Overview of Artificial Neural Networks Applications in Groundwater Studies

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Abstract - *The application of Artificial Neural Networks (ANNs) has increased in many fields of engineering and sciences. In groundwater studies, ANNs have been successfully used to solve many problems. In this research, the literature review shows that ANNs have been applied successfully in groundwater hydrodynamic, water management, water resources, hydrochemistry, time series forecasting, hydro-geotechnical engineering, sea-aquifer interaction, hydro-geochemistry, data collection in harsh environments and pit dewatering. The aim of this research is to provide an overview of the capacity of ANNs to solve some hydrogeological problems. This paper does not intend to show each single application of ANNs that can be found in the literature.*

Key Words: Artificial Neural Networks, Neurophysiological process, Architecture, Groundwater.

1. INTRODUCTION

Artificial Neural Networks (ANNs) are part of Artificial Intelligence. They are a mechanism that reproduces the cognitive function of the brain by simulating its architecture. By imitating the human brain's structure and function, ANNs are well-known to be powerful in solving complex, noisy and non-linear problems (Hsieh, 1993). They are successfully used for approximating functions, task classifications and clustering (Allende *et al*., 2002; Hsieh, 1993; Khashei and Bijari, 2009; Wilamowski, 2007). ANNs learn from the available data describing the behaviour of a system and attempt to establish a relationship between these data, even if the physical mechanisms controlling the behaviour of the system are poorly understood. They are thus suitable to model the complex behaviour of aquifers which by nature are anisotropic and heterogeneous.

The learning and generalisation processes of ANNs are based on neurophysiological processes, and are described through mathematical relations that mimic the neurophysiological functioning.

2. NEUROPHYSIOLOGICAL PROCESSES

The human brain contains almost 100 billion neurons with 1 000 to 10 000 synapses by neuron. The way the brain processes information is not yet well known, although there are many available applications (Ellis *et al.,* 1995; Park et *al.*, 2009, Goh *et al.*, 2005; Cho, 2009; Shi, 2000). Neurons can be defined as biological cells which have body cells and nuclei. Information is collected by fine structures called dendrites. A neuron produces an electrical signal and sends it through an axon, which is divided into several branches. That electrical signal is converted in an effect at each end of the branch by a synapse which then generates activity in connected neurons.

When a neuron is excited enough, compared to its input, it generates electricity and sends its signal to its axon. Learning occurs when the effectiveness of the synapses changes, causing neurons to influence each other.

3. MATHEMATICAL MODELS

Biological neurons can perform various tasks such as body recognition, signal processing and generalisation. The performance of the neurons can be described by mathematical relations, which can be transformed into algorithms, leading to the development of Artificial Intelligence. ANNs are models of the neurophysiology of the brain that may be described by their components, descriptive variables and interactions between components (Rojas, 1996). Together, the components of the ANNs and the interactions between these components form the architecture of the ANNs.

3. 1. NEURAL NETWORK ARCHITECTURE

An ANN is based on an interconnection of nodes, called neurons, that works as a collective system. This system comprises neurons and links. Each link has a weight, which is a numerical value representing the connection strength between the neurons (see Figure -1). The sum of the input weights is converted to outputs through a transfer function (TF) (Wilamowski, 2003).

ANNs contain three kinds of layers:

- An input layer which has the predicator variable;
- One or more hidden layers which function as a collection of feature detectors;
- An output layer used to produce a response relative to the inputs.

ANNs can function using either feed-forward or feedback methods, using single or multiple hidden layers.

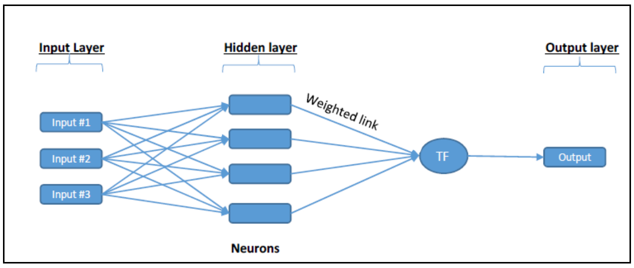

Figure -1: Example of an ANN with one hidden layer (Li E., 1994)

3. 1. 1 FEED-FORWARD NETWORKS

Feed-Forward Neural Networks (FFNNs) are widely used. One such FFNN is the Multi-Layer Perceptron (MLP). In these neural networks, information progressions are unidimensional going from input layer to output layer through hidden layers (Millar and Calderbank, 1995).

3. 1. 2 FEEDBACK NETWORKS

Feedback Networks (FBNs) are neural networks that process information in both directions by introducing loops in the network. They have an interactive or recurrent architecture. Their output is often used to create feedback connections in single layer organization. They can become very complex, but are often useful for solving complex problems (Rojas, 1996).

3. 2 TRANSFER FUNCTION

An ANN should be able to reproduce the correct output for the related inputs. Its behaviour depends on the weights and the input-output function operating at each neuron, called the transfer function. While using an ANN, the choice of the transfer function can deeply impact the behaviour of the whole network. The most commonly used transfer functions are (Hajek, 2005):

- Linear, where the output from the neuron is directly proportional to the total weighted input that it receives from the other neurons connected to it;
- Threshold, where the output is set to a higher or lower level depending on whether the total input is greater or less than some threshold value;
- Sigmoidal (logistic), where the output changes progressively but not linearly according to changes in the weighted input;
- Hyperbolic tangent, where the fluctuation between consecutive inputs is relative to the hyperbolic tangent derivative.

It is important to note that the threshold, sigmoidal and hyperbolic transfer functions are non-linear (Pushpa and Manimala, 2014).

3. 3 OPTIMISATION OF THE MODEL

The process of optimisation of ANNs is also called the "training" or "learning" process. According to Rumelhart *et al.* (1986), the most commonly used method is the back-propagation algorithm. This algorithm is non-linear and is more often applied when using multi-layer perceptrons (Brown and Harris, 1994). Perceptrons are algorithms, which can be computed by a binary variable coding. They can be linear or spherical according to the way outputs are computed. It is expensive to compute the back-propagation algorithm, especially during the learning process. It is then important to find an alternative simplified method, which can speed the learning process and produce reasonable outputs for new inputs.

3. 4 STOPPING CRITERIA

When optimising ANNs, it is important to decide when the training process has to be stopped. The stopping criteria determine when the ANN has been optimally trained. The training process can be stopped when a) a fixed number of training inputs have been reached, or b) when the training error becomes acceptably small. The first stopping criterion could lead a prematurely cessation of training, while the second could lead to over-training.

Cross-validation is a valuable technique to avoid such problems (Smith, 1993). When available inputs are limited, Amari *et al.* (1997) suggested using the cross-validation technique because it presents many advantages. In this technique, the data are divided in three parts: training, testing and validation. The training part is used to train and build the model. The testing part measures the ability of generalisation of the model. The training is stopped when the error of the testing set starts to increase, even if the number of iterations has not been reached. The validation part is used for performance analysis. It is also possible to divide the dataset into two parts where one part is used for training and the other for validation.

3. 5 APPLICATION OF ANNs IN GROUNDWATER STUDIES

An ANN can be seen as a universal approximator. Its ability to learn and generalise makes the ANN a powerful tool able to solve various complex problems, such as: pattern recognition, stock forecasting, non-linear modelling, and classification of data according to type. In geohydrology, ANNs have had a significant growth since Rumelhart *et al.* (1986) developed their computational mechanism. This approach is now used in all branches of engineering and the sciences.

Many water-related problems need to be solved by prediction and estimation. Most hydrogeological processes show high fluctuation, both spatially and temporally. They are often non-linear physical processes. Often there is large uncertainty in the parameters affecting the processes (McCuen, 1997).

Geohydrologists or hydrogeologists have to provide answers to complex problems related to water management. To provide answers to these problems, ANNs offer the possibility of finding relationships between the inputs and outputs of processes even if these processes are not well understood. The applicability of ANNs in geohydrology is extensive. These networks can identify the relation between noisy data and help to generate simple rules (Sarkar, 2012).

ANNs can be applied to mimic temporally and spatially distributed human influences, such as water extraction patterns, on a regional scale with high predictive accuracy for complex groundwater system, as shown by Feng *et al*. (2008). Sensitivity studies done with ANNs are an effective and efficient tool, which can help decision-makers to understand the impact of human activity on the aquifer.

Using ANNs, Joorabchi *et al*. (2009) found that tide variation is the main parameter impacting the water table in coastal anisotropic aquifers. Abrahart and See (2007) concluded that these networks can be used to produce understandable non-linear transformations in the study of aquifers.

The power of ANNs to model complex non-linear problems is one of its strengths which can provide output datasets ready to be used in other areas of groundwater research, such as hydrochemistry (Seyam, 2010) and hydrodynamics (Aziz and Wong, 1992).

ANNs are known to be able to generate accurate predictions. The accuracy of these networks may be further improved by using them in combination with numerical models (Szidarovszky *et al*., 2007). This hybridisation method can be used to evaluate the performance of Finite Difference-based models and ANNS, as shown by Mohanty *et al.* (2013).

ANNs are able to forecast time series (Sudheer *et al.*, 2002; Yoon *et al.*, 2007; Kumar *et al.*, 2013) and compared to the performance of a hybrid model, the results suggest that both the ANN and hybrid model can successfully be used for the prediction of the temporal behaviour of groundwater levels.

ANNs combined with numerical based-models have been used for predicting liquefaction potential in soil deposits (Farrokhzad *et al*., 2010). This combination provides results that are more accurate.

In studies to protect coastal aquifers against seawater intrusions, ANNs have been developed, optimized and then combined with numerical models to provide better predictions, even for complex pumping system (Kourakos and Mantoglou, 2009). Additional to the study of groundwater quality in coastal areas, Yoon *et al*. (2011) developed two hydrogeological models based on Support Vector Machines (another form of machine learning) and ANNs to forecast the short-term fluctuations of the groundwater table of a coastal aquifer in Korea. It was observed that the Support Vector Machines gave more accurate results for long prediction times than ANNs. Seawater intrusion can increase the salinity of islands. It was observed by Banerjee *et al*. (2011) that when the pumping rate increases, the salinity of the aquifer also increases. Thus, they used both ANNs and SUTRA (Saturated-Unsaturated Transport; an FEM code) to predict the minimum acceptable pumping rate which would leave the salinity below an acceptable threshold. Comparing the results founds with SUTRA and ANNs to the observations, they concluded that ANNs provided more accurate predictions even though these networks required fewer inputs than SUTRA.

Juan *et al*. (2015) used ANNs to forecast suprapermafrost groundwater levels. Since permafrost areas are typically harsh environments, data collection in these areas is demanding, with the result that only a limited number of studies have focussed on understanding the behaviour of the aquifers in such areas. Juan *et al*. (2015) stated that the groundwater hydrodynamics of permafrost areas is not controlled by Darcy flow, but by thermodynamics. The authors employed ANNs in their investigations and used temperature, rainfall data and previous suprapermafrost groundwater levels as inputs to the ANNs to predict the suprapermafrost groundwater level. They observed that the results were satisfactory when compared to the field observations, although the accuracy of the predictions decreased with increasing prediction time.

Mohanty *et al.* (2013) developed a groundwater model based on FDM, as well as ANNs, to predict the depletion of water in a region of India. After comparing the results of these studies to the field observations, they found ANNs to be more accurate for short-term predictions while FDM are more suitable for long-term predictions. They therefore recommended the combined use of these two methods to complement one another and ensure good decision-making in groundwater management.

The coupling of numerical models and ANNs have been used to evaluate the interaction between rivers and aquifers, providing rapid results. These hybrid models can easily be extended to other complex scenarios (Parkin *et al.*, 2001). Tapoglu *et al.* (2014) combined the use of ANNs and Kriging methods to predict the groundwater level changes in Bavaria (Germany). They used the hydraulic head data recorded at 64 piezometers to train 64 ANNs, one for each piezometer. At positions removed from the piezometers interpolation with Kriging was used to estimate the hydraulic heads. It was found that this approach was powerful and required few inputs, making it a useful tool for the prediction of groundwater level changes in areas with limited geological and hydrogeological data.

Hybridisation of approaches were shown in the last decade to be a more powerful technique for estimation and prediction of groundwater behaviour (Yeh, 1992; Das and Datta, 2001). Thus, Bahrami *et al*. (2016) developed a hybrid model to predict the groundwater inflow during the advance of an open pit during mining. First they developed an ANN to perform the predictions. Since the performance of ANNs depends on the architecture of the network and a proper selection of weights for the connections between neurons, the authors used the Genetics Algorithm (GA) and Simulated Annealing (SA) to determine initial weights so as to obtain more accurate solutions. Thus, they developed a hybrid model based on ANN-GA and ANN-SA to predict the groundwater inflow during the pit advance. The comparison between the measured groundwater inflows and the predicted inflows gave better results for hybrid models than when using a simple ANN.

Ardejani *et al.* (2013) used ANNs to predict the water table rebound in an excavation were the water table was below the floor of the pit. The authors stated that the methods commonly used to predict groundwater rebound require a lot of inputs, such as hydraulic conductivities, transmissivities, initial hydraulic heads, rainfall data and specific storages. Accurate information on these parameters is often difficult to obtain. Furthermore, since the system is nonlinearly dependent on these parameters, inaccuracies in the parameter estimates could lead to large errors in the predicted responses. To avoid such errors, the authors used ANNs to predict the behaviour of the groundwater level during rebound in the open pit mine. The predicted hydraulic heads were compared to the observed field data, and a correlation coefficient (R-value) of 0.986 was obtained, showing good agreement between the observed and predicted water levels.

However, if the available input data are sparse, it is important to use alternative methods, which start by using real or synthetic observations where the number of inputs can be reduced. Using this approach, Mohammadi (2008) employed synthetic observations generated from a groundwater model based on the finite difference method to implement an ANN model. The objective of his study was to investigate the applicability of ANNs in groundwater level simulation without any well boundary conditions and with limited data. In this research, different ANNs were used to predict the groundwater elevation. Although a few networks gave poor results, the majority of the ANNs predicted the groundwater elevations with a high degree of accuracy. It was therefore concluded that ANNs could be effectively used for groundwater modelling.

7. DISCUSSION AND CONCLUSION

From literature, it can be seen that ANNs have been used successfully in many area of groundwater studies including groundwater hydrodynamic, water management, water resources, hydrochemistry, time series forecasting, hydro-geotechnical engineering, sea-aquifer interaction, hydro-geochemistry, data collection in harsh environments and pit dewatering.

Based on these applications, analysis indicate that ANNs provide better and more accurate results than “conventional methods” in many situations.

Despite the accuracy of ANNs results, they are have some shortcomings (not enough theory for their development, inability to explain clearly how the solution was found). Thus, some guidelines has to be developed to make a clear design process of ANNs.

Finally, despite these weaknesses, ANNs are powerful tools to model and predict nonlinear behaviours encountered in groundwater studies.

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BIOGRAPHY

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