APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN WATER RESOURCES

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INTRODUCTION

The research in Artificial Neural Networks (ANNs) started with attempts to model the biophysiology of the brain, creating models which would be capable of mimicking human thought processes on a computational or even hardware level. Humans are able to do complex tasks like perception, pattern recognition, or reasoning much more efficiently than state-of-the-art computers. They are also able to learn from examples and human neural systems are to some extent fault tolerant. The most common ANNs consist of several layers of simple processing elements called neurons, interconnections among them and weights assigned to these interconnections. The information relevant to the input–output mapping of the net is stored in the weights. A neural network is not programmed like a conventional computer program, but is presented with examples of the patterns, observations and concepts, or any type of data which it is supposed to learn. Through the process of learning (also called training) the neural network organizes itself to develop an internal set of features that it uses to classify information or data. Due to its massively parallel processing architecture the ANN is capable of efficiently handling complex computations, thus making it the most preferred technique today for high speed processing of huge data. Other advantages include:

1. ***Adaptive learning:*** An ability to learn how to do tasks based on the data given for training or initial experience.
2. ***Self-Organisation:*** An ANN can create its own organisation or representation of the information it receives during learning time.
3. ***Real Time Operation:*** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. ***Fault Tolerance via Redundant Information Coding:*** Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

These properties make ANN suitable candidates for various engineering applications such as pattern recognition, classification, function approximation, system identification, hydrological modeling etc.

This lecture describes the concept of artificial neuron, ANN structure, back propagation algorithm, and ANN applications in water resources.

BIOLOGICAL NEURON

It is claimed that the human central nervous system is comprised of about 1,3x1010 neurons and that about 1x1010 of them takes place in the brain. At any time, some of these neurons are firing and the power dissipation due this electrical activity is estimated to be in the order of 10 watts. A neuron has a roughly spherical cell body called soma (Figure 1). The signals generated in soma are transmitted to other neurons through an extension on the cell body called ***axon*** or ***nerve fibres.*** Another kind of extensions around the cell body like bushy tree is the ***dendrites***, which are responsible from receiving the incoming signals generated by other neurons.

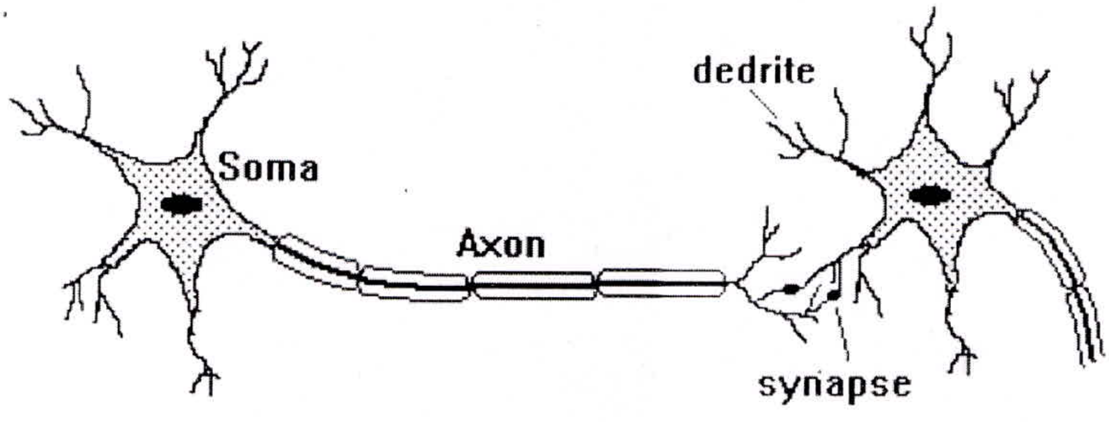

Figure 1: Typical Neuron

As it is mentioned in the previous section, the transmission of a signal from one neuron to another through synapses is a complex chemical process in which specific transmitter substances are released from the sending side of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If this graded potential reaches a threshold, the neuron fires. It is this characteristic that the artificial neuron model proposed by McCulloch and Pitts, (McCulloch and Pitts 1943) attempt to reproduce.

Research into *models* of the human brain already started in the 19th century (James, 1890). It took until 1943 before McCulloch and Pitts (1943) formulated the first ideas in a mathematical model called the McCulloch-Pitts neuron. In 1957, a first multilayer neural network model called the perceptron was proposed. However, significant progress in neural network research was only possible after the introduction of the backpropagation method (Rumelhart, et al., 1986), which can train multi-layered networks.

ARTIFICIAL NEURON

Mathematical models of biological neurons (called artificial neurons) mimic the functionality of biological neurons at various levels of detail. A typical model is basically a static function with several inputs (representing the dendrites) and one output (the axon). Each input is associated with a weight factor (synaptic strength). The weighted inputs are added up and passed through a nonlinear function, which is called the *activation function* (ASCE, 2000a; APPENDIX-I). The value of this function is the output of the neuron (Figure 2).

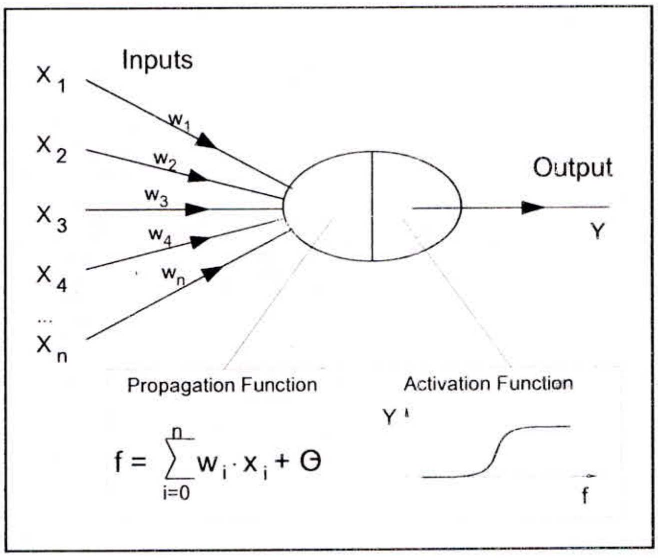

Figure 2: Processing Element of ANN

NEURAL NETWORK ARCHITECTURE

A typical ANN model consists of number of layers and nodes that are organised to a particular structure. There are various ways to classify a neural network. Neurons are usually arranged in several *layers* and this arrangement is referred to as the *architecture* of a neural net. Networks with several layers are called *multi-layer* networks, as opposed to *single-layer* networks that only have one layer. The classification of neural networks is done by the number of layers, connection between the nodes of the layers, the direction of information flow, the non linear equation used to get the output from the nodes, and the method of determining the weights between the nodes of different layers. Within and among the layers, neurons can be interconnected in two basic ways: (1) *Feedforward networks* in which neurons are arranged in several layers. Information flows only in one direction, from the input layer to the output layer, and (2) *Recurrent networks* in which neurons are arranged in one or more layers and feedback is introduced either internally in the neurons, to other neurons in the same layer or to neurons in preceding layers. The commonly used neural network is three-layered feed forward network due to its general applicability to a variety of different problems and is presented in Figure 3

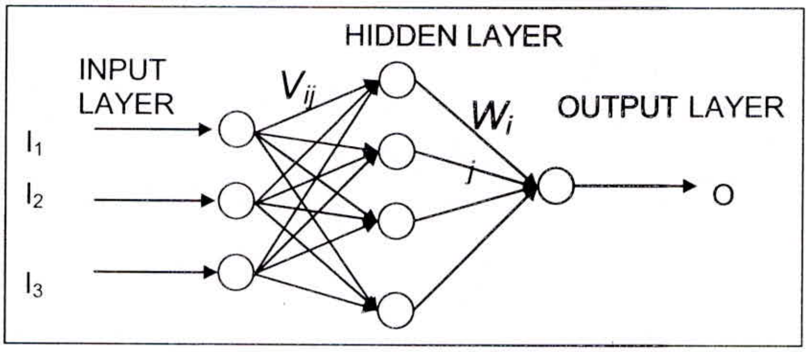

Figure 3: A Typical Three-Layer Feed Forward ANN (ASCE, 2000a)

LEARNING

The learning process in biological neural networks is based on the change of the interconnection strength among neurons. Synaptic connections among neurons that simultaneously exhibit high activity are strengthened. In artificial neural networks, various concepts are used. A mathematical approximation of biological learning, called Hebbian learning is used, for instance, in the Hopfield network. Multi-layer nets, however, typically use some kind of optimization strategy whose aim is to minimize the difference between the desired and actual behavior (output) of the net. Two different learning methods can be recognized: supervised and unsupervised learning:

Supervised learning: the network is supplied with both the input values and the correct output values, and the weight adjustments performed by the network are based upon the error of the computed output.

Unsupervised learning: the network is only provided with the input values, and the weight adjustments are based only on the input values and the current network output. Unsupervised learning methods are quite similar to clustering approaches.

MULTI-LAYER NEURAL NETWORK

A multi-layer neural network (MNN) has one input layer, one output layer and a number of hidden layers between them. In a MNN, two computational phases are distinguished:

1. *Feedforward computation.* From the network inputs (xi, $i = 1, \ldots, n$), the outputs of the first hidden layer are first computed. Then using these values as inputs to the second hidden layer, the outputs of this layer are computed, etc. Finally, the output of the network is obtained.
2. *Weight adaptation.* The output of the network is compared to the desired output. The difference of these two values called the error, is then used to adjust the weights first in the output layer, then in the layer before, etc., in order to decrease the error. This backward computation is called error backpropagation. The error backpropagation algorithm was proposed by and Rumelhart, et al. (1986) and it is briefly presented in the following section.

Feedforward Computation

In a multi layer neural network with one hidden layer, step wise the feed forward computation proceeds as:

I. Forward Pass

Computations at Input Layer

Considering linear activation function, the output of the input layer is input of input layer:

$$O_l = I_l \tag{1}$$

where, O_l is the l^{th} output of the input layer and I_l is the l^{th} input of the input layer.

Computations at Hidden Layer

The input to the hidden neuron is the weighted sum of the outputs of the input neurons:

$$I_{hp} = u_{1p}O_1 + u_{2p}O_2 + \ldots.. + u_{lp}O_l \quad (2)$$

for $p = 1,2,3,\ldots..m$

where, I_{hp} is the input to the p^{th} hidden neuron, u_{lp} is the weight of the arc between l^{th} input neuron to p^{th} hidden neuron and m is the number of nodes in the hidden layer.

Now considering the sigmoidal function the output of the p^{th} hidden neuron is given by:

$$O_{hp} = \frac{1}{(1 + e^{-\lambda(I_{hp} - \theta_{hp})})} \quad (3)$$

where O_{hp} is the output of the p^{th} hidden neuron, I_{hp} is the input of the p^{th} hidden neuron, θ_{hp} is the threshold of the p^{th} neuron and λ is known as sigmoidal gain. A non-zero threshold neuron is computationally equivalent to an input that is always held at -1 and the non-zero threshold becomes the connecting weight values.

Computations at Output Layer

The input to the output neurons is the weighted sum of the outputs of the hidden neurons:

$$I_{Oq} = w_{1q}O_{h1} + w_{2q}O_{h2} + \ldots.. + w_{mq}O_{hm} \quad (4)$$

for $q = 1,2,3,\ldots.n$

where, I_{Oq} is the input to the q^{th} output neuron, w_{mq} is the weight of the arc between m^{th} hidden neuron to q^{th} output neuron.

Considering sigmoidal function, the output of the q^{th} output neuron is given by:

$$O_{Oq} = \frac{1}{(1 + e^{-\lambda(I_{Oq} - \theta_{Oq})})} \quad (5)$$

where, O_{Oq} is the output of the q^{th} output neuron, λ is known as sigmoidal gain, θ_{Oq} is the threshold of the q^{th} neuron. This threshold may also be tackled again considering extra 0^{th} neuron in the hidden layer with output of -1 and the threshold value θ_{Oq} becomes the connecting weight value.

Computation of Error

The error in output for the r^{th} output neuron is given by:

$$\xi^{l} = \frac{1}{2}\sum_{r=1}^{n}(T_{Or} - O_{or})^{2} \tag{6}$$

where O_{Or} is the computed output from the r^{th} neuron and T_{Or} is the target output.

Equation (4.19) gives the error function in one training pattern. Using the same technique for all the training patterns the error function become

$$\xi = \sum_{j=1}^{N}\xi^{j} \tag{7}$$

where, N is the number of input-output data sets.

Training of Neural Network

Training is the adaptation of weights in a multi-layer network such that the error between the desired output and the network output is minimized.

II. Backword Pass

For k^{th} output neuron, E_k is given by

$$\xi_{k} = \frac{1}{2}(T_{k} - O_{ok})^{2} \tag{8}$$

where, T_k is the target output of the k^{th} output neuron and O_{ok} is the computed output of the k^{th} output neuron. The output of the k^{th} output neuron is given by

$$O_{Ok} = \frac{1}{(1 + e^{-\lambda(I_{Ok} - \theta_{Ok})})} \tag{9}$$

The change of weight for weight adjustment of synapses connecting hidden neurons and output neurons is expressed as:

$$\Delta w_{ik} = -\eta\frac{\partial \xi_{k}}{\partial w_{ik}} = -\eta \cdot O_{hi} \cdot d_{k} \tag{10}$$

where, $d_k = \lambda \cdot (T_K - O_{Ok}) \cdot O_k \cdot (1 - O_{Ok})$ and η is learning rate constant

Learning rate coefficient determines the size of the weight adjustment made at each iteration and hence influences the rate of convergence. Poor choice of the learning coefficient can result in a failure in convergence. For a too large learning rate coefficient the search path will oscillate and jump past the minimum. For a very small learning rate coefficient the descent will progress in a small steps and thus significantly increase the time of convergence.

Therefore, change of weight for weight adjustment of synapses connecting input neurons and hidden neurons is expressed as:

$$\Delta u_{ij} = -\eta \frac{\partial \xi_k}{\partial u_{ij}} = -\eta[\{-w_{ik} d_k\} \cdot \{\lambda(O_{hi})(1-O_{hi})\} \cdot \{I_{ij}\}] \tag{11}$$

The performance of the backpropagation algorithm depends on the initial setting of the weights, learning rate, output function of the units (sigmoidal, hyperbolic tangent etc.) and the presentation of training data. The initial weights should be randomized and uniformly distributed in a small range of values. Learning rate is important for the speed of convergence. Small values of learning parameter may result in smooth trajectory in the weight space but takes long time to converge. On the other hand large values may increase the learning speed but result in large random fluctuations in the weight space. It is desirable to adjust the weights in such a way that all the units learn nearly at the same rate. The training data should be selected so that it represents all data and the process adequately. The major limitation of the backpropagation algorithm is its slow convergence. Moreover, there is no proof of convergence, although it seems to perform well in practice. Some times it is possible that result may converge to local minimum and there is no way to reduce its possibility. Another problem is that of scaling, which may be handled using modular architectures and prior information about the problem.

ANN: MODEL DESIGN & TRAINING

Before applying ANN, the input data need to be standardized so as to fall in the range [0,1]. A typical hydrological variable, say river discharge (Q), which can vary between Qmin to some maximum value Q_{max} can be standardized by the following formula:

$$Q_s = \frac{Q - Q_{min}}{Q_{max} - Q_{min}} \tag{12}$$

where Q_s is the standardized discharge.

For a specific modeling problem, an ANN is designed in such a way to obtain a simple architecture which yields the desired performance. As there is no analytical solution to determine an optimal ANN architecture and therefore, a unique solution cannot be guaranteed. The numbers of input and output nodes are decided from the modeling problem. Further, the number of hidden layers and the number of nodes in each hidden layer are determined to produce most suitable ANN model architecture. Generally, a trial-and-error approach is used to find out the number of hidden layers and the number of nodes in each hidden layer. The number of nodes should be chosen carefully since the performance of a network critically depends on it. A network with too few nodes gives poor results, while it overfits the training data if too many nodes are present.

The primary goal of training is to minimize the error function by searching for a set of connection strengths and threshold values that cause the ANN to produce outputs that are equal or close to targets. There are different types of learning algorithms that are quite suitable for specific problems. The supervised training algorithm uses a large number of inputs and outputs patterns. The inputs are cause variables of a system and the outputs are the effect variables. This training procedure involves the iterative adjustment and optimization of connection weights and threshold values for each of nodes. In contrast, an unsupervised training algorithm uses only an input data set. The ANN adapts its connection weights to cluster input patterns into classes with similar properties. Supervised training is most common in water resources applications.

ANN IN WATER RESOURCES

Rainfall runoff modelling

Minns and Hall (1996) investigated the use of multi-layer perceptron NN for rainfall- runoff modelling successfully. Minns and Fuhrman (2000) are also studied the rainfall-runoff modelling in snow covered catchment on the basis of measurement data. Gautam (1998) applied regressive neural networks for modeling and forecasting the rainfall runoff relations. Intensive research efforts have been made to identify optimal network structures, find appropriate training algorithms, and select proper training patterns for improving runoff prediction accuracy (Dawson & Wilby, 2001; Campolo *et al.*, 2003; Solomatine *et al.*, 2003). Despite the encouraging results

(Raman & Sunilkumar, 1995; Minns & Hall, 1996; Shamseldin *et al.*, 1997; Wilby *et al.*, 2003), Tokar & Johnson (1999), Zhang & Govindaraju (2000) and (Hu *et al.*, 2001).

Reservoir inflow prediction

Raman and Sunilkumar (1995) investigated the problem of modelling of monthly inflow to reservoir by ANN and statistical techniques. The study is based on the measured monthly inflow data of two reservoirs for a period of 14 years in Kerala, India. In the hydrological forecasting context, recent experiments have reported that NN may offer a promising alternative for rainfall–runoff modeling (Smith & Eli, 1995; Tokar & Johnson, 1999; Solomatine & Dulal, 2003; Lin & Chen, 2004), streamflow prediction (Raman & Sunilkumar, 1995; Clair & Ehrman, 1998; Chibanga *et al.*, 2003; Cigizoglu, 2003; Kisi, 2004a; Cigizoglu & Kisi, 2005); suspended sediment modelling (Tayfur, 2002; Kisi, 2004b, 2005), and reservoir inflow forecasting (Saad *et al.*, 1996; Coulibaly *et al.*, 1998; Jain *et al.*, 1999).

Stage-discharge relationship

A comparative study of conventional and the ANN techniques on discharge prediction from stage-discharge relationship was carried out by Bhattacharya et al. (2000). Jain & Chalisgaonkar (2000) used a multi-layer perceptron NN (MLP) with backpropagation training algorithm to establish a S-D relationship and found that the NN compares favourably to other conventional approaches. Sudheer & Jain (2003) used radial basis NN for modeling rating curves. Suppharatid (2003) used MLP with Levenberg-Marquardt (LM) training algorithm to derive a S-D relationship.

Water Quality Management in a River Basin

The ANN application for prediction problem of decision maker's preferences in the objective-weight relationships was studied by Wen and Lee (1998). The study focused mainly on the environmental quality, treatment cost of wastewater, assimilative capacity of a river to provide a solution to water quality problem in the basin.

Control strategy in multi-reservoir system

Determining the quasi-optimal control strategy for a multi-reservoir system, using error back propagation network was addressed by Solomatine and Torres (1996). Raman & Chandramouli (1996) used Multi Layer Perceptron (MLP) for a similar problem of determining control strategy in reservoir system. Jain et al. (1999) applied ANN for reservoir inflow prediction and operation.

Groundwater Modelling and management

The ability of an artificial neural network (ANN) to provide a data-driven approximation of the explicit relation between transmissivity and hydraulic head as described by the ground water flow equation is demonstrated by Garcia and Shigidi (2006). Nayak et al (2006) reported 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 model predictions are reasonably accurate as evaluated by various statistical indices. In general, the results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Such forecasts may be useful in conjunctive use planning of groundwater and surface water in the coastal areas that help maintain the natural water table gradient to protect seawater intrusion or water logging condition.

REMARKS

The computing world has a lot to gain from neural networks. Their ability to learn by example makes them very flexible and powerful. Furthermore there is no need to devise an algorithm in order to perform a specific task; i.e. there is no need to understand the internal mechanisms of that task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture. Neural networks also contribute to hydrological modeling and forecasting. They are successfully used to model various hydrological processes. Even though neural networks have a huge potential one will only get the best of them when they are integrated with computing, AI, fuzzy logic and related subjects.

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