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UTILIZATION OF ARTIFICIAL NEURAL NETWORKS IN HYDROLOGICAL STUDIES: A COMPREHENSIVE REVIEW

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Abstract: This paper presents a thorough review of the use of Artificial Neural Networks (ANNs) in addressing hydrological challenges, offering a simpler and more efficient alternative to traditional computational methods, which are often complex and computationally intensive. ANNs, leveraging artificial intelligence, have been effectively applied in areas such as rainfall-runoff modeling, streamflow forecasting, water quality assessment, and groundwater management. A clear understanding of the hydrological processes being modeled is crucial for selecting appropriate input parameters and designing efficient ANN architectures. This review highlights various ANN applications, demonstrating their accuracy and utility in solving hydrological problems, making them a valuable tool for engineering applications.
Keywords: Artificial Neural Network (ANN), Feed-Forward Neural Network, Hydrology, Rainfall-Runoff Modeling, Streamflow Forecasting, Water Quality, Groundwater.

Introduction. Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks in the human brain, which consist of billions of interconnected neurons. Advances in computational technology have enabled ANNs to emulate the brain's parallel processing and distributed data storage capabilities. ANNs are mathematical frameworks capable of modeling complex, non-linear relationships between inputs and outputs in various systems.

An ANN comprises multiple interconnected processing units, or neurons, organized into layers: an input layer, one or more hidden layers, and an output layer. The connections between neurons are assigned weights, which represent the strength of the signal transmitted, akin to synaptic strengths in biological systems. During training, these weights are adjusted iteratively to minimize the difference between predicted and actual outputs. The training process relies on specific rules to optimize the network's performance based on provided input-output data pairs.

A widely used ANN architecture is the Multi-Layer Perceptron (MLP), a feed-forward neural network consisting of input, hidden, and output layers. In an MLP, data flows unidirectionally from the input to the output layer, with processing occurring in the hidden layers. Figure 1 illustrates a typical MLP with one hidden layer, showcasing its fully connected structure.

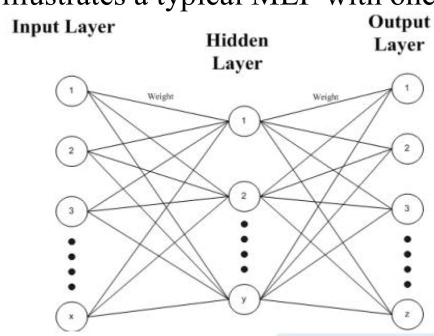

Figure 1: Schematic representation of a Multi-Layer Perceptron (MLP) with one hidden layer.

The Feed-Forward Back-Propagation (FFBP) algorithm is a common supervised training method for MLPs. In this approach, the network is trained using input-output pairs, and the error between predicted and actual outputs is calculated. The weights are then adjusted backward from the output layer to the input layer to minimize this error, improving the network's predictive accuracy.

Rainfall-Runoff Modeling

Rainfall-runoff modeling is inherently complex due to the non-linear, spatially variable, and time-dependent nature of hydrological processes. Traditional modeling approaches, such as conceptual, physically-based, or empirical models, often require intricate mathematical formulations and extensive calibration, making them challenging to implement. For instance, unit hydrograph models assume linear relationships between rainfall and runoff, which fail to capture the non-linear dynamics of the process.

ANNs offer a robust alternative by establishing direct relationships between rainfall (input) and runoff (output) without requiring detailed knowledge of the catchment's physical characteristics. The ANN learns these relationships through training, implicitly accounting for the underlying hydrological processes. Early applications of ANNs in rainfall-runoff modeling include the work of French et al. (1992), who pioneered the use of ANNs in hydrology. Halff et al. (1993) employed a three-layer feed-forward ANN to predict hydrographs, while Kothayari (1995) and Raman & Sunil Kumar (1995) used ANNs to estimate mean monthly runoff and rainfall, respectively.

Subsequent studies have advanced ANN applications in this domain. Mason et al. (1996) demonstrated that Radial Basis Function (RBF) networks offer faster training compared to standard back-propagation for rainfall-runoff modeling. Sajikumar & Thandaveswara (1999) applied a Temporal Back-Propagation Neural Network (TBP-NN) for monthly rainfall-runoff modeling in data-scarce regions. The ASCE Task Committee (2000a, b) conducted a comprehensive evaluation of ANNs in hydrology, comparing their performance with other modeling techniques. Rajurkar et al. (2002) combined ANNs with a Multiple-Input-Single-Output (MISO) model to improve runoff predictions for large catchments. More recent studies, such as those by Kalteh (2008), Goyal et al. (2010), and Chen et al. (2013), have further refined ANN-based rainfall-runoff models using techniques like Neural Interpretation Diagrams, dimensionless variables, and Feed-Forward Back-Propagation, respectively, achieving high accuracy in complex scenarios like typhoon-induced runoff.

Streamflow Forecasting

Streamflow forecasting is critical for water resource management, supporting decisions related to hydropower, irrigation, drought mitigation, and flood control. Accurate forecasts enable real-time operations (hours to days) and long-term planning (weeks to months). Unlike rainfall-runoff modeling, streamflow forecasting often focuses on predicting flow without directly incorporating precipitation data, treating streamflow as an estimate of watershed runoff.

ANNs have been widely applied in streamflow forecasting. Kang et al. (1993) compared ANN models with autoregressive moving average (ARMA) models for daily and hourly streamflow predictions in the Pyung Chang River basin, Korea, concluding that ANNs outperformed traditional methods. Karunanithi et al. (1994) used a Cascade-Correlation algorithm to predict flows in the Huron River, demonstrating ANNs' ability to capture flow variations. Markus et al. (1995) applied a back-propagation ANN to forecast monthly streamflows in the Rio Grande Basin, incorporating snow water equivalent and temperature as inputs, and found improved performance with temperature inclusion.

Other notable studies include Poff et al. (1996), who used ANNs to assess streamflow changes under climate change scenarios, and Shrivastava & Jain (1999), who compared ANN and ARIMA models for reservoir inflow predictions, favoring ANNs. Birikundayyi et al. (2002), Kumar et al. (2004), and Kişi (2004) further demonstrated the superiority of ANN-based models, including Recurrent Neural Networks (RNNs), over ARMA and autoregressive (AR) models for daily and

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monthly streamflow forecasting. Wang et al. (2005) explored hybrid ANN models, such as Threshold-based ANN (TANN), Cluster-based ANN (CANN), and Periodic ANN (PANN), for enhanced daily streamflow predictions.

Water Quality Modeling

Water quality modeling involves predicting physical, chemical, and biological parameters influenced by factors such as flow rates, contaminant loads, and environmental conditions. The non-linear and interdependent nature of these parameters makes ANNs an ideal tool for water quality assessment.

Maier and Dandy (1996) used ANNs to predict salinity levels in the River Murray, Australia, using inputs like upstream salinity, water levels, and flow data. The model, trained with a back-propagation algorithm and two hidden layers, accurately forecasted salinity up to 14 days in advance. Rogers (1992) and Rogers & Dowla (1994) applied ANNs for groundwater remediation, training the network with a solute transport model to optimize remediation strategies. Morshed & Kaluarachchi (1998) used ANNs to estimate hydraulic conductivity and grain size distribution for free product recovery, enhancing efficiency with genetic algorithm guidance.

Further applications include Hui (2000) and Xiaohua (2000), who modeled eutrophication in the Singapore Strait, and Zaheer & Bai (2003), who developed an ANN-based decision-making framework for water quality management. Muhammad et al. (2004) forecasted groundwater contamination levels for hazardous metals, while Diamantopoulos et al. (2007) used Cascade Correlation ANNs (CCANNs) to estimate missing water quality parameters in rivers like the Axios and Strymon. Huiqun & Ling (2008) combined ANNs with fuzzy logic for water quality assessment in Dongchang Lake, China.

Groundwater Modeling

Groundwater is a critical resource for domestic, agricultural, and industrial use, and accurate forecasting of groundwater levels is essential for sustainable management, particularly in water-scarce regions. ANNs have proven effective in modeling groundwater levels and aquifer properties due to their ability to handle periodic and non-linear variations.

Aziz & Wong (1992) used ANNs to estimate aquifer parameters from pumping test data, addressing the inverse problem in groundwater hydrology. Ranjithan et al. (1993) employed a feed-forward ANN to identify critical aquifer realizations, leveraging the pattern recognition capabilities of ANNs. Rizzo & Dougherty (1994) introduced neural kriging, combining a counter-propagation ANN with kriging to estimate hydraulic conductivity, demonstrating its utility in aquifer characterization.

Johnson & Rogers (1995) combined ANNs with genetic algorithms for groundwater remediation planning, while Yang et al. (1997) predicted water table elevations in subsurface-drained farmlands using rainfall, evapotranspiration, and prior water table data as inputs. Nayak et al. (2005) forecasted groundwater levels in a shallow coastal aquifer in India, achieving reliable predictions up to four months in advance. Nourani et al. (2012) used a three-layer feed-forward ANN to model groundwater levels in Ardabil, Iran, optimizing monitoring costs and improving resource management.

Conclusions

This review underscores the versatility and effectiveness of ANNs in hydrological modeling, particularly in rainfall-runoff prediction, streamflow forecasting, water quality assessment, and groundwater management. The Feed-Forward Back-Propagation (FFBP) algorithm is the most commonly used training method, though other architectures, such as Multiple-Input-Single-Output (MISO) models for rainfall-runoff, Recurrent Neural Networks (RNNs) for streamflow, and Cascade Correlation ANNs (CCANNs) for water quality, have also been successfully employed. A deep understanding of the underlying hydrological processes is essential for

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designing effective ANN models that incorporate relevant input variables and network architectures. As ANNs gain wider acceptance in the hydrological research community, ongoing advancements are expected to yield even more accurate and robust models for real-world applications.

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