to improve the hydrological representation and generalization. Junsawang et al., (2007) proposed ANN to predict runoff hydrograph for the Mae Tun River in Thailand. A feed-forward ANN is trained by using back-propagation algorithm. Kisi and Ozturk (2007) forecasted the daily river flows and infilled missing data of Filyos and Soganli Stream, in Black Sea Basin, Turkey, by adaptive neuro-fuzzy and ANN techniques. Yang et al., (2007) have used conceptual model for the hydrograph estimation and tried to predict the runoff from ungauged river using ANN.

Calvo et al., (2008) have simplified the structure of the tevere basin (Rome)flood forecasting (TFF) model by minimizing numbers of parameters to be calibrated and compared the results with a neural network model developed simultaneously. Fajardo Toro, et al., (2008) developed a hydrologic estimation model utilizing radial basis function (RBF) neural networks to forecast flow of Ulloa river in the north west of the Iberian Peninsula, in an automated fashion. Kelteh (2008) has developed a rainfall-runoff model using an ANN approach and described different approaches including Neural Interpretation Diagram, Garson's algorithm, and randomization approach to understand the relationship learned by the ANN model. Mohamoud (2008) attempted ANN to the prediction of river runoff using readout of the daily flow duration curves and streamflow for ungauged catchments using regional flow duration curves.

Abghari et al., (2009) introduced a preprocessed neural network (PNN) with recurrent back propagation feed forward (RBF) hybrid model in conjunction with clustering and applied to flow prediction by Simulation of Nazloochaei river flow in North - West Iran. Agrawal et al., (2009), forecasted runoff and sediment yield from the Vamsadhara river basin (situated between Mahanadi and Godavari river basins in South India) during the monsoon period for daily and weekly time periods using the back propagation artificial neural network (BPANN) modeling technique. Aktar et al., (2009) analyzed the flow length and travel time as a basis for pre-processing remotely sensed (satellite) rainfall data together with local stream flow measurements in the Ganges river basin. Corzo et al., (2009) used of several pre-processing approaches for training of hydrological parameters influencing rainfall runoff to ANN models in order to improve the hydrological representation and generalization. Modarres (2009) proposed a comprehensive multi-criteria validation test for rainfall-runoff modeling by artificial neural network which included 17 global statistics and 3 additional non-parametric tests to evaluate the ANNs. Solaimani (2009) modeled the rainfall runoff relationship using ANN in a semiarid Jarahi Watershed of Iran. Yazdani et al., (2009) employed ANN models for runoff estimation in Plaszjan River basin of Iranusing Multiple Perceptron (MLP) and Recurrent Neural Network (RNN).

Besaw et al., (2010), developed two ANN models to forecast streamflow in ungauged basins. Chiang et al., (2010), proposed recurrent neural networks (RNNs) to build a relationship between rainfalls and water level patterns of an urban sewerage system based on historical torrential rain/storm events. Deshmukh and Ghatol, (2010, 2010a, 2010b, and 2010c) have conducted many ANN study to predict rainfall-runoff for the upper area of Wardha River in India using different modeling arrangements. Roy et al., (2010), predicted flood flows at each of the upstream and a downstream section of a river network in Tar basin of USA using focused Time Lagged Recurrent Neural Network with three different memories like TDNN, Gamma and Laguarre memory.

Abrahart (2011) discussed the problem in tropical upland river systems (on the Caribbean island of Puerto Rico) due to sediment discharges. These were predominantly episodic and intense; and greatly affected the river flow consequently ANN could not accurately predict the flow. Emiroglu et al., (2011) estimated the discharge capacity of triangular labyrinth side-weirs by using artificial neural networks (ANN). The performance of the ANN model was compared with multi nonlinear regression models. Krishna et al., 2011 have developed a hybrid model which combines wavelets and Artificial Neural Network (ANN) called as wavelet neural network (WNN) model for time series modeling of the Malaprabha River basin (Karnataka state, India) flow. The observed runoff data were decomposed into sub-series using discrete wavelet transform and used the neural network for forecasting hydrological variables.

Forecasts Uncertainty

Predictive uncertainty has been the focus of a vast number of studies during the last decade (Beven, 1992; Beven and Freer, 2001; Christiaens, 2002; Prudhomme, 2003; Butts et al 2004; Beven 2005). Due to the spatial distribution of rainfall and the multiple precipitation forecasts provided by the weather agencies, the rainfall forecast is one of the main sources of uncertainty in the models. For the reduction in the uncertainty generated by the multiple options in the precipitation forecast, an ensemble of precipitation forecasts driven by computational intelligent algorithms will be used as input. There are two main sources of uncertainty in real-time flood forecasting: The input data (measured or predicted), and the hydrological models (Krzysztofowicz 1999). The hydrological model uncertainty originates from the "degree of ability" of the different models transforming the input data into the flood forecast. The different types of input data uncertainty are:

- The measurement uncertainty, which is mainly related to spatial distribution and dynamics of rainfall fields
- The meteorological forecasting uncertainty, arising from the possibility of extending the forecasting horizon beyond the response time of the physical system by means of quantitative precipitation forecast.

Models can provide information solutions that maximize welfare, or minimize damage, and on tradeoffs between alternative outcomes, and risk and uncertainty. The results from any model, positive or negative, will depend on the model assumptions embedded in the objective function, the constraints, and all the factor relationships. By nature, models are based on assumptions that are inherent uncertainty and are therefore limited by the accuracy of the specification the data used to parameterize the model, and the solution techniques used to solve the model (Haimes, 1977). Additionally, qualitative factors and subjective inference also part of the decision making process, may necessarily be omitted from the model (Loucks, 1981).

Conclusions about the Artificial Neural Network Modeling Efforts

An efficient simulation of river runoff by ANN requires proper understanding of rainfall runoff phenomenon and catchment characteristics and expert command / maneuver over ANN tools. All together, these studies are valuable contribution towards the understanding of rainfall runoff forecast modeling and watershed specific neural network architecture. However, these works do not arrive on a single solution towards the operational use of neural networks in flood forecasting. Models based on artificial neural networks are fast and reliable.

This review provides extensive and meticulous details about river runoff modeling using ANN. The nonlinear ANN model provides better forecast for the hydrological relationship than the conceptual models. Though, ANN essentially belongs to the theoretical (black box) model category and bears the weaknesses of this category (Gautam et al., 2000). ANN are by no means a substitute for conceptual watershed modeling as it does not employ physically realistic components and parameters (Hsu et al., 1995). Nevertheless, the lack of physical concepts and relations has been one of the major limitations and reasons for the skeptical attitude towards ANN methodology (ASCE, 2000a and 2000b). Therefore, instead of using ANNs as simple black box models, the development of hybrid NN has received considerable attention (VanCan et al., 1997; Zhao et al., 1997). The hybrid NN has shown the potential of obtaining more accurate predictions of process dynamics by combining mechanistic and ANN in such a way that it can properly accounts for unknown and nonlinear parts of the mechanics (Lee et al., 2002).

Unfortunately, current strategies are all built upon purely empirical approaches. In general, ANN has been found to perform well in predicting short-term flood stage resembling the magnitude of previous flood events used for network training. ANN models, tend to perform poorly during extreme events, and, thus, features the same shortcomings – as they are not suited for extrapolating beyond the range of their training data i.e. ANN cannot reliably predict a rare extreme flood event if it is not part of the training data. Also, it is difficult to determine the optimal ANN architecture for a given watershed, and in most cases, a trial-and-error approach is still used. Therefore, Elshorbagy and Simonovic (2000) warn against use of ANN models as the sole runoff prediction strategy.

REFERENCES

- Abbott, M.A., 1993. The electronic encapsulation of knowledge in hydraulics. Journal of Hydrology and Water Resources, Advanced Water Resources, Vol. 16, pp 22-39.
- Abghari, H., Giesen, V.N., Mahdavi, M., and Salajegheh, A., 2009. Classification of hydrological time series using probabilistic neural network for river flow modeling by RBF networks. Geophysical Research Abstracts, EGU2009-3648-1, EGU General Assembly, Vol. 11.
- Abrahart, R.J., 2011. The pros and cons of different strategies to avoid overfitting: revisiting neural network suspended sediment modelling of two small watersheds in Puerto Rico. Geophysical Research Abstracts, EGU2011-9736, Vol. 13.
- Abrahart, R.J., and See, L., 2000. Comparing neural network and autoregressive moving average techniques for the provision of continuous river flow forecasts in two contrasting catchments. Hydrological Processes, Vol. 14(11-12), pp 2157-2172. [doi:10.1002/1099-1085]
- Abrahart, R.J., Heppenstall, A.J., and See, L.M., 2007. Timing error correction procedure applied to neural network rainfall-runoff modelling. Journal of Hydrology Science, Vol. 52, pp 414–431.
- Abrahart, R.J., Kneale, P.E., and See, L.M., 2004. Neural networks for hydrological modeling. leiden: A. A. Balkema publishers.
- Agarwal, A., Rai, R.K., and Upadhyay, A., 2009. Forecasting of runoff and sediment yield using artificial neural networks. Journal of Water Resource and Protection, Vol. 1, pp 368-375 [doi:10.4236/jwarp.2009.15044], http://www.sciRP.org/journal/jwarp.
- Akhtar, M.K., 2006. Flow forecasting with ANNs using satellitle observed rainfall long-term discharge prediction. Journal of Hydrology and Science, Vol. 51, 599–612.
- Akhtar, M.K., Corzo1, G.A., Andel1 Van, S.J., and Jonoski, A., 2009. River flow forecasting with artificial neural networks using satellite observed precipitation pre-processed with flow length and travel time information: case study of the Ganges river basin. Hydrology and Earth System Science, Vol. 13, pp 1607–1618, www.hydrol-earth-syst-sci.net/.
- Allen, J.D., 1995. Stream Ecology: Structure and function of running waters, springer, Dordrecht, Netherland, pp 388.
- Anmala, J., Zhang, B., and Govindaraju, R.S., 2000. Comparison of ANNs and empirical approaches for predicting watershed runoff. Journal of Water Resources Planning and Management, Vol. 126 (3), pp 156-166.
- Antar, M.A., Elassiouti, I. and Allam, M.N., 2006. Rainfall-runoff modeling using ANNi technique: a Blue Nile catchment case study. Hydrological Processes, Vol. 20, pp 1201-1216.
- Antcil, F. and N. Lauzon, 2004. Generalisation for neural networks through data sampling and training procedures, with applications to stream of predictions. Hydrology and Earth Systems Science, Vol. 8 (5), pp 940-958.
- ANDERSON D., and MCNEILL G., 1992. Artificial Neural Networks Technology. Data and Analysis Center for Software, Kaman Sciences Corporation.
- Arnell, N., and Liu, C., 2001. Hydrology and water resources; in Climate Change 2001: Impacts, Adaptation and Vulnerability, (ed.) J.J. McCarthy, O.F. Canziani, N.A. Leary, D.J. Dokken and K.S. White, contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, p. 191-233
- ASCE, 2000a. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology,. Artificial neural networks in hydrology I: preliminary concepts. Journal of Hydrologic Engineering, Vol. 5 (2), pp 115–123.
- ASCE, 2000b. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000b. Artificial neural networks in hydrology II: Hydrologic applications. Journal of Hydrologic Engineering, Vol. 5 (2), pp 124–137.
- Atiya, A.F, El-Shoura, S.M, Shaheen, S.I., and El-Sherif, M.S., 1999. A comparison between neural-network forecasting techniques – Case Study: River flow forecasting. IEEE Transactions on Neural Network, Vol. 10(2), 402-409.

- Ayewah, N., 2003. Prediction of spatial temporal events using a hidden markov model. Department of Computer Science and Engineering, Southern Methodist University, Dallas, TX.
- Baratti, R., Cannas, B., Fanni, A., Pintus, M., Sechi, G.M., and Toreno, N. 2003. River flow forecast for reservoir management through neural networks. Neurocomputing, Vol. 55(3/4), pp 421–437.
- Bartholmes, J., and Todini, E., 2005. Coupling meteorological and hydrological models for flood forecasting. Journal of Hydrology, Earth System and Sciences, Vol. 9, pp 333-346.
- Bazartseren, B., Hildebrandt, G. and Holz, K.P., 2002. Hydroinformatic web application and web Service for Real-time water level prediction and short-term prediction. Cottbus, Germany
- Besaw, L.E., Rizzo, D.M., Bierman, P.R., and Hackett, W.R., 2010. Advances in ungauged streamflow prediction using artificial neural networks, Journal of Hydrology, Vol. 386, pp 27–37, www.elsevier.com/locate/jhydrol
- Bhattacharya, B., Lobbrecht, A.H., and Solomatine, D.P., 2003. Neural Networks and reinforcement learning in control of water system. J. of Water Resource Planning Management, Vol. 129(6), pp1-8.
- Birikundavyi, S., Labib, R., Trung, H.T., and Rousselle, J., 2002. Performance of neural networks in daily streamflow forecasting. Journal of Hydrologic Engineering, Vol. 7 (5), pp 392-398.
- Bonafe, A., Galeati, G., and Sforna, M., 1994. Neural networks for daily mean flow forecasting. Hydrology and Engineering . Software V, W. R. Blain and K. L. Katsifarakis, editionComputational Mechanics Publications, Southampton, U.K., Vol. 1, pp 131–138.
- Boogaard, H.L., van Diepen, C.A., Rötter, R.P., Cabrera, J.M.C.A., and van Laar, H.H., 1998. User's Guide for the WOFOST 7.1 Crop Growth Simulation Model and WOFOST Control Center 1.5. Technical Document 52, DLO Winanad Staring Centre, Wageningen
- Bowden, G.J., Dandy, G.C., and Maier, H.R. 2005b. Input determination for neural network models in water resources applications. Part 2. Case study: forecasting salinity in a river, Journal of Hydrology, Vol. 301, pp 93–107.
- Bowden, G.J., Dandy, G.C., and Maier, H.R., 2005a. Input determination for neural network models in water resources applications. Part 1-background and methodology, Journal of Hydrology, Vol. 301, pp 75–92.
- Brath, A., Montanari, A., and Toth, E., 2002. Neural networks and nonparametric methods for improving real-time flood forecasting through conceptual hydrological models. Journal Hydrology and Earth Systems Science, Vol. 6, 627–639, http://www.hydrol-earth-syst-sci.net/6/627/2002/.
- Brion, Gail Montgomery ,Lingireddy, and Srinivasa, 1999. A neural network approach to identifying non-point sources of microbial contamination. Journal of Water Resources Reserch, Vol. 33(14), pp. 3099-3106.
- Brooks, K.N., Ffolliott, P.F., Gregersen, H.M., and DeBani, L.F., 2003. Hydrology and the Management of Watersheds. Iowa State Press, Ames, IA.
- Burnash, R.J.E., R.L. Ferral and R.A. McGuire, 1973. A generalized stream flow simulation system, report 220. Jt. Fed.-State River Forecasting Center, Sacramento, CA.
- Bustami, R., Bessaih, N., Bong, C., and Suhaili, S., 2007. Artificial neural network for precipitation and water level predictions of bedup river, IAENG. International Journal of Computer Science, Vol.34(20), IJCS_34_2_10.
- Calvo, B., Napolitano, G., Savi, F., and See, L., 2008. A conceptual and neural network model for real time flood forecasting of Tiber river in Rome. Geophysical Research Abstracts, Vol. 10, pp 13-18, Ref-ID: 1607-7962/gra/EGU2008-A-02626, European Geosciences Union-General Assembly, Wien (Austria).
- Campolo, M., Andreussi, P., and Soldati, A., 1999. River flood forecasting with a neural network model. Journal of Water Resources Research, Vol. 35(4), pp 1191-1197.
- Campolo, M., Soldati, A., and Andreussi, P., 2003. Artificial neural network approach to flood forecasting in the River Arno.Journal of Hydrology and Science,Vol. 48(3), pp 381–398.
- Cannon, A.J. and P.H. Whitfield, 2002. Downscaling recent stream-flow conditions in British Columbia. Canada Using Ensemb le Neural Networks. Journal of Hydrology, Vol. 259, pp 136-151.
- Cao L., Mees, A., and Judd, K., 1998. Dynamics from multivariate time series. Physica D, Vol. 121, pp 75-88.
- Castellano-Méndeza, M., González-Manteigaa, W., Febrero-Bande, M., Manuel Prada-Sáncheza, J., and Lozano-Calderón, R., 2004. Modeling of the monthly and daily behavior of the runoff of the Xallas river using Box–Jenkins and neural networks methods. Journal of Hydrology, Vol. 296, pp 38–58.
- Caudill, M., 1987. Neural networks primer I. AI Expert.
- Caudill, M., 1988. Neural networks primer II, III, IV and V. AI Expert.
- Caudill, M., 1989. Neural networks primer VI, VII and VIII. AI Expert
- Chang, F.J. and Chen, Y.C., 2001. A counterpropagation fuzzy-neural network modeling approach to real time stream flow prediction. Journal of Hydrology, Vol. 245, pp 153– 164.
- Chang, F.J., Chang, L.C., and Huang, H.L., 2002. Real-time recurrent learning neural network for stream-flow forecasting. Hydrological Processes ,Vol. 16(13), pp 2577–2588.
- Chang, F.J., Chiang, Y.M., and Chang, L.C., 2007. Multi-step-ahead neural networks for flood forecasting. Journal of Hydrological Sciences, Vol. 52(1), pp 114-130
- Chang, L.C., Chang, F.J. and Chiang, Y.M., 2004. A two-step ahead recurrent neural network for streamflow forecasting. Journal of Hydrological Processes, Vol. 18, pp 81–92.
- Chiang, Y.M. and Chang, F.J., 2009. Integrating hydro-meteorological information for rainfall-runoff modelling by artificial neural networks. Journal of Hydrological Processes, Vol. 23(11), pp 1650–1659.
- Chiang, Y.M., Chang, L. C. and Chang, F.J., 2004. Comparison of static-feedforward and dynamicfedback neural networks for rainfall-runoff modeling. Journal of Hydrology, Vol. 290, pp 297-311.
- Chiew, F., McMahon, T., 1994. Application of the daily rainfall runoff model MODHYDROLOG to 28 catchments. Journal of Hydrology, Vol. 153 (1–4), pp 383–416.

- Cigizoglu, H.K., 2003. Estimation, forecasting and extrapolation of river flows by artificial neural networks. Journal of Hydrological Sciences, Vol. 48 (3), pp 349–361.
- Cigizoglu, H.K., 2005a. Application of generalized regression neural networks to intermittent flow forecasting and estimation. Journal of Hydrologic Engineering, Vol. 10(4), pp 336–341.
- Cigizoglu, H.K., 2005b. Generalized regression neural network in monthly flow forecasting. Civil Engineering and Environmental Systems, Vol. 22(2), pp 71–84.
- Corzo, G.A., and Solomatine, D.P., 2007a. Knowledge-based modularization and global optimization of artificial neural network models in hydrological forecasting, Neural Networks.Vol. 20, pp 528–536.
- Corzo, G.A., and Solomatine, D.P., 2007b. Baseflow separation techniques for modular artificial neural networks modelling in flow forecasting.Journal of Hydrology and Science. Vol. 52, pp 491–507.
- Coulibaly, P., Anctil, F. & Bobée, B., 2000. Neural network-based long-term hydropower forecasting system. Computer- Aided Civil and Infrastructure Engineering ,Vol. 15, pp 355–364.
- Coulibaly, P., Anctil, F. & Bobée, B., 2001. Multivariate reservoir inflow forecasting using temporal neural networks. Journal of Hydrologic Engineering, ASCE , Vol. 6(5), pp 367–376.
- Coulibaly, P., Anctil, F., and Bobée, B., 2000. Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. Journal of Hydrology, Vol. 230(3-4), pp 244-257. [doi:10.1016/ S0022-1694(00) 00214-6]
- CWC, 2002. Office of Superintending Engineer, Central Water Commission, Bhopal vide letter no. 5/1/2000/CE(NBO)/416 dated 21.05.2002.
- Damle, Chaitanya, 2005. Flood Forecasting Using Time Series Data Mining. A thesis (M.S.) in Department of Industrial and Management Systems Engineering, College of Engineering, University of South Florida
- Daniell, T. M,. Neural networks—Applications in hydrology and water resources engineering. International Hydrology and Water Resources Symposium, Perth, 2–4 October 1991, pp 791–802.
- Dastorani, M.T., and Wright,N.G., 2002,. Artificial neural network based real-time river flow prediction. Proceedings of Hydroinformatics.
- Dawson, C., See, L., Abrahart, R., and Heppenstall, A.,2006. Symbiotic adaptive neuro-evolution applied to rainfall–runoff modelling in northern England, Neural Networks, Vol. 19, pp 236–247.
- Dawson, C.W. and R. Wilby, 1998. An artificial neural network approach to rainfall-runoff modeling.Journal of Hydrology and science, Vol. 43(1), pp 47-66.
- Dawson, C.W., Harpham, C., Wilby, R.L., and Chen, Y., 2002. Evaluation of artfcial neural network techniques for flow forecasting in the River Yangtze, China, Hydrology and Earth System Sciences, Vol. 6, pp 619 - 626.
- Dawson, C.W., See, L.M., Abrahart, R.J., Wilby, R.L., Shamseldin, A.Y., Anctil, F., Belbachir, A.N., Bowden, G., Dandy, G., and Lauzon, N., 2005. A comparative study of artificial neural network techniques for river stage forecasting,
- De Vos, N.J., and Rientjes, T.M., 2005. Constraints of artificial neural networks for rainfall-runoff modeling: Trade-offs in hydrological state representation and model evaluation. Journal Hydrology and Earth Systems Science, European Geosciences Union, Vol. 9, 111-126.
- DeLurgio, S.A., 1979. Forecasting principles and application, 1st. edition, McGraw- Hill, Boston.
- Demirel, M.C., A. Venancio, and E. Kahya, 2009. Flow forecast by SWAT model and ANN in Pracana basin, Portugal. Advances in Engineering Software, Vol. 40, pp. 467-473, Jul 2009.
- Deo, M. C. and Thirumalaiah, K., 2000. Real time forecasting using neural networks. Artificial neural networks in Hydrology, R. S. Govindaraju and A. Ramachandra Rao (eds), Kluwer Academic Publishers, Dordrecht, 53-71.
- Deshmukh, R.P., and Ghatol, A.A., 2010. Short Term Flood Forecasting using Static Neural Networks a Comparative Study, IJCSNS International Journal of Computer Science and Network Security, Vol. 10(8), pp 69-74.
- Deshmukh, R.P., and Ghatol, A.A., 2010a. Short term flood forecasting using general recurrent neural network modeling a comparative study. International Journal of Computer Applications (0975 – 8887), Vol. 8(12), pp 5-9.
- Deshmukh, R.P., and Ghatol, A.A., 2010b. Static and dynamic neural network approach for short term flood forecasting a comparative study. International Journal of Computer Applications (0975 – 8887), Vol. 7(4), pp 34-38.
- Deshmukh, R.P., and Ghatol, A.A., 2010c. Comparative study of temporal neural networks for short term flood forecasting. International Journal of Computer Applications (0975 – 8887), Vol. 5(12), 24-28.
- Diamantopoulou, M. J., Georgiou, P. E., and Papamichail, D. M., 2006. A time delay artificial neural network approach for flow routing in a river system.Journal of Soil Science, Vol. 3, 2375-2756.
- Diamantopoulou, M.J., Georgiou, P.E., and Papamichail, D.M., 2006. Daily reservoir inflow forecasting using time delay artificial neural network models. Proceedings of IASME/WSEAS International Conference on Energy & Environmental Systems, Chalkida, Greece, 2006, pp 1-6.
- Dibike, Y.B., and Solomatine, D.P. 2001. River flow forecasting using artificial neural networks. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, Vol. 26(1), pp 1-7. [doi:10.1016/S1464- 1909(01)85005-X]
- Dolling, O.R., and Varas, E.A., 2002. Artificial neural networks for streamflow prediction. Journal of Hydraulic Research, Vol. 40(5), pp 547-554.
- Dooge, J.C.I., 1977. Problems and methods of rainfall-runoff modeling. In: Ciriani, T.A., U. Maione and J.R. Wallis (eds.). Mathematical Models for Surface Water Hydrology: The Workshop Held at the IBM Scientific Center, Pisa. Wiley, London, pp: 71-108.
- Drecourt, J. P., 1999. Application of neural network and genetic programming to rainfall-runoff modeling. D2K Technical Report, Danish Hydraulic Institute.
- Elshorbagy A, Simonovic S.P and Panu U.S., 2000. Performance evaluation of artificial neural networks for runoff predication. Journal of Hydrologic Engineering. Vol. 5(4), pp 424-427.
- Emiroglu, E.M., Bilhan, O., and Kisi, O., 2011. Neural networks for estimation of discharge capacity of triangular labyrinth side-weir located on a straight channel. Expert Systems with Applications, Vol. 38, pp 867–874.

- Fahlman, S.E., and Lebiere, C., 1990. The cascade-correlation learning architecture. Advances in neural information processing systems 2, D. S. Touretzky, ed., Morgan Kaufmann, San Mateo, Calif., pp 524–532.
- FajardoToro, C.H., González Peña, D., Soto González, B., and Riverola, F.F., 2008. Water flows modelling and forecasting using a RBF neural network, SISTEMAS & TELEMÁTICA, ICESI, Vol. 6(12), pp 13-31.
- Farmer, J.D., and Sidorowich, J.J., 1987. Predicting chaotic time series. Physics Review Letter , Vol. 59(8), pp 845-848.
- Fausett, and Laurene, 1994. Fundamentals of Neural Networks: Architectures, Algorithms and Applications, Prentice-Hall, Englewood Cliffs, New Jersey, USA.
- Fekete, B.M., Vörösmarty, C.J., Roads, J.O., Willmott, C.J., 2004. Uncertainties in Precipitation and their Impacts on Runoff Estimates. Journal of Climate, 17, 294–304
- FFWC: Flood Forecasting and Warning Centre; Annual Flood Report 2007, Technical Rep., Dhaka, Bangladesh, 4, 86 pp., 2007.
- Firat, M., 2008. Comparison of artificial intelligence techniques for river flow forecasting. Hydrology and Earth System Sciences 12, 123–139.
- Foka, A., 1999. Time series prediction using evolving polynomial neural networks. A dissertation submitted to the University of Manchester Institute of Science and Technology for the degree of MSc.
- French, M. N., Krajewski, W. F. and Cuykendall, R. R., 1992. Rainfall forecasting in space and time using a neural network. Journal of Hydrology, Elsevier Science Publication, Vol. 137, pp 1-31.
- Galka A., 2000. Topics in nonlinear Time Series Analysis-With Implications for EEG Analysis, World Scientific Publishing Company
- Gautam, M.R., K. Watanabe and H. Saegusa, 2000. Runoff analysis in humid forest catchment with artificial neural network. Journal of Hydrology ,Vol. 235, pp 117-136.
- Giustolisi, O., and Laucelli, D., 2005. Improving generalization of artificial neural networks in rainfall–runoff modelling. Journal of Hydrological Sciences, Vol. 50(3), pp 439–457.
- Govindaraju, R.S., 2000. Artificial neural networks in hydrology II: hydrogeologic applications. Journal of Hydrologic Engineering, Vol. 5(2), pp 124–137.
- Govindaraju, R.S., 2000. Artificial Neural Networks in Hydrology: II, Hydrologic Applications. Journal of Hydrology Engineering, Vol. 5(2), pp 124-137.
- Govindaraju, R.S., and Rao, A.R., 2000. Artificial Neural Networks in Hydrology. Kumar Academic Publishers, Dordrecht, The Netherlands, Water Science and Technology Library.
- Grayson, R. B., Moore, I.D., and McMahon, T.A., 1992. Physically based hydrologic modelling, 2: is the concept realistic?. Journal of Water Resources Research, Vol. 28(10), pp 2659–2666.
- Guhathakurta, P. and Rajeevan, M., 2006. Trends in the rainfall pattern over India, Research Report No: 2/2006, National Climate Centre, India Meteorological Department, PUNE, INDIA.
- Gupta, H., Hsu, K., and Sorooshian, S. 1997: Superior training of artificial networks using weight-space partitioning. Proc. IEEE, Intl. Conf. on Neural Networks, Houston, TX, Institute of Electrical and Electronics
- Halwiindi, M., 2009. Rainfall-runoff modeling for real-time ecological reserve implementation, A Research Report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand
- Haykin, S., 1994. Neural network-a comprehensive foundation. Macmillan College Publishing Company, New York.
- Haykin, S., 1999. Neural networks: a comprehensive foundation. Prentice Hall, second edition. Chapter 7, Committee machines.
- Hettiarachchi, P., Hall, M. J., and Minns, A.W., 2005. The extrapolation of artificial neural networks for the modelling of rainfall-runoff relationships. Journal of Hydroinformatics, Vol. 7(4), pp 291–296.
- Hjelmfelt, A. T., and Wang, M. 1993c. Runoff hydrograph estimation using artificial neural networks. Proceeding , ASAE Conference, American Society of Agricultural Engineers, St. Joseph, Mich.
- Hjelmfelt, A. T., and Wang, M., 1993a. Artificial neural networks as unit hydrograph applications. Proceeding of Engrg. Hydrology, ASCE, New York, pp 754–759.
- Hjelmfelt, A. T., and Wang, M., 1993b. Runoff simulation using ANN. Proceeding, 4th International Conference in the Application of Artificial Intelligence to Civil and Structure Engrg.: NN and Combinatorial Optimization in Civ. and Struct. Engrg., B. H. V. Topping and A. I. Khan, eds., Civl-Comp Ltd., Edinburgh, U.K., pp 517–522.
- Hjelmfelt, A. T., and Wang, M., 1996. Predicting runoff using artificial neural networks. Journal of Surface-Water Hydrology , pp 233–244.
- Hogue, T.S., Gupta, H., and Sorooshian, S., 2006. A 'User-Friendly' approach to parameter estimation in hydrologic models. Journal of Hydrology ,Vol. 320, pp 202-217.
- Holger R. Maier, Graeme C. Dandy, 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications, Environmental Modelling & Software, ELSEVIER, Vol. 15, pp 101-124.
- Hopfield, J.J., 1982. Neural networks and physical systems with emergent collective computational abilities. Procedings of National Academy of Scientists, Vol. 79, pp 2554–2558.
- Hsu, K. L., Gupta, H. V., Gao, X.G.,and Sorooshian, S., 1999 Estimation of physical variables from multichannel remotely sensed imagery using a neural network: application to rainfall estimation. Journal of Water Resource Research, Vol. 35(5), pp 1605–1618.
- Hsu, K., Gao, X., Sorooshain, S., 1997. Precipitation estimation from remotely sensed Information using artificial neural network. Journal of Applied Meteorology ,Vol. 36(9), pp 1176–1190.
- Hsu, K., Gupta, H.V., and Sorooshian, S., 1995. Artificial neural network modeling of the rainfall-runoff process. Journal of Water Resources Research, Vol. 31(10), pp 2517-2530.
- Hsu, KL., Gupta, H.V., Gao, X., Sorooshian, S., and Imam, B., 2002. Self-Organizing Linear Output map (SOLO): An artificial neural network suitable for hydrologic modeling and analysis . Water Resource Research. Vol. 38, pp 1302.

- Hu, T. S., Lam, K. C. and Ng, S. T. , 2005 A modified neural network for improving river flow prediction.Journal of Hydrology Science ,Vol. 50(2), pp 299–318.
- Hu, T., and Yuan, P., 1995. Applications of artificial neural network to hydrology and water resources. Advances in Water Science, NHRI, , Vol. 1, pp. 76-82.
- Huang, W., Xu, B., and Hilton, A.C., 2004. Forecasting flows in Apalachicola River using neural networks. Hydrological Processes, Vol. 18(13), pp 2545-2564. [doi:10.1002/hyp.1492]
- Hurst, H.E., 1951. Long term storage capacities of reservoirs, Trans. American Society and Civil Engineers, Vol. 116, pp 776–808.
- Imrie C.E., Durucan, S., and Korre, A., 2000. River flow prediction using artificial neural networks: generalization beyond the calibration range. Journal of Hydrology , Vol. 233, pp 138-153.
- Ishihara, T., and Takasao, T., 1963. A study on runoff pattern and its characteristics. Bull. Disaster Prevention Research Institute, Kyoto University, Vol. 65, pp 1-23.
- Islam M.N., and Shivkumar, B., 1996. Characterization and Prediction of runoff dynamics: a nonlinear dynamical view. Advances in Water Resources, Vol. 25 , pp 179-190.
- Jagadeesh, A., Zhang, B. and Govindaraju, R.S., 2000. Comparison of ANNs and empirical approaches for predicting watershed runoff. Journal of Water Resources and Planning Management, Vol. 126(3), pp 156-166.
- Jain, A. and Srinivasulu, S., 2006. Integrated approach to model decomposed flow hydrograph using artificial neural network and conceptual techniques, Journal of Hydrology, Vol. 317, pp 291–306.
- Jain, A., and Srinivasulu, S., 2004. Development of effective and efficient rainfall–runoff models using integration of deterministic, real-coded genetic algorithms, and artificial neural network techniques.Journal of Water Resource Research, Vol. 40(4), W04302.[doi:10.1029/2003WR002355].
- Jain, A., Indurthy, S.K.V.P., 2003. Comparative analysis of event based rainfall–runoff modeling techniques—deterministic, statistical, and artificial neural networks. Journal of Hydrology Engineering, ASCE, Vol. 8(2), pp 1–6.
- Jain, A., Sudheer, K.P., and Srinivasulu, S., 2004. Identification of physical processes inherent in artificial neural network rainfall-runoff models. Journal of Hydrology Process, Vol. 118(3), 571-581.
- Jain, A., Varshney, A.K., and Joshi, U.C., 2001. Short-term water demand forecast modeling at IIT Kanpur using artificial neural networks. Journal of Water Resource Planning and Management, Vol. 15(5), pp 299–321.
- Jain, S.K. and Chalisgaonkar, D., 2000. Setting up stage-discharge relations using ANN. Journal of Hydrologic Engineering, Vol. 5(4), pp 428-433.
- Jain, S.K., Das, D., and Srivastava, D.K., 1999. Application of ANN for reservoir inflow prediction and operation. Journal of Water Resource Planning and Management, ASCE, Vol. 125(5), pp 263–271.
- Jakeman, A. J., and Hornberger, G.M., 1993. How much complexity is warranted in a rainfall-runoff model? Journal of Water Resources Research, Vol. 29, pp 2637–2649.
- Jakeman, J.J., Littlewood, I.G., Whitehead, P.G., 1990. Computation of the instantaneous unit hydrograph and identifiable component flows with application to two small upland catchments. Journal of Hydrology, Vol. 117, pp 275–300.
- Jayawardena, A.W., and Lai, F., 1994. Analysis and prediction of chaos in rainfall and stream flow time series.24 Journal of hydrology, Vol. 153, pp 23-52.
- Jun Han, 2002. Application of artificial neural networks for Flood warning systems, Ph.D. Thesis, The North Carolina State University, Raleigh, North Carolina
- Junsawang, P., Asavanant, J., and Lursinsap, C., 2007. Artificial neural network model for rainfall-runoff relationship, ASIMMOD2007, Chiang Mai, Thailand, pp 267-273
- Kalas M., Wachter, K., Szabo, J. A., Bodis, K.,Niemeyer, S., Van Der Knijef, J. & DE Roo, A., 2005. Setup, calibration and testing of the LISFLOOD model for the Upper Danube River basin on 1km. Geophysical Research Abstracts, Vol. 7, 09183, SRef-ID:1607-7962/gra/EGU05-A-09183, European Geosciences Union.
- Kang, K.W., Kim, J. H., Park, C.Y., and Ham, K.J., 1993. Evaluation of hydrological forecasting system based on neural network model. Proceeding of 25th Congress of International Association for Hydraulic Research, Delft, The Netherlands, pp 257–264.
- Kang, M.S., Kang, M.G., Park, S.W., Lee, J. J., Yoo, K.H., 2006. Application of grey model and artificial neural networks to flood forecasting. Journal of the American water resources association, Vol. 42, pp. 473- 489.
- Kantz, H., and Schrieber, T., 1999. Nonlinear Time Series Analysis. Cambridge Nonlinear Science Series, No. 7,
- Karim, A.M.B., Sheta, A.F., and Khaled, Al, K., 2006. Forecasting River Flow in the USA: A Comparison between Auto-Regression and Neural Network Non-Parametric Models. Journal of Computer Science, Vol. 2(10), pp 775-780.
- Karunanithi, N., Grenney, J.W., Whitley, D., and Bovee, K., (1994). Neural networks for river flow prediction. Journal of Computing in Civil Engineering, Vol. 8(2), pp 201-219.
- Kingston, G.B., Lambert, M.F., and Maier, H.R., 2003. Development of stochastic artificial nural networks for hydrological prediction. Centre for Applied Modeling in Water Engineering, University of Adelaide, Australia.
- Kingston, G.B., Maier, H.R., Lambert, M.F., 2005. Calibration and validation of neural networks to ensure physically plausible hydrological modeling. Journal of Hydrology, Vol. 314, pp 158–176.
- Kisi, O., 2004. River flow modeling using Artificial Neural Networks. Journal of Hydrologic Engineering ASCE, Vol. 9(1), pp 60–63.
- Kisi, O., 2005. Daily river flow forecasting using artificial neural networks and autoregressive models. Turkish Journal of Engineering and Environmental Sciences, Vol. 29(1), pp 9–20.
- Kisi, O., 2007. Stream flow forecasting using different artificial neural network algorithms. Journal of Hydrologic Engineering, Vol. 12(5), pp 532-539.
- Kisi, O., 2008. River flow forecasting and estimation using different artificial neural network techniques. Journal of Hydrology Research, Vol. 39(1), pp 27-40.

- Kisi, O., and Ozturk, O., 2007. Forcasting river flows and estimating missing data using soft computing techniques. International Congress On River Basin Management, Erciyes University, Civil Engineering Department, 38039, Kayseri, pp 655-668
- Kokkonen, T.S. and Jakeman A.J., 2001. A comparison of metric and conceptual approaches in rainfall runoff modeling and its applications. Journal of Water Resources Research, Vol. 37(9), pp 2345-2352.
- Kothyari, U. C., and Garde, R. J., 1991. Annual runoff estimation from catchments in India. Journal of Water Resources Planning and Management, (ASCE), Vol. 117 (1), pp 1-10.
- Krause, P., Boyle, D.P., Base, F., 2005. Comparison of different efficiency criteria for hydrological model assessment. Advances in Geosciences, Vol. 5, pp 89–97.
- Krishna, B., Satyaji Rao, Y.R., Nayak, P.C., 2011. Time series modeling of river flow using wavelet neural networks. Journal of Water Resource and Protection, Vol. 3, pp 50-59
- Kumar, A.P.S., Sudheer, K.P., Jain, S.K., Agarwal, P.K., 2005. Rainfall-runoff modeling using artificial neural networks: comparison of network types. Hydrological Processes, Vol. 19, 1277– 1291
- Kumar, D.N., Raju, K.S., and Sathish, T., 2004. River flow forecasting using recurrent neural networks, Water Resour. Manag., Vol. 18(2), pp 143–161.
- Laio, F., Porporato A., Revelli R. and Ridolfi L., 2003. A comparison of nonlinear forecasting methods. Journal Water Resources Research, Vol 39(5), pp 1129.
- Lallahem, S., and Mania, J., 2003. Evaluation and forecasting of daily groundwater outflow in a small chalky watershed. Journal of Hydrologic Processes ,Vol. 17, pp 1561–1577.
- Lauzon, N., Anctil, F., and Baxter, C. W., 2006. Clustering of heterogeneous precipitation fields for the assessment and possible improvement of lumped neural network models for streamflow forecasts. Journal of Hydrology Earth System and Science, Vol. 10, pp 485–494.
- Lee, D.S., C.O. Jeon, J.M. Park and K.S. Chang, 2002. Hybrid neural network modeling of a fullscale industrial wastewater treatment process. Biotechnology. Bioeng., Vol. 78(6), pp 670-682.
- Legates, D.R., and McCabe, G.J., 1999. Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation, Water Resources Research. Vol. 35(1), pp 233–241.
- Lin, C. T., and Lee, C.C., 1996. Neural Fuzzy Systems. A Neuro-Fuzzy Synergism to Intelligent Systems,Prentice Hall, New York.
- Liong, Shie-yui, Lim, W. and Paudyal, G.N., 2000. River stage forecasting in Bangladesh: Neural network approach . Journal of Computing in Civil Engineering, Vol. 14(1), pp 1-8.
- Lorrai, M. and Sechi, G.M., 1995. Neural nets for modelling rainfall-runoff transformations. Journal of Water resources management, Vol. 9, pp. 299-313.
- Luk, K. C., Ball, J. E. & Sharma, A., 2000. A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting. Journal of Hydrology , 227, 56–65.
- Luk, K., Ball, J.E., and Sharma, A. 2001. An application of artificial neural networks for rainfall forecasting. Mathematical and Computer Modeling ,Vol. 33, 683-693.
- Madsen, H., Wilson, G., and Ammentorp, H.C., 2002. Comparison of different automated strategies for calibration of rainfall-runoff models. Journal of Hydrology, Vol. 261, pp 48-59.
- Maier, H. R., and Dandy, G. C., 1996. The use of artificial neural networks for the prediction of water quality parameters. Water Resources Research, Vol. 32(4), pp 1013-1022.
- Maier, H.R., and Dandy, G.C., 2000. Neural Networks for the Prediction and Forecasting of Water Resources Variable: A Review of Modeling Issues and Application. Environmental Modeling and Software, Vol.15, pp 101-124.
- Malff, A. H., Halff,. M. , and Azmoodeh, M., 1993. Predicting runoff from rainfall using neural networks. In Proceeding and Engineering and Hydrology , ASCE, Vol. 14, pp 768-765.
- Mandelbrot, B.B. and Wallis, J.R., 1968. Noah, Joseph and operational hydrology. Journal of Water Resource Research, Vol. 4(5), pp 909-918.
- Markus, M., Salas, J.D., and Shin, H., 1995. Predicting stream flows based on neural networks. New York: American Society of Civil Engineers, Proceedings of the First International Conference on Water Resources Engineering, pp 1641-1646.
- Minns, A.W., and Hall, M.J., 1996. Artificial neural networks as rainfall–runoff models. Hydrological Science Journal, Vol. 41(3), pp 399–417.
- Modarres, R., 2009. Multi-criteria validation of artificial neural network rainfall-runoff modeling. Journal of Hydrology and Earth System Sciences, Vol. 13, pp 411–421.
- Mogil, H.M., Monro, J.C., and Groper, H.S., 1978. NWS's flash flood warning and disaster preparadness programs. Bulletine of American Meteorology Society, Vol. 79 (6), 690-699.
- Montgomery D.C., Runger, G.C., and Hubele, N.F., 1997. Engineering Statistics. John Wiley & Sons.
- Moradkhani, H., Hsu, K.L., Gupta, H.V., Sorooshian, S., 2004. Improved streamflow forecasting using self-organizing radial basis function artificial neural networks. Journal of Hydrology, Vol. 295, pp. 246−262.
- Muhamad, J.R., and Hassan, J.N., 2005. Khabur River Flow Modeling using Artificial Neural Networks. Al_Rafidain Engineering, Vol. 13(2), pp 33-42.
- Muttiah, R.S., Srinivasan R., and Allen P.M., 1997. Prediction of two-year peak stream discharges using neural networks. Journal of American. Water Resources Association, vol. 33 (3), pp 625-630.
- Nagy, H.M., K. Watanabe, and M. Hirano, 2002. Prediction of sediment load concentration in rivers using artificial neu-ral network model. Journal of Hydraulic Engineering., Vol. 128(6), pp. 588−595.
- O’Connell, P.E., J.E. Nash and J.P. Farrell, 1970. River flow forecasting through conceptual models. Part 2. The Brosna catchment at Ferbane. Journal of Hydrology, Vol. 10, pp 317-329.

- Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. Science Journal, 263, 641–646
- Palmer, T.N., and Raisanen, J., 2002. Quantifying the risk of extreme seasonal precipitation events in changing climate Nature, Vol. 415, pp 512-514.
- Parlos, A.G., Rais, O.T., and Atiya, A.F., 2000. Multi-step-ahead prediction using dynamic recurrent neural networks. Neural Networks, Vol. 13, pp 765–786.
- Plate, E.J., 2009. Classification of hydrological models for flood management.Journal of Hydrology and Earth System Science, Vol. 13, pp 1939–1951.www.hydrol-earth-syst-sci.net/13/1939/2009/
- Porporato A., and Ridolfi L., 2001. Multivariate nonlinear prediction of river flows. Journal of Hydrology, Vol. 248 (1-4), pp 109-122.
- Povinelli R.J., 1999. Time series data mining: Identifying temporal patterns for characterization and prediction of time series events. Ph.D. Dissertation, Marquette University, Milwaukee, WI.
- Price, R. K., 2009. Volume conservative, non-linear flood routing. Journal of Hydrology and Engineering , ASCE, Vol. 135(10).
- Price, R., 2005. The growth and significance of hydroinformatics,. Chapter 5 in River basin modelling for flood risk mitigation, Springer , pp 93.
- Pukdeboon, C., Nitivattananon, V., and Asavanant, J. 2006. Modeling the rainfall-runoff relationship in a small watershed for area development planning. Poster Presentation in the 3rd Asia Pacific Association of Hydrology and Water Resources (APHW) Conference, Bangkok, Thailand.
- Rajurkar, M.P., Kothyari, U.C., and Chaube, U.C., 2002. Artificial neural networks for daily rainfall–runoff modelling. Hydrological Sciences , Vol. 47(6), pp 865–877.
- Rajurkar, M.P., Kothyari, U.C., and Chaube, U.C., 2004. Modeling of the daily rainfall-runoff relationship with artificial neural networks. Journal of Hydrology, Vol. 285, pp 96−113.
- Raman, H., and Sunilkumar, N., 1995. Multivariate modeling of water resources time series using artificial neural 27 networks. Journal of Hydrological Sciences, Vol. 40(2), pp 145-163.
- Razavi, S. and Karamouz, M., 2007. Adaptive neural networks for flood routing in river systems, International Journal of Water, Vol. 32(3), pp 360–375.
- Reddy, A., J.M., Babu, S., and Mallikarjuna, P., 2008. Rainfall – rnoff modeling: Combination of simple time-series, linear autoregressive and artificial neural network models, WSEAS Transactions On Fluid Mechanics, ISSN: 1790-5087, Vol. 3(2), pp 126-136.
- Refsgaard, J.C., 1997. Parameterisation, calibration and validation of distributed hydrological models. Journal of Hydrology, Vol. 198, pp 69-97.
- Roy, P., Choudhury, P.S., and Saharia, M., 2010. Dynamic ANN Modeling for Flood Forecasting in a River Network, CP1298, International Conference on Modeling, Optimisation and Computing (ICMOC 2010), American Institiute of Physics 978-0-7354-0854, pp 219-225.
- Sajikumar, N., and Thandaveswara, B.S., 1999. A non-linear rainfall–runoff model using an artificial neural network. Journal of Hydrology, Vol. 216, pp 32–55.
- Salas, J. D., Markus, M., and Tokar, A.S., 2000. Streamflow forecasting based on artificial neural networks. Govindaraju, R.S., and Rao, A.R., eds., Artificial neural networks in hydrology, 23-51. Dordrecht: Kluwer Academic Publishers.
- Schmitz, G.H., Puhlmann, H., Droge, W., Lennartz., F., 2005. Artificial neural networks for estimating soil hydraulic parameters from dynamic flow experiments. European Journal of Soil Sciences, Vol. 56, pp 19-30
- See, L., and Openshaw, S., 2000. Applying soft computing approaches to river level forecasting. Journal of Hydrological Sciences, Vol. 44 (5), pp 763 –779.
- Shamseldin, A.Y., 1997. Application of a neural network technique to rainfall-runoff modeling. Journal of Hydrology, Vol. 199(3-4), pp 272-294. [doi:10.1016/S0022-1694(96)03330-6]
- Shamseldin, A.Y., 2006. Topics related to rainfall–runoff models. Chapter 10 in river basin modelling for flood risk mitigation (ed. D. W. Knight & A. Y. Shamseldin), Taylor and Francis, London.
- Shaw, E.M., 1994. Hydrology in Practice. (3rd edition). Chapman and Hall, Abington, London, UK.
- Sherman, L.K., 1932. Streamflow from Rainfall by the Unit Graph Method. Engineering News Records, Vol. 108, pp 501-505.
- Shrestha, R.R., Theobald, S., and Nestmann, F., 2005. Simulation of flood flow in a river system using artificial neural networks. Journal of Hydrology Earth System and Science, Vol. 9, pp 313–321.
- Singh, P., Deo, M.C., 2007. Suitability of different neural networks in daily flow forecasting. Journal of Applied Soft Computing, Vol. 7, pp 968–978.
- Singh, V.P., 1989. Hydrologic Systems, Vol II, Watershed Modeling, Prentice Hall, Englewood Cliffs, New Jersey 07632.
- Singh, V.P., 1994. Elementary Hydrology, Prentice Hall of India Private Ltd, New Delhi.
- Singh, V.P., and Woolhiser, D.A., 2002. Mathematical modeling of watershed hydrology. Journal of Hydrology Engineering, Vol. 7(4), pp 270-292.
- Sivakumar B., 2004. Chaos theory in geophysics: past, present and future. Chaos, Solutions & Fractals, Vol. 19, pp 441-462.
- 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, Vol. 265(1), pp 225–245.
- Smith, J. and Eli, R.N., 1995. Neural-network models of rainfall-runoff process. Journal of Water Resources Planning and Management, Vol. 121(6), pp page 499-508.
- Smith, P.J. , and Kojiri, T., 2003. Probabilistic short-term distributed flood forecasting. Annuals of the Disaster Prevention ,Research Institute, Kyoto University, Vol. 46(B), pp 885-897.
- Smith, P.J., 2005. Probabilistic flood forecasting using a distributed rainfall-runoff Model. Ph.D. Thesis, Water Resources Research Center, Disaster Prevention Research Center, Kyoto University.

- Solaimani, Karim, 2009. Rainfall-runoff prediction based on artificial neural network (A Case Study: Jarahi Watershed). American-Eurasian Journal of Agriculture & Environmental Science, ISSN 1818-6769, Vol. 5(6), pp 856-865.
- Solomatine, D. P., and Price, R. K., 2004. Innovative approaches to flood forecasting using data driven and hybrid modelling. In 6th International Conference on Hydroinformatics, edited by Liong, Phoon, and Babovic, pp. 1639-1646, World Scienti¯c Publishing Company, Singapore,
- Solomatine, D.P., Rojas, C., Velickov S., and Wust, H., 2000. Chaos theory in predicting surge water levels in the North Sea. Proceedings 4th International Conference on Hydro informatics. Iowa, USA.
- Somvanshi, V.K., Pandey, O.P., Agrawal, P.K., Kalanker, N.V., Ravi Prakash, M., and Ramesh Chand, 2006. Modelling and prediction of rainfall using artificial neural network and ARIMA techniques. Journal of Ind. Geophysics, Union, Vol. 10(2), pp 141-151.
- Sonne, M.B., Anmala, Jagadeesh, Zhang, Bin, and Govindaraju, Rao S., 2002. Discussion of comparison of ANNs and empirical approaches for predicting watershed runoff . Journal of Water Resources Planning and Management, Vol. 128(5), pp 377-382.
- Srinivas , V.V., and Srinivasan, K., 2005. Hybrid moving block bootstrap for stochastic simulation of multi-site multi-season streamflows. Journal of Hydrology, Elsevier, Vol. 302(1-4), pp. 307-330.
- Srinivasulu, S., Jain, A., 2006. A comparative analysis of training methods for artificial neural network rainfall–runoff models. Journal of Applied Soft Computing, Vol. 6, pp 295–306.
- Srivastava, P., McVair, J.N., and Johnson, T.E., 2006. Comparison of process-based and artificial neural network approaches for streamflow modeling in an agricultural watershed. Journal of American Water Resources Association, Vol. 42, pp 545-563.
- Su, H.T., McAvoy, T.J., and Werbos, P., 1992. Long-term prediction of chemical processes using recurrent neural networks: a parallel training approach. Industrial Application Chemical Engineering Research, Vol. 31, pp 1338–1352.
- Subramanya, K., 1997. Engineering Hydrology, 2nd edition, Tata McGraw-Hill Publishing Company Limited, New Delhi, India.
- Sudheer, K. P., Srinivasan, K., Neelakantan, T. R., and Srinivas, V.V., 2008. A nonlinear data-driven model for synthetic generation of annual streamflows, Journal of Hydrologic Process, Vol. 22(12), pp 1831–1845.
- Sudheer, K.P., P.C. Nayak, and Ramasastri, K.S., 2003. Improving peak flow estimates in artificial neural network river flow models. Journal of Hydrologic Process, Vol. 17 (3), pp 677–686.
- Sudheer, K.P., and Jain, A.,, 2004. Explaining the internal behavior of artificial neural network river flow models. Journal of Hydrologic Process, Vol. 118(4), pp 833–844.
- Sudheer, K.P., and Jain, S.K., 2003. Radial basis function neu-ral network for modeling rating curves. Journal of Hydrologic Engineering, Vol. 8(3), pp 161−164.
- Sudheer, K.P., Gosain, A.K., and Ramasastri, K.S., 2002. A data-driven algorithm for constructing artificial neural network rainfall-runoff models. J.of Hydrological Process, Vol. 16, pp 1325-1330.
- Sugawara, M., 1974. Tank model with snow component. National research center for disaster prevention, Japan.
- Sugawara, M., 1995. In: Singh, V.P. (Ed.). Tank model, in Computer Models of Watershed Hydrology. Water Resources Publications, Littleton, CO.
- Tan, C., and Beklioglu, M., 2006. Modeling complex nonlinear responses of shallow lakes to fish and hydrology using artificial neural networks. Ecological Modeling, Vol. 196, pp 183-194.
- Tawfik, M., Ibrahim, A., and Fahmy, H., 1997. ‘‘Hysteresis sensitive neural network for modeling rating curves.’’ Journal of Computation in Civil Engineering, ASCE, Vol. 11(3), pp 206–211.
- Thirumalaiah, K., and Deo, M.C., 1998. River stage forecasting using artificial neural networks. Journal of Hydrologic Engineering, Vol. 3(1), pp 26-31.
- Thirumalaiah, K., and Deo, M.C., 2000. Hydrological forecasting using artificial neural networks. Journal of Hydrologic Engineering, Vol. 5(2), pp 180-189.
- Thurston, J., 2002. GIS & Artificial Neural Networks: Does Your GIS Think? GISVision Magazine.
- Tokar, A.S, and Johnson, P.A., 1999. Rainfall-runoff modeling using artificial neural networks. Journal of Hydrologic Engineering, Vol. 4(3), pp 232-239.
- Tokar, A.S., and M. Markus, 2000. Precipitation-runoff model-ling using artificial neural networks and conceptual models. Journal of Hydrologic Engineering, Vol. 5(2), pp 156−161.
- Tokar, A.S., and Markus, M., 2000. Precipitation-runoff modeling using artificial neural networks and conceptual models. Journal of Hydrologic Engineering, Vol. 5(2), pp 156-161.
- Toth, E., 2009. Classification of hydro-meteorological conditions and multiple artificial neural networks for streamflow forecasting. Journal of Hydrology, Earth System and Science, Vol. 13, pp 1555–1566. http://www.hydrol-earth-syst-sci.net/
- Toth, E., Brath, A., Montanari, A., 2000. Comparison of short-term rainfall prediction models for real-time flood forecasting. Journal of Hydrology (Elsevier) , Vol. 239, pp 132–147
- Tu, M., Hall, M. J., Laat, P. J. M., and Wit, M. J. M., 2004. Detection of long-term changes in precipitation and discharge in the Meuse basin, in: GIS and Remote Sensing in Hydrology. 548 Water Resources Environment., Proceedings of ICGRHWE held at the three Gorges Dam, China, IAHS Published, 289.
- Uhlenbrook, S., Mc Donnell, J., and Leibundgut, C., 2001. Foreword to the special issue: Runoff generation and implications for river basin modelling, Freiburger Schriften. Journal of Hydrology, Vol. 10 (13), pp 4–13.
- Valenca, M., Ludermir, T., and Valenca, A. 2005. Modeling of the rainfall-runoff relationship with artificial neural network. Proceedings of the 5th Int. Conference of Hybrid Intelligent System. IEEE.
- Van, Can, H.J.L., H.A.B., Braake, C. Hellinga, K.C.A.M, Luyben and Heijnen, J.J., 1997. An efficient model development strategy for bioprocesses based on neural networks in macroscopic balance. Biotechnology. Bioengineering, Vol. 54, pp 549-566.
- Vladan, B. and Christian, L. 1998. Hydroinformatics 98, Vol. 2, Rotterdam, Netherlands.

- Wang, W., 2006. Sochasticity, nonlinearity and forecasting of streamflow processes, Technichal university of Delft, Amsterdam: IOS Press, Delft.
- Wang, W., Van-Gelder, P.H.A.J.M., Vrijling, J.K., and Ma, J., 2006. Forecasting daily stream flow using hybrid ANN models. Journal of Hydrology, Vol. 324, pp 383–399.
- Warner, B., and Misra, M., 1996. Understanding neural networks as statistical tools. The American Statistician, Vol. 50, pp 284-293.
- Wasserman, L., 2000. Bayesian model selection and model averaging, Journal of Mathematics and Psychology, Vol. 44, pp 92 – 107.[doi:10.1006/jmps.1999.1278].
- Wasserman, P. D., 1989. Neural computing: theory and practice. Van Nostrand Reinhold, NewYork.
- Web Resource, 2008. http://wrmin.nic.in/index1.asp?linkid=140&langid=1 accesed 25.01.2008
- Web Resource, 2011a. http://encyclopedia2.thefreedictionary.com/Flood accessed on 29.04.2011.
- Web Resource, 2011b. http://www.azadindia.org/social-issues/flood-management-in-india.html accessed on 30.4.2011
- Wilby, R.L., Abrahart, R.J., and Dawson, C.W., 2003. Detection of conceptual model rainfall–runoff processes inside an artificial neural network. Journal of Hydrology Science, Vol. 48(2), pp 163–181.
- Willmot, C. J., 1981. On the validation of models. Physical Geography, Vol. 2, pp 184–194.
- Willmot, C. J., 1984. On the evaluation of model performance in physical geography. In: Spatial Statistics and Models, edited by: Gaile, G.L., and Willmot, C. J., D. Reidel, Dordrecht, pp 443–460.
- Willmott, C.J., and Matsuura, K., 2005. Advantages of the mean absolute error(MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research Vol. 30, pp 79–82
- Xu, Z.X., and J. Y. Lijy, 2002. Short term inflow forecasting using an artificial neural network model. Hydrological Processes, Vol. 16, pp. 2423−2439.
- Yang, M.D., Chen, B.P.T., and Chen, C.S., 2007. Using artificial neural network for outflow estimation in an engaged area. IEEE International Conference on Neural Networks, pp 3551–3555.
- Yapo, P. O., Gupta, H. V., and Sorooshian, S., 1998. Multi-objective global optimization for hydrologic models. Journal of Hydrology , Vol. 204, pp 83–97.
- Yazdani, M.R., Saghafian, B., Mahdian, M.H., and Soltani, S., 2009. Monthly Runoff Estimation Using ANN. Journal of Agriculture Science and Technology, Vol. 11(3), pp 355-362
- Yu, P.S., and Tseng, T.Y., 1996. A model to forecast flow with uncertainty analysis. Journal of Hydrological Sciences-35, Vol. 41(3), pp 327-344.
- Yu, P.S., and Yang , T.C., 2000. Fuzzy multi-objective function for rainfall-runoff model calibration. Journal of Hydrology, Vol. 238(1-2), pp 1–14.
- Yue, S., and Hashino, M., 2000. Unit hydrographs to model quick and slow runoff components of streamflow. Journal of Hydrology, Vol. 227, pp 195-206.
- Yule, G.U., 1927. On a method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers. Philosophical Transactions of the Royal Society of London, Vol. A(226), pp 267-298.
- Yurekli, K., Kurung, A., Ozturk, F., 2005. Testing the residuals of an ARIMA model on the Cekerek Stream Watershed in Turkey. Turkish Journal of Engineering and Environmental Sciences, Vol. 29(2), pp 61-74.
- Zaldivar, J.M., Gutierrez, E., Galvan, I.M., Strozzi, F. and Tomasin, A., 2000. Forecasting high waters at Venice Lagoon using chaotic time series analysis and non-linear neural networks. Journal of Hydroinformatics, Vol. 2(1), pp 61-84.
- Zealand, C.M., Burn, D.H., and Simonovic, S.P., 1999. Short term streamflow forecasting using artificial neural networks., Vol. 214, pp 32-48.
- Zhang, B. and R.S. Govindaraju, 2003. Geomorphology-based artificial neural networks (GANNs) for estimation of direct runoff over watersheds. Journal of Hydrology, Vol. 273 (1-4), pp 18-34.
- Zhang, B., and Govindaraju, S., 2000. Prediction of watershed runoff using bayesian concepts and modular neural networks. Journal of Water Resources Research, Vol. 36(3), pp 753-762.
- Zhao, H., O.J., Hao, T.J., McAvoy and C.H., Chang, 1997. Modeling nutrient dynamics in sequencing batch reactor. Journal of Environment Engineering, Vol. 123, pp 311-319..
- Zhao, R.J., Y.L., Zhang, L.R., Fang, X.R., Liu and Q.S., Zhang, 1980. The Xinanjiang model, in Hydrological forecasting. Proceedings of the Oxford Symposium, IAHS, Vol. 129, pp 351-356. Am-Euras. Journal of Agric. & Environ. Sci., Vol. 5(6): 856-865, 2009
- Zhu, M.L., Fujita, M., 1994. Comparisons between fuzzy reasoning and ANN methods to forecast runoff discharge. Journal of Hydro science and Hydraulic Engineering, Vol.12(2), pp 131–141.
- Zhu, M.L., Fujita, M., Hashimoto, N., 1994. Application of neural networks to runoff prediction, in: K.W. Hippel, et al. (Eds.), Stochastic and Statistical Methods in Hydrology and Environmental Engg., Kluwer Academic Publishers, Norwell, MA, pp 205–216.