Chapter - 1
Introduction
The neurons are the structural constituent of the brain. The brain is a highly complex, nonlinear and parallel computer (information processing system). It can organize its neurons to perform certain tasks such as pattern recognition, perceptron many times faster than the fastest computer of the present day. The brain routinely performs perceptual recognition tasks (e.g. face recognition from a set of unrecognized faces) in micro seconds, whereas even a less complex task will take days on a fastest conventional computer today[1].

Typically, brain cells, i.e. neurons are five to six orders of magnitude slower than the silicon logic gates: events in a silicon chip happen in the nanosecond (i.e. $10^{-9}$ s) range, whereas neural events happen in the brain in the orders of millisecond (i.e. $10^{-3}$ s) range. It is estimated that the human brain contains about $10^{11}$ neural cells. Further each neuron receives information from about 10,000 neighbouring neurons. Thus there are over $10^{15}$ connections (synapses) in the brain. Because of modification in synaptic weights, neural networks can be compared with linear adaptive filter theory which is very important in the field like communication, control, radar, sonar, seismology and biomedical engineering [2-4].

According to Aleksander and Morton [5], the definition of an Artificial Neural Network is given as follows:

A neural network is a massively parallel distributed processor that has a natural property for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.
1.1 Various Potentials of ANN

The Neural Network (NN) provides following useful benefits:

(a) Nonlinearity

A neuron is a nonlinear device. A Neural Network (NN) is an interconnection of such neurons. Thus it is also nonlinear. Nonlinearity is a very important feature for many useful applications such as speech signal etc.

(b) Input-output mapping

There are various algorithms for learning of an NN. One of these is supervised learning. In this case the NN is given a set of inputs and desired outputs. The network is trained with a known input to obtain the output which is also known. The training is repeated many times so that the synaptic weights which are untrained (random) in the beginning try to adapt in such a manner such that after further training there is no significant change in their magnitudes. Then the network can predict the output which is almost same as the desired output. This is also called supervised learning.

(c) Adaptivity

It has built-in capacity to adapt their synaptic weights. An NN trained to operate in a specific environment can easily be trained to deal with minor changes in the operating environmental conditions. This property makes it an ideal tool for adaptive pattern classification, adaptive signal processing and adaptive control.

(d) Evidential response

NN can be designed to provide information about the selection of a particular pattern and the confidence in the decision made. The latter property can reject the ambiguous patterns in patterns.
(e) Contextual Information

Knowledge is represented by the structure and the activation state of an NN. The global activity of all other neurons in the network can affect a neuron in its activity.

(f) Fault Tolerance

ANN, implemented in hardware form, is potentially fault tolerant and its performance degrades in a graceful manner under adverse operating conditions.

1.2 Artificial neurons

A neuron is an information-processing unit that is fundamental to the operation of a neural network. Fig. 1.1 shows the model of a neuron. The three basic elements of a neuron model are as follows:

1. A set of synapses or the connecting links, each of which is characterized by a weight or strength of its own, a signal \( x_j \), at the input of synapse \( j \) connected to neuron \( k \) is multiplied by the synaptic weight \( w_{jk} \). Normally the first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers. In this thesis this notation has been used throughout.

2. An adder for summing the input signals, weighted by the respective synapses of the neuron.

3. An activation function for controlling the amplitude of the output of a neuron. This function is also referred sometimes as sigmoid.

In Fig. 1.1, a threshold has also been shown. The threshold has the effect of lowering the net input of the activation function. However the net input of the
activation function can be increased by adding a bias term $w_b$, which is negative of threshold.

![Fig. 1.1 Nonlinear model of a neuron](image)

1.3 Networks of Neurons

By networks of neurons we mean the connections of neurons under various schemes.

There are basically three main ingredients to a neural network, namely:

(a) the disposition of the nodes and links between them.

(b) an algorithm for the first mode of operation of the network, the training phase;

(c) a method of interpreting the network's response during its second mode of operation, the "recall" phase. The useful properties of the network usually involve nonlinearities, which help the stability and the robustness properties of the network[6], but also make it difficult to treat analytically.
Due to variations in the three ingredients, different structures of ANNs are being suggested for various applications. From a structural point of view, neural network architecture may be classified as either static, dynamic, or fuzzy and single layer or multilayer. Moreover the synaptic connections among the neurons can be feed-forward one, laterally connected, topologically ordered, feed-forward - feedback, and hybrid[7].

Some other ANN structures are McCulloch-Pitts’ nerve nets [8], Rosenbalttt’s perceptron [9]; adaptive resonance theory (ART) from Carpenter and Grossberg [10], Fukushima ‘s Neocognition [11], cellular neural networks of Chua [12], multilayer perceptron [13], time-delay neural networks of Waibel [14], counterpropagation networks of Nielson [15], radial basis function network [16], bi-directional associative memory [17], Hopfield’s network[18], fuzzy multilayer perceptron[19], Kohonen’s associative memory [20].

There are basically three different classes of networks based on the number of layers and the contribution of output during learning as given below:

(a) Single Layer Feedforward Networks

The simplest type of ANN is a single layer network. It has only one input layer such that the input nodes project onto an output layer of neurons. Fig. 1.2 depicts a single layer network with three input nodes and only one neuron at the output layer.
(b) Multilayer Feedforward Networks

A multilayer network has one or more than one hidden layer in addition to a single layer feedforward network. The nodes of these hidden layers are called hidden nodes. Hidden layers are added to perform higher and more complex statistics by virtue of extra set of synaptic connection. Fig. 1.3 shows a multilayer network with one hidden layer. There are 3 inputs nodes in the first layer or the hidden layer and 2 nodes in the output layer. This structure is often referred to as a 3-3-2 network.

![Fig. 1.3 A multilayered feedforward ANN with 3-3-2 structure](image)

Fig. 1.3 is a fully connected network as all the nodes of first layer of every two consecutive layers have connection to all the nodes of the other layer. If however some connections are missing, such networks are called partially connected networks.

(c) Recurrent Networks

Recurrent networks are similar to the feedforward network with only one difference that one or more than one output is fed back to the input. Thus one or more nodes of the input are supplied data from the output usually after some delay. Fig. 1.4 shows such a recurrent network with 3-3 structure. Out of the 3 current inputs, one is derived from one of the outputs of the previous time.

![Fig. 1.4 A recurrent ANN 3-3 structure and one feedback](image)
All the above three types of the networks described above have been used to solve many practical problems proposed in the thesis.

1.4 Comparison of NN with the conventional computers

<table>
<thead>
<tr>
<th>Neural Networks</th>
<th>Conventional computers</th>
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<tbody>
<tr>
<td>Many simple processors (computing nodes)</td>
<td>Few complex processors</td>
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<tr>
<td>Few processing steps</td>
<td>Many computational steps</td>
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<tr>
<td>Distributed or parallel processing</td>
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<td>Trained by example</td>
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1.5 Perspectives

The formal realization that the brain in some way performs information processing task was first spelt out by McCulloch and Pitts in 1943[8]. They represented the activity of individual neurons using threshold logic elements and showed how networks made out of these units interconnected could perform arbitrary logical operations. It was also pointed out by Hopfield that the present ANN models are almost a parody of biological neural structures. Later the understanding about mechanism of learning in biological systems grew, the study of neurodynamics intensified[21]. Yet, there was no understanding as how the networks could be set up to solve particular problem, how to set the network connectivity, and the roles of different network architecture. It was in the context that excessive claims were made about the learning capabilities of one scheme in particular, Rosenblatt’s perceptron. Subsequently Minsky and Papert elegantly showed that there were classes of simple tasks which the perceptron could not perform[22]. While theoretical work in the field continued, developing new and well-founded learning algorithms [23-28], with even a small number of published demonstrator projects [29,30], resurgence of mass interest
had to wait for the publication of training algorithms capable of overcoming the limitations of the early perceptron[31,32].

Although there are a number of neural-network models, the two commonly used models are feedforward and feedback (recurrent) networks. Most commonly used network for the engineering applications are the feedforward network where no information is fed back during operation. This model has been used quite successfully for varieties of engineering and DSP applications like system identification and control, pattern recognition, and channel equalization. One major drawback of this network is its very slow learning characteristics. Though a number of dynamic neural architecture have been proposed by various researchers, general theory with regard to architecture, learning algorithms and functional approximation has yet to be studied and developed more. The present state-of-art, the various available architecture, learning algorithms, applications, implementations and other issues o the ANNs may be found in several survey papers and books [33-39].

1.6 Problem Statements

Digital Signal Processing (DSP) is an important area of research which finds extensive applications in almost all fields of Engineering. In this thesis attempt has been made to solve many of the burning DSP problems. The mathematical tool that is used to solve these problems is Artificial Neural Network. The DSP problems undertaken for investigations are:

(i) Logarithm and antilogarithm of decimal numbers.
(ii) Simulation of Discrete Transforms like Discrete Fourier Transform (DFT), Discrete Hartley Transform (DHT), Discrete Walsh Transform (DWT).
(iii) Digital Convolution and Deconvolution operations.
(iv) Adaptive nonlinear System Identification.
(v) Adaptive Communication Channel Equalization.
Each of the above five DSP problems have been efficiently solved using the latest mathematical tool of ANN technique.

1.7 Organization of the Thesis

The present thesis is organized in eight chapters.

In Chapter 1, the definition, potentiality, the variations of ANN have been discussed. Six different DSP problems have been identified and attempt has been made to solve them using the latest mathematical tool known as ANN. This chapter also includes the organization of the complete thesis.

A neural network is trained by various learning algorithms. To solve proposed DSP problems, different network models and learning algorithms have been employed. The details of these algorithms have been outlined in Chapter 2.

In Chapter 3, a simple DSP problem has been attempted to be solved by ANN technique. A single layer ANN has been designed for predicting logarithm of a decimal number. Similarly another ANN network has been modeled to predict the inverse operation i.e. from antilog value to original decimal number. The simple Least Mean Square (LMS) technique is used to learn the network.

The discrete transforms such as DFT, DHT and DWT play important roles in DSP, therefore simulation of these transforms in neural models is quite useful. In Chapter 4, we have undertaken this problem and the computational complexities involved in these transforms have been compared.

Convolution and Deconvolution are two important tools of DSP which are extensively used for many applications. Efficient computations of these tools are
of prime importance. In Chapter 5, ANN based convolver and deconvolver have been designed. Models for both, circular and linear convolution and deconvolution have been developed in this chapter.

The issue of static nonlinear system identification has been investigated in Chapter 6. Since a neuron inherently contains nonlinearity, the ANN based structure is quite suitable for identifying static nonlinear systems.

Adaptive channel equalization is key to digital communication as proper equalization of the channel aims to reconstruct the transmitted image faithfully. Therefore in the present age of communication revolution, channel equalization plays an important role. An efficient solution to the channel equalization problem has been outlined in Chapter 7. ANN technique has been used for the solution of this problem also.

The overall conclusion of the investigation of different DSP problems has been outlined in Chapter 8. This chapter also contains some additional problems which can be undertaken as an extension of the work proposed in the thesis.
References


