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Application of Artificial Neural Network in Hydrology- A Review

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Abstract: **In this research paper exhaustive review is conducted on artificial neural network (ANN) which is employed in the field of hydrological related problems, whereas the conventional approaches are cumbersome and complex in view of computational analysis. Artificial intelligence operation can be well exemplified through application in rainfall-runoff modelling, modelling streamflow, water quality modelling, and application in ground water. A good physical understanding of the hydrologic process being modelled can help in selecting the input vector and designing a more efficient network. This review provides examples for ANN model that provides reasonable accuracy for hydrological problems, and a more effective tool for engineering applications.**

Keywords- Artificial Neural Network (ANN), Feed Forward, Hydrology, Precipitation, Rainfall-Runoff, Stream-flow.

1. INTRODUCTION:

Artificial neural networks have been basically inspired by the biological neural network consisting of a billion of interconnected neurons in the brain. With the advances in the field of information processing the massive parallel processing and distributed storage properties of the brain have been simulated through artificial neural networks, 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.

An artificial neural network is a data processing system consists of a highly interconnected network of simple processing elements called neurons. The neurons in an ANN are arranged in layers within the network such that the neurons of one layer are connected to those of the adjacent layer. The strength of these connections between two adjacent layers is called the “weight” and is equivalent to the strength of the signals in a biological neural network. During the process of learning or training the weights of the interconnections are adjusted such until the inputs produce the desired output. Depending upon the training data provided to the network different training rules are required for weights adjustment is order to obtain the desired output.

One of the most common neural network models is Multi-Layer Perceptron (MLP). An MLP is a network that consists of three different types of Layers i.e. Input, hidden, and output layers. Patterns are introduced to the network via the input layer. In the hidden layers the processing is done, and the result produced for the given input pattern is transmitted to the output
layer. An MLP is a feed forward neural network. It is called “feed-forward” because all of the data information flows in one direction. Feedback is avoided by connecting the neurons connecting with following neurons. Fig.1. shows a fully connected MLP with one hidden layer.

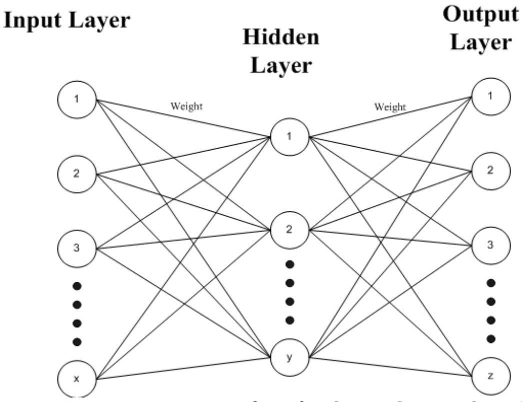

Fig. 1. Structure of Artificial Neural Network model.

Feed Forward Back-propagation is a form of supervised training. When supervised training method is being used, the network must be provided with both sample inputs and outputs. The back-propagation training algorithm predicts the output for a given data and compares it with the actual output. If there an error occurs then weights of the various layers are adjusted moving backwards from the output layer to the input range.

2. APPLICATION IN RAINFALL-RUNOFF MODELLING:

The complexity in hydrological phenomenon is due to the presence transformative phases. The rainfall water through runoff goes to a catchment area which is spatially distributed, time varying and non-linear. Various simulation platforms are being used for modelling of this complex phenomenon. For evaluating the performance of the models, categorization is based on the complexities as conceptual, black-box, empirical or physically-based distributed model. Earlier models are conceptual based which represent the physical transformation using linear or non-linear mathematical transformation, which are tedious and highly complicated from the implementation and calibration perspective. Governing the fact, to design simple model, there are models which are developed by establishing linear relationship between input and output by avoiding the complex physical laws. Such linear rainfall runoff process is well exemplified by unit hydrograph. But these models fail to depict the non-linear dynamics of rainfall-runoff transformation.

A latest development in the system-conceptual modelling approach is the application of ANN technique in rainfall-runoff modelling. The advantage of ANN technique is that it does not require the detailed knowledge of catchment characteristics; it simply establishes a relationship between the input (rainfall) and output (runoff) on the basis of learning through the process of training of the neural network. Thus the physical characteristics though not given weightage separately are very much an inherent part of the model.

ANN based modelling was first applied in the field of hydrology by French et al. 1992. Thereafter the sphere of applications of ANN has been continuously in the field of hydrology. Halff et al 1993 used a three feed forward ANN for the prediction of hydrographs. In 1995 Kothayari proposed a simple ANN for estimation of mean monthly runoff while Raman & Sunil Kumar 1995 proposed the same ANN model for estimation of monthly rainfall. In 1996 Mason et al. developed a virtual hydrological system using ANN they showed that Radial basis function network provides faster training as compared to the regular back propagation technique for rainfall-runoff modelling using ANN.

For predicting monthly rainfall-runoff modelling in scarce data conditions Sajikumar & Thandaveswara (1999) used the temporal back-propagation neural network (TBP-NN) technique. A task committee of American Society of Civil Engineers (ASCE) has discussed thoroughly and established the role of ANN in hydrology (ASCE 2000, a, b) and also compared it with the other modelling methods. Rajurkar et al. (2002) provide a better representation of the rainfall-runoff relationship for large size catchments by coupling ANN with multiple-input-single-output (MISO) model. Kalteh (2008) developed a rainfall-runoff model using Artificial Neural Network (ANN) approach and describes different approaches including Neural Interpretation Diagram, Garson's algorithm to understand the relationship learned by the ANN model. Results show that the ANNs are promising tools for accurate modelling of complex processes. Goyal et. al. (2010) analysed the mean monthly rainfall runoff data of Indian catchments using dimensionless variables by Artificial Neural Network (ANN). Results indicate that ANN model using dimensionless variables were able to provide a better representation of rainfall-runoff process. Chen et. al. (2013) used Artificial Neural Network (ANN) approach for modelling rainfall-runoff due to typhoon. Interpretations were made by applying Feed Forward Backpropagation (FFBP) and Conventional Regression Analysis (CRA) models.

3. APLLICATION IN STREAM-FLOW MODELLING:

Streamflow forecasting is an important element of water resource system and a challenging task for water resources engineers. Forecasting of streamflow helps in enhancing the systematic operation of water resources under the priorities like economical, legal, technical and political. An efficient and precise control of water resource management can be obtained by a forecasting system which accounts for spatial variability and temporal of entire streamflow fields. A real time operation of water resource system in a lead time of hours and days could be easily implemented with streamflow forecast. Forecast ranging from weeks to months are used for analysing the system management and planning, i.e. mitigation, drought analysis, hydropower planning and development, allotment of irrigation water.

Streamflows are often treated as estimates of runoff from watershed and could be considered as part of the previous section. The focus here is on papers that have directly dealt with streamflow itself, usually without involving precipitation as input. In some studies, streamflow prediction was an intermediate goal. In some of the previous application of streamflows Kang et al. (1993) has implemented autoregressive moving average models and ANNs to predict daily and hourly streamflows in the Pyung Chang River basin in Korea. Different three-layered ANN architectures were investigated. This preliminary study concluded that ANNs are useful tools for forecasting streamflows. Karunanithi et al. (1994) estimate the flow prediction of the Huron river by applying Artificial Neural Network approach using Cascade-Correlation algorithm. Results show that the artificial neural networks (ANN) are capable to the match changes in the flow history.

Markus et al. (1995) used back-propagation algorithm to predict monthly streamflows at the Del Norte gauging station in the Rio Grande Basin in Southern Colorado. The inputs used were snow water equivalent alone, or snow water equivalent and temperature. As an alternative form of prediction they used Periodic Transfer Functions (PTFs) to predict streamflows based on similar inputs. For training, monthly data from 1948–1977 were used, and they tested model performance on monthly data from 1978–1987. The results indicated that both ANNs and PTFs did a good job of predicting streamflows, and including temperature as input improved model performance.

Poff et al. (1996) used ANNs to evaluate the changes in stream hydrograph from speculative climate change scenarios based on precipitation and temperature changes. Karabörk and Kahya (1998) obtained mathematical expressions of multivariate periodic autoregressive (PAR) and periodic autoregressive moving average (PARMA) models for monthly streamflow observations of 12 stations located in the Sakarya Basin. Shrivastava and Jain (1999) used ANN models to predict reservoir inflows in reservoir operations. They compared ANN and Autoregressive Integrated Moving Average (ARIMA) model, and concluded that ANN produced better result. Birikundavyi et. al. (2002) used ANN methods in prediction of daily streamflow and investigated the performance of ANN.

Results show that ANN yielded better results than ARMA models. Kumar et. al. (2004) employed Recurrent Neural Network (RNN) model in streamflows forecasting. Kişi (2004) investigated the application of artificial neural networks (ANNs) in predicting mean monthly streamflow and compared with Auto Regressive (AR) models. Huang et. al. (2004) compared ANN and ARIMA models in streamflow forecasting. Wang et. al. (2005) used Hybrid ANN Models for forecasting of daily streamflow. Three different forms of hybrid artificial neural networks (ANNs) were used, namely, the Threshold-based ANN (TANN), the Cluster-based ANN (CANN), and the Periodic ANN (PANN).

4. APPLICATION IN WATER QUALITY MODELLING:

Quality of water body is generally characterized by physical, chemical, and biological parameters, which are mutually interrelated. In recent years, ANN have been applied in the area of water quality modelling also. Quality of water is mainly influenced by flow rate, contaminant load, medium of transport, initial conditions, water levels and other site-specific parameters. Application of ANN is most suited for such complex and non-linear problems.

Maier and Dandy (1996) demonstrated the utility of ANNs for estimating salinity at the Murray Bridge on the River Murray in South Australia. In this study, the inputs to the ANN model were daily salinity values, water levels and flow at upstream stations and at antecedent times. Two hidden layers and back-propagation function were used for training purposes. Number of nodes found in second and third layer was found to be in the ratio of 3:1. It was observed that ANN is able to reproduce salinity levels fairly accurately based on 14 day forecasts (Maier and Dandy 1986).

Rogers (1992) and Rogers and Dowla (1994) employed an ANN, which was trained by a solute transport model, to perform optimization studies in ground-water remediation. Using the back propagation training algorithm a multilayer feed-forward ANN was trained. Results obtained by this method were consistent with those resulting from a conventional optimization technique using the solute transport model and nonlinear programming using a quasi-Newton search. Morshed and Kaluarachchi (1998) used an ANN to estimate the saturated hydraulic conductivity and the grain size distribution parameter for application in the problem of free product recovery. They also concluded that the search process in the parameter space could be accelerated when the ANN was guided by a genetic algorithm. Hui (2000) and Xiaohua (2000) study water quality and eutrophication in Singapore Strait. To understand complex, highly non-linear water quality dynamics that vary in space and time, one can use either a process-based, three-dimensional eutrophication model or data-driven models. Sundarambal and Tkalich, 2003 carried numerical water quality modelling studies of tropical coastal waters in Singapore.

Zaheer and Bai (2003) studied the application of ANN for water quality management. ANN based decision-making approach for water quality management to control environmental pollution was presented in their work. Previous research on water quality management problems has shown that traditional optimization techniques and an expert-system approach do not provide an educated solution comparing with decision making approach, which is related to the interpretation of data based on certain set of rules. Muhammad et al (2004) conducted a comprehensive study using ANN model for forecasting ground water contamination. In their study, a Neural Network Model for forecasting the concentration of different hazardous metals in groundwater has been developed. ANN model was implemented for future prediction of effluent quantities. Diamantopoulos et al (2007) used Cascade Correlation Artificial neural Network (CCANN) for estimating the missing monthly values of water quality parameters in rivers. Other existing water quality parameters are taken as input variables. A detailed study on the water quality of Axios River was conducted during 1980 to 1994 stationed near Greek FYROM borders and Strymon River stationed at Greek- Bulgarian border during 1980 to 1990 were the subjects of study. Huiqun and Ling (2008) introduced ANN and Fuzzy logic interface for water quality assessment of Dongchang lake in Liaocheng city.

5. APPLICATION IN GROUND WATER MODELLING:

Groundwater is valuable supply resource for domestic, farming and industrial-based activities. Accuracy and liability are the significant factors in a ground water level model. As the water level changes periodically hence sustainability can only be ensured by a perfect forecasting model. Groundwater level forecasting in a watershed plays an important role in management of groundwater resources, especially in a semi-dry area where there is huge need of groundwater resources in order to prepare the requirement water for farming, municipal and industrial affairs. It is difficult to separate ground water and water quality as different sections.

Aziz and Wong (1992) determine aquifer parameter values from normalized drawdown data obtained from pumping tests by using ANN model. This is commonly referred to as the reverse problem in ground-water hydrology. Ranjithan et al. (1993) used a three-layer feedforward network to screen such critical realizations by first identifying characteristics that cause a realization to be a critical one. The network predicted a single output that represented how critical realization was going to be on a normalized. The authors concluded that the pattern recognition strengths of ANNs are particularly useful for identifying the more critical realizations.

Rizzo and Dougherty (1994) introduced the idea of neural kriging for characterization of aquifer properties. A three-layer neural network utilizing the counter propagation algorithm was combined with kriging for estimating hydraulic conductivity. The input nodes represented the coordinates of observation points. The output nodes predicted the class of hydraulic conductivity at various locations. They concluded that ANNs could be useful tools in geohydrology when applied to specific problems of aquifer characterization. Johnson and Rogers (1995) they concluded that ANNs, combined with a genetic algorithm, result in robust and flexible tools that can be used for planning effective strategies in ground-water remediation. Yang et al. (1997) predicted water table elevations in subsurface drained farmlands by using ANN model. Inputs which they used are daily rainfall, previous water table locations and potential evapotranspiration. The output was the current location of the water table. They found that a three-layer feedforward ANN could predict water table elevations satisfactorily after training using observed values.

Nayak et. al (2005) used Artificial Neural Network(ANN) approach for groundwater level forecasting in a shallow aquifer. This paper reports a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India. The most appropriate set of input variables to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. The results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Nourani et. al. (2012) estimates ground water level (GWL) by mathematical based model of Ardabil located at northwest of Iran. Three layer Feed Forward Artificial Neural Network (ANN) was used to correlate the model via groundwater level records from representative wells and relevant hydrological data. Results can be used to frame the corresponding strategies to reduce the monitoring cost and to increase the effective cost-benefits.

6. CONCLUSIONS:

The review work conducted here concludes that ANN models act as impeccable forecasting tool especially for rainfall-runoff prediction, stream-flow prediction, groundwater hydrology etc. as compared to other models. Feed-Forward-Back-Propagation (FFBP) method is widely being used in many of the hydrological problem. However some other approaches like multiple input single output (MISO) model are used in case of rainfall-runoff, in case of streamflow modelling recurrent neural network (RNN) is employed, in water quality modelling cascade correlation artificial neural network (CCANN) model is used and so-on.

A deep understanding of the hydrological process, would impart a great help in designing perfect ANN model endeavouring all the factors. As ANN is gaining acceptance among researchers, it should produce improved models with remarkable results.

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