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Hydrological Analysis by Artificial Neural Network: A Review

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ABSTRACT

In this paper, a deep review is conducted on Artificial Neural Network. ANN is used for real-world problems which are related to the hydrological field. Computational Intelligence methods such as Artificial Neural Network are very necessary because conventional methods are very complex and vexatious. Artificial Intelligence operation is based on the transformation of unknown relationship into a known sensible relationship, and hence this transformation helps in modeling real-world problems. Various applications of AI operation are carried out at present time, such as Rainfall-Runoff modeling, Groundwater modeling, water quality modeling, modeling stream flow etc. In recent years, Artificial Neural Network has shown exceptional performance as regression tools, especially when it is used for pattern recognition and function estimation. This paper mainly focuses on various ANN models for solving real and complex hydrological problems with great accuracy, and these are proposed as efficient tools for prediction in hydrology.

Keywords: *Artificial neural network (ANN), Feedforward, Hydrology, Precipitation, Rainfall-runoff, Stream-flow.*

1. INTRODUCTION

Artificial neural networks (ANNs) are computer programs basically inspired by Biological Neural Network, designed to simulate the way in which the human brain processes information. ANNs collect their knowledge by knowing the relationships and patterns in data and trained through experience, not from programming. In simple words, ANN can be described as a mathematical structure capable of representing the arbitrary, complex and non-linear process correlating the input and output of any system [1].

ANNs essentially have 3 components- Nodes/Neurons, Weights, and Activation/Transfer Function. Each neuron is connected to other neurons by means of direct links Through an activation or transfer function the received information or input is processed by the neuron to produce a transformed output signal [1]. The basic structure of ANN usually consists of three layers: the input layer, where the data are introduced to the network; the hidden layer or layers, where data are processed; and the output layer, where the results of given outputs are produced as shown (Fig 1).

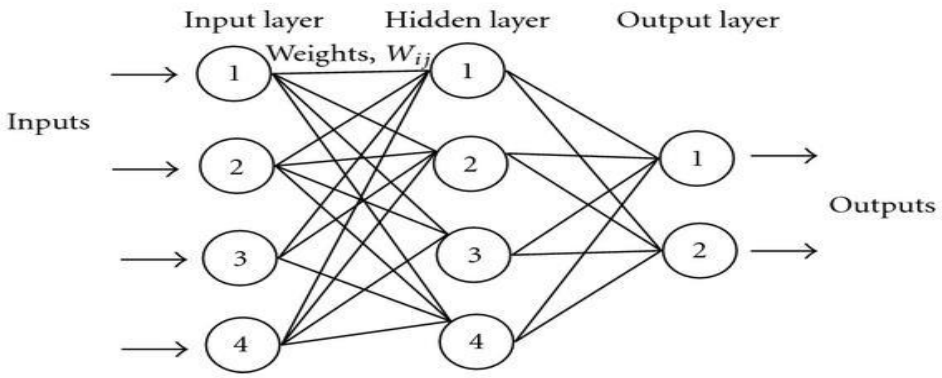

Fig 1. Neural network architecture [2]

The behavior of a neural network is determined by the architecture itself, by the learning rule, and by the transfer functions of its neurons. A neural network is a parameterized system as weights are the adjustable parameters. The activation signal is passed to produce a single output of the neuron. Transfer function introduces non-linearity to the network. During the time of training, the inter-unit connections are made effective and functional until the error in predictions is reduced such that the network reaches the specified level of accuracy. Once the network is trained and tested it can be given new input information to predict the output [2].
Multi-Layer Perceptron (MLP): It is one of the most common neural network models. It is a feedforward neural network with one or more layers between input and output layer. It is called feed-forward because all the data information flows in one direction from input to output layer. MLP consists of three different types of Layers i.e. Input, hidden, and output layers. Patterns are introduced to the network via the input layer. The processing is carried out in the hidden layer, and output layer produces a result for the given input pattern. MLP utilizes a supervised learning technique called backpropagation for training. MLPs are widely used for pattern classification, recognition, prediction, and approximation. Fig.2. shows a fully connected MLP with one hidden layer [3, 4].

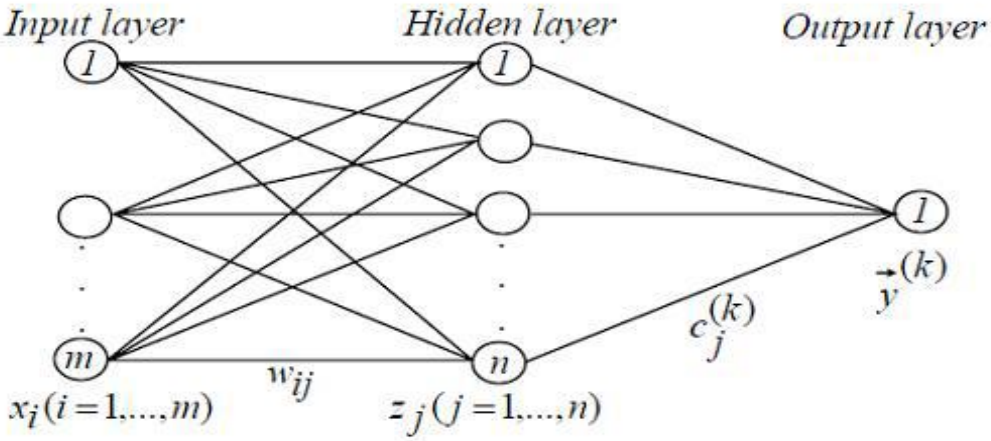

Fig 2. Feed-forward Back-propagation network [5]

Feed Forward Back-propagation is a form of supervised training. The network must be provided with both sample inputs and outputs when supervised training method is used. The back-propagation algorithm is a supervised iterative training method for multilayer feed-forward nets with a differentiable nonlinear function. A typical nonlinear function used is the sigmoid function defined by Eq. (1) -

$$\emptyset(x) = \frac{1}{1+exp(-x)} \qquad \text{Eq. (1)}$$

The back-propagation training algorithm predicts the output from given input data and compares it with the actual output. If there an error occurs then weights of the various layers are adjusted moving backward from the output layer to the input range [5].
Radial Basis Function (RBF): Radial basis networks may involve more neurons than typical feed-forward back-propagation networks, but repeatedly they can be considered in an element of the time it takes to train standard feed-forward networks. RBF network can approximate any continuous function with arbitrary accuracy and hence called a universal approximator. RBF network uses sigmoidal and Gaussian kernel functions which were most common nonlinearities. The Gaussian functions are also used in regularization networks. The response of such a function is positive for all values of y; the response decreases to 0 as $|y| \rightarrow 0$ [6]. The Gaussian function is generally defined as Eq. (2)

$$f(y) = e^{-y^2} \text{ [6]} \qquad \text{Eq. (2)}$$

2. RAINFALL-RUNOFF MODELLING USING ANN

Prediction of the elements of hydrological cycle like Rainfall & River flow is one of the most complex hydrologic phenomena. Rainfall and runoff prediction importantly depends on climatic and geometric features of the basin under study and these features led to producing a highly complex relationship between rainfall and runoff. Factors may be precipitation, percolation, infiltration, evaporation, stream flow and air temperature. Sometimes it is very difficult to predict rainfall-runoff relation by use of conventional models (SCN-CN, GA, CN4GA) with regression equation. The Computational intelligence such as ANN plays a very important role to solve such complex rainfall-runoff relationship. An important feature of ANN is their ability to extract the relation between inputs and outputs of a process, without the physics being directly provided. This shows that ANN may be well suited for the problems of estimation and prediction. ANNs are supposed to possess the capability to reproduce the unknown relationship existing between a set of input variables (e.g., rainfall) of the system and one or more output variables (e.g., runoff).

French et al. 1992 was the first one who applied ANN based modeling in hydrology. Thereafter in the field of hydrology, the applications of ANN have been continuing [7]. Three feed-forward ANN was used for the prediction of hydrographs by Halff et al (1993) [8]. For estimation of mean monthly runoff, a simple ANN model was proposed by Kothayari (1995) while Raman & Sunil Kumar (1995) proposed the same ANN model for estimation of monthly rainfall [9]. Minns and Hall developed a rainfall-runoff

forecasting ANN model which is trained with back propagation algorithm [10]. A virtual hydrological system by using ANN has been developed by Mason et al. (1996) and they showed that Radial basis function network provides faster training as compared to the regular back propagation technique for rainfall-runoff modeling using ANN [11]. Dawson, C. W., and Wilby, R. (1998) carried out discussion on the development and application of artificial neural networks to flow forecasting in two flood-prone UK catchments using real hydrometric data [12]. Dawson, C. W., and Wilby, R. (2001) discussed the wide variety of techniques for the application of rainfall-runoff modeling and flood forecasting using ANN. This review underlines the need for clear guidance in current modeling practice, as well as the analogy of ANN methods with more conventional statistical models [13].

Rajurkar et al. (2002) done coupling ANN with multiple-input-single-output (MISO) model to provide a better representation of the rainfall-runoff relationship for large size catchments [14]. Cigizoglu H. K**. (**2005) employed an ANN algorithm, generalized regression neural network (GRNN), in monthly mean flow forecasting. The performance of GRNN is compared with the feed forward back propagation (FFBN) method. Observed data (based on the comparison) used to train the neural network and forecasting is carried out using AR model. After comparing the model performance based on performance criteria it is found that GRNN performs better than FFBN [15]. Adamowski (2008) compared multiple linear regression, time series analysis and artificial neural networks as techniques for peak daily water demand forecast modeling. Analysis has been done over thirty-nine multiple linear regression models, nine-time series model and 39 ANN models of their relative performance [16].
Harun S. et. al. (2010), presented the potential of artificial neural network models for prediction of runoff. They describe the application of multilayer perceptron (MLP) and radial basis function (RBF) to predict daily runoff as a function of daily rainfall for the Sungai Lui, Sungai Klang, Sungai Bekok, Sungai Slim and Sungai Ketil catchments area. The performance of ANN is evaluated based on the efficiency and the error. It has been found that the ANN has a potential for successful application to the problem of runoff prediction [17].

Sarkar and Kumar (2012) presented the application of artificial neural network (ANN) methodology for rainfall-runoff modeling. A case study has been carried out for Ajay river basin (spreads between Latitude 23°25'N to 24°35'N and Longitude 86°15'E to 88°15'E) to develop an event-based rainfall-runoff model for the basin to simulate the hourly runoff at Sarath gauging site. Back propagation models have been designed and developed for the hourly runoff simulation of Ajay river basin at Sarath gauging site. Various combinations of the flood events have been considered during training. Root mean square error (RMSE), the coefficient of correlation (R), and coefficient of determination (DC) are criteria used for evaluation of model performance. The result indicated that ANN models are able to provide a good representation of an event-based rainfall-runoff process [18]. Mishra et. al. (2014) examined various approaches of ANN for hydrological forecasting and also proposed ANN modeling approach for the hydrological forecast. The coefficient of determination (R^2), mean squared error (MSE), mean relative error (MRE) were the performance criteria for model evaluation. Result found that ANN models are able to provide a good representation of hydrological forecast. The back propagation approach is suitable for above research perspective [19]. Gupta et. al. (2014) used to discharge and rainfall data of 10 years (2000-2010) to train the network. In this study, model taking input as rainfall and discharge data and next year rainfall data as a desired output parameter. Number of experiments had been carried out on the model by changing the number of neurons, number of hidden layer and activation function. Finally, it has found that model with two hidden layer is optimum for this work [20]. Mishra et. al. (2014) developed Hydrolprocess framework for hydrological time series analysis and applied to the monthly discharge time series historical records of the Brahmaputra river basin. The developed new Hydrolprocess is a combination of clustering, regression analysis and Artificial Neural Network (ANN) which gives the complete result of data analysis, discovering pattern, and prediction of hydrological parameters for the catchment [21].

3. WATER QUALITY MODELLING USING ANN

Modeling water quality within complex, man-made and natural environmental system is a challenge to researchers. Many conventional methods of modeling tools is not capable of representing the complexities of physical and chemical processes observed in this system. Since the sets of physical, chemical, and biological parameters are generally used to characterize the quality of water body. Nowadays, ANN technique of artificial intelligence is becoming the trustful technique in the area of water quality modeling also. Quality of water is mainly influenced by water level, flow rate, contaminant load, initial conditions, the medium of transport and some other site-specific parameters. The purpose of water quality index (WQI) is to transform the large quantity of data into information that is easily understandable by the general public. Based on several water quality parameters, WQI exhibits the overall water quality at a specific location and specific time. Hence, application of ANN is most suited for such complex and non-linear problems.

Rogers (1992) and Rogers and Dowla (1994) used an ANN model. This ANN model was trained by a solute transport model. This study was carried out to perform optimization studies in ground-water remediation. A multilayer feed-forward ANN was trained by using back propagation training algorithm. It was found that the results acquired by this method were consistent as compared to those resulting from a conventional optimization technique using the solute transport model and nonlinear programming using a quasi-Newton search [22, 23]. Maier and Dandy (1996) demonstrated the use of artificial neural networks (ANNs) as an efficient tool for forecasting water quality parameters. A case study has been carried out on the River Murray at the Murray Bridge in South Australia in which ANN methods are used to forecast salinity in the River Murray. Daily salinity values, water levels, and flow at upstream stations and at antecedent times were taken as input to ANN model. For training, back-propagation function is used consisting two hidden layers. The ratio of a number of nodes in the second and third layer was found to be 3:1. It was concluded that ANN has the ability to accurately reproduce salinity levels based on 14-day forecasts [24]. Muhammad et al (2004) demonstrated the application of ANN model for forecasting ground water contamination. In this study, they developed a Neural Network Model for forecasting the various hazardous metals present in groundwater. It was shown that ANN model was implemented for future prediction of effluent quantities.

Khalil et. al. (2012), demonstrated the potential of the Artificial Neural Network (ANN) on simulating interrelation between water quality parameters. They used various ANN inputs, structures and assessed all training possibilities and finally select the best ANN model and modeling procedure. They compared prediction capabilities of the ANN with the linear regression models with auto correlated residuals. In last it has been concluded that for the same inputs and output the ANN models are more accurate than the linear regression models [25].

Sarkar and Pandey (2015) used feed-forward error back propagation neural network technique for their study. For the analysis purpose, they used monthly data sets on flow discharge, biochemical oxygen demand (BOD) and dissolved oxygen (DO), temperature, pH at three locations, namely, Mathura (upstream), Mathura (central) and Mathura (downstream). They developed three types of ANN models using Feed forward error back propagation algorithm by using different combinations of input variables and input stations. The performance of the ANN technique has been evaluated using statistical tools (in terms of root mean square error and coefficient of correlation) [26].

4. GROUND WATER MODELLING USING ANN

Groundwater is an important to resource of water supply for domestic, industrial and farming-based activities. Ground water level forecasting is very important for ground water management especially for dry areas where there is strong need to manage groundwater resources in such a way so that they should be available for farming, municipal and industrial needs. Complexity, non-linearity are some features of groundwater system which make predictions highly complicated. Sometimes obtaining accurate predictions is more important in case of insufficient data than understanding the actual physics of the situation. In recent years, a modern technique such as ANN has been attempted by many hydrologists for water resource forecasting because of nonlinearity in groundwater level fluctuations. ANN has been proved as an efficient and effective tool in hydrologic analyses and prediction, and the evaluation of water quality.

Rizzo and Dougherty (1994) introduced the idea of neural kriging for characterization of aquifer properties. For estimating hydraulic conductivity a three-layer neural network utilizing the counter propagation algorithm was combined with kriging. The coordinates of observation points are represented by input nodes. And the class of hydraulic conductivity at various locations was predicted by output nodes. The result showed that ANNs is effective tools in geohydrology in case of specific problems of aquifer characterization [27]. Maskey et.al. (2000) carried groundwater model approximation with Artificial Neural Network for selecting optimum pumping strategy. To approximate the groundwater models MODFLOW and MODPATH, ANNs were trained by using the data generated by these models. The resulting ANN models were then coupled with a GO tool, GLOBE, to find optimal pumping strategies. The experiments were carried out using a different number of pumping wells and different GO algorithms [28].

Yang et.al. (2008) demonstrate the Back-Propagation Artificial Neural Network (BPANN) model for forecasting the groundwater level based on the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and coefficient of efficiency (R2). The case study has been carried out on arid and semi-arid areas of western Jilin province (China) where groundwater levels decline due to overexploitation. The result shows that BPANN is accurate in reproducing and forecasting the groundwater levels. It was concluded that the BPANN is capable to predict the groundwater levels reasonable [29]. Mayilvaganam and Naidu (2011) used Feed-Forward Neural Network to predict the groundwater levels. Training of ANN model was done by using back propagated algorithm with two hidden layers, and with logsig activation function. Mean Average Error (MAE), Regression coefficient (R^2) and Root Mean Squared Error (RMSE) are three performance criteria for model evaluation. It was concluded that ANN is able to predict groundwater level in a hard rock region with great accuracy even when applied to limited data situation [30].

Chitsazan et. al. (2015) applied to feed forward back propagation neural network (FNN) to predict groundwater level of Aghili plain (southwestern Iran). Designed with two hidden layers with four different algorithms: scaled conjugate gradient (SCG), resilient Back propagation (RP), Levenberg Marquardt (LM) and descent with momentum (GDM). Observation data is used for obtaining training ANN. Input layer consists of relative humidity, Rain, evaporation, temperature and groundwater recharge while future groundwater level was used as the output layer. Performance evaluation of ANN is based on Mean-Square-Error (MSE) and correlation coefficient (R). The result showed that ANN is highly accurate in predicting groundwater level [31].

5. STREAM-FLOW MODELLING USING ANN

One of an essential part of water resource system is streamflow and a difficult task for water resources engineers. Estimating river flow helps in agricultural water management and this protects from water shortages and possibly from disasters such as flood damage. It can play a very vital economic impact. A forecasting system provides a strong basis for proper control and management of the water resources system, and it deals with all the significant temporal and spatial variability of the whole stream-flow field. For flood warning and for real-time operation of water resources systems, stream flow forecast with lead times of hours and days are often used. Forecasts, with lead times ranging from weeks to months, are generally used for water system planning and management, such as allocation of irrigation water, hydropower planning, and drought analysis and mitigation [32].

Estimates of runoff from the watershed are often treated as streamflow and could be taken as part of the Rainfall-runoff modeling section. Here those papers are reviewed which directly deal with streamflow without taking precipitation as input. Kang et al. (1993) have used ANNs and autoregressive moving average models to predict daily and hourly stream flows. The case study has been carried out in the Pyung Chang River basin in Korea. An investigation did for different three-layered ANN architectures. They concluded that ANNs are effective tools for forecasting stream flows [33]. Shrivastava and Jain (1999) predicted reservoir inflows in reservoir operations by using ANN model. They compared Autoregressive Integrated Moving Average (ARIMA) model and ANN model. The result indicates that ANN produced a better result than ARIMA model [34].

Huang et. al. (2004) compared ANN and ARIMA models in streamflow forecasting [35]. Ozgur Kisi (2005) carried out a numerical and graphical comparison between neural networks and auto-regressive (AR) models for river flow prediction. This study investigated various suitable artificial neural network (ANN) architectures, in terms of hidden layers and nodes for hydrological forecasting. Finally selects three simple neural networks (NN) architectures for comparison with the AR model forecasts. Models performances was evaluated by using criteria such as the sum of square errors (SSEs) and correlation statistic. The result showed that for given same input data Neural Network models produce better results than AR models [36].

Edossa and Babel (2010) present the application of artificial neural networks in long-term streamflow forecasting model. A study carried out at stream gauging station in the Awash River Basin, Ethiopia. Based on water requirements for irrigation and environmental purposes and forecasted streamflow time series, appropriate agricultural water management strategies have been proposed for the irrigation scheme [37]. Xu et. al. (2016) develop an ANN model for daily stream flow forecasting and also compare the performance of ANN models and a rainfall-runoff model-XXT, which is a new efficient hybrid model of Xinanjiang model and TOPMODEL, in one day in advance stream flow forecasting. The study has been carried out on Yingluoxia basin with a drainage area of 10009 km^2. This study concluded that for ANN modeling in this basin requires stream flow, evaporation, and precipitation [38]. Adnan et.al. (2017) investigates the capability support vector machine (SVM) and artificial neural network (ANN) models in modeling monthly streamflow. Model performance was evaluated based on determination coefficient (R2), root means square error (RMSE) and mean absolute error (MAE) measures. Later on, results of ANN and SVM models are compared. This comparison showed that the SVM is superior in forecasting monthly streamflow than the ANN models. It was concluded that SVM models can be successfully used in predicting monthly stream-flows [39].

6. CONCLUSION

By reviewing various papers it has been concluded that ANN models are an efficient and perfect tool for forecasting mainly for Rainfall-runoff prediction, ground water, water quality, stream flow prediction etc. In many of the complex hydrological problems, a most widely used method is Feed-Forward-Back-Propagation (FFBP) method. However in case of rainfall-runoff prediction model such as multiple input single output (MISO) model are also used, in case of water quality modeling cascade correlation artificial neural network (CCANN) model is used, in case of streamflow modeling, recurrent neural network (RNN) is employed and so-on. For designing perfect ANN model, a deep understanding of the hydrological process would impart a great help. As ANN is gaining acceptance among researchers, it should produce improved models with good results.

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