A STUDY ON NEURAL NETWORK BASED SYSTEM IDENTIFICATION WITH APPLICATION TO HEATING, VENTILATING AND AIR CONDITIONING (HVAC) SYSTEM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

ELECTRONIC SYSTEMS AND COMMUNICATIONS

By

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National Institute of Technology, Rourkela
May, 2009

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CERTIFICATE

This is to certify that the thesis entitled, "**A STUDY ON NEURAL NETWORK BASED SYSTEM IDENTIFICATION WITH APPLICATION TO HEATING, VENTILATING AND AIR-CONDITIONING (HVAC) SYSTEM**" submitted by **Mr. SATHYAM BONALA** in partial fulfillment of the requirements for the award of Master of Technology Degree in **Electrical Engineering** with specialization in **"ELECTRONIC SYSTEMS AND COMMUNICATIONS"** at the National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Date: **PROF. BIDYADHAR SUBUDHI**

SUPERVISOR

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This project is by far the most significant accomplishment in my life and it would be impossible without people who supported me and believed in me.

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SATHYAM BONALA

CONTENTS

ABSTRACT

Recent efforts to incorporate aspects of artificial intelligence into the design and operation of automatic control systems have focused attention on techniques such as fuzzy logic, artificial neural networks, and expert systems. Although LMS algorithm has been considered to be a popular method of system identification but it has been seen in many situations that accurate system identification is not achieved by employing this technique. On the other hand, artificial neural network (ANN) has been chosen as a suitable alternative approach to nonlinear system identification due to its good function approximation capabilities i.e. ANNs are capable of generating complex mapping between input and output spaces. Thus, ANNs can be employed for modeling of complex dynamical systems with reasonable degree of accuracy.

The use of computers for direct digital control highlights the recent trend toward more effective and efficient heating, ventilating, and air-conditioning (HVAC) control methodologies. The HVAC field has stressed the importance of self learning in building control systems and has encouraged further studies in the integration of optimal control and other advanced techniques into the formulation of such systems. In this thesis we describe the **functional link artificial neural network (FLANN), Multi-Layer Perceptron (MLP) with Back propagation (BP) and MLP with modified BP called the emotional BP and Neuro fuzzy** approaches for the HVAC System Identification.

The thesis describes different architectures together with learning algorithms to build neural network based nonlinear system identification schemes such as Multi-Layer Perceptron (MLP) neural network, Functional Link Artificial Neural Network (FLANN) and ANFIS structures. In the case of MLP used as an identifier, different structures with regard to hidden layer selection and nodes in each layer have been considered. It may be noted that difficulty lies in choosing the number of hidden layers for achieving a correct topology of MLP neural identifier. To overcome this, in the FLANN identifier hidden layers are not required whereas the input is expanded by using trigonometric polynomials i.e. with $\cos(n\pi u)$ and $\sin(n\pi u)$, for $n=0,1,2,\ldots$. The above ANN structures MLP, FLANN and Neuro-fuzzy (ANFIS Model) have been extensively studied.

LIST OF FIGURES

ABBREVIATIONS USED

ANN	Artificial Neural Network
MLP	Multilayer Perceptron
FLANN	Functional Link Artificial Neural Network
BP	Back Propagation
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
MSE	Mean Square error
HVAC	Heating ventilating and Air conditioning
IAQ	Indoor air quality
ICU	Intensive air uit
CFM	Cubic feet for minute
BPA	Back propagation algorithm
EmBP	Emotional Back propagation
RTU	Roof top unit
CER	Clean Environment Rooms
ISI	Inter Symbol Interference
VOC	Volatile organic compounds
ANFIS	Adaptive Neuro-fuzzy inference system

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

System Identification is an essential requirement in areas such as control, communication, power system and instrumentation for obtaining a model of a system (plant) of interest or a new system to be developed. For the purpose of development of control law, analysis fault diagnosis, etc.

Major advances have been made in adaptive identification and control, in past few decades for identifying linear time-invariant plants with unknown parameters. The choice of the identifier structure is based on well established results in linear systems theory. Stable adaptive laws for the adjustment of parameters in these which assures the global stability of the relevant overall systems are also based on properties of linear systems as well as stability results that are well known for such systems [1]. In this thesis, the major interest is in the identification of nonlinear dynamic systems using Neural Networks.

The climatisation of rooms in buildings can be quite a complex control problem if high degrees of comfort and energy saving are required. There are many factors influencing an environment: humidity, outdoor temperature, solar radiation, neighbouring rooms, people presence, furniture in the room, heat sources (as computers), windows, heaters, coolers etc. All these factors have a complex interaction with the comfort and the energy demand.

From the automation point of view, the objective of modeling a building is not to precisely calculate the temperature in every point of a room, but to have information that can lead to a successful controller design. This means that the distributed, continuous, and eventually non-linear process should, with sufficient precision, be described by a lumped LTI parameters model. If the room is architecturally well designed and the actuators well placed, comfort and energy-saving can be obtained.

A predictive HVAC controller can potentially obtain the best compromise between comfort and energy saving. The scheduled room occupation can be prepared with the just needed in-advance acclimatization, a quite unique characteristic of predictive controllers.

The nonlinear functional mapping properties of *neural networks* are central to their use in identification and control. Although a number of key theoretical problems remain, results pertaining to the approximation capabilities of neural networks demonstrate that they have great promise in the modeling of nonlinear systems. An important question in system identification is whether a system under study can be adequately represented within a given model structure. In the absence of such concrete theoretical results for neural networks, it is usually assumed that the system under consideration belongs to the class of systems that the chosen network is able to represent.

1.2 BACKGROUND STUDY

The area of system identification is one of the most important areas in engineering because most of the dynamical system behavior can be obtained exploiting system identification techniques. For identifying an unknown dynamic systems two things are important i.e. model structure and then parameters.

Adaptive Modeling and System Identification are prerequisite before going to design a controller for an on-line plant, say for a scenario an on-line plant requires a controller for improving its performance. The controller cannot be operated on the on-line plant as it may disturb the entire production which may be cost effective, so a model is required which represents the on-line plant. Here comes the concept of modeling a plant. If there is Adaptability in modeling there is more chance of controlling the model on-line thus Adaptive modeling of a plant is done.

System identification concerns with the determination of a system, on the basis of input output data samples. The identification task is to determine a suitable estimate of finite dimensional parameters which completely characterize the plant. The selection of the estimate is based on comparison between the actual output sample and a predicted value on the basis of input data up to that instant. An adaptive automaton is a system whose structure is alterable or adjustable in such a way that its behavior or performance improves through contact with its environment. Depending upon input-output relation, the identification of systems can have two groups

A. Static System Identification

In this type of identification the output at any instant depends upon the input at that instant. These systems are described by the algebraic equations. The system is essentially a memory less one and mathematically it is represented as $y(n) = f\,[x(n)]$ where $y(n)$ is the output at the n^{th} instant corresponding to the input $x(n)$.

B. **Dynamic System Identification**

In this type of identification the output at any instant depends upon the input at that instant as well as the past inputs and outputs. Dynamic systems are described by the difference or differential equations. These systems have memory to store past values and mathematically represented as $y(n)=f\,[x(n), x(n-1),x(n-2)\ldots\ldots\ldots y(n-1),y(n-2),\ldots\ldots]$ where $y(n)$ is the output at the n^{th} instant corresponding to the input $x(n)$.

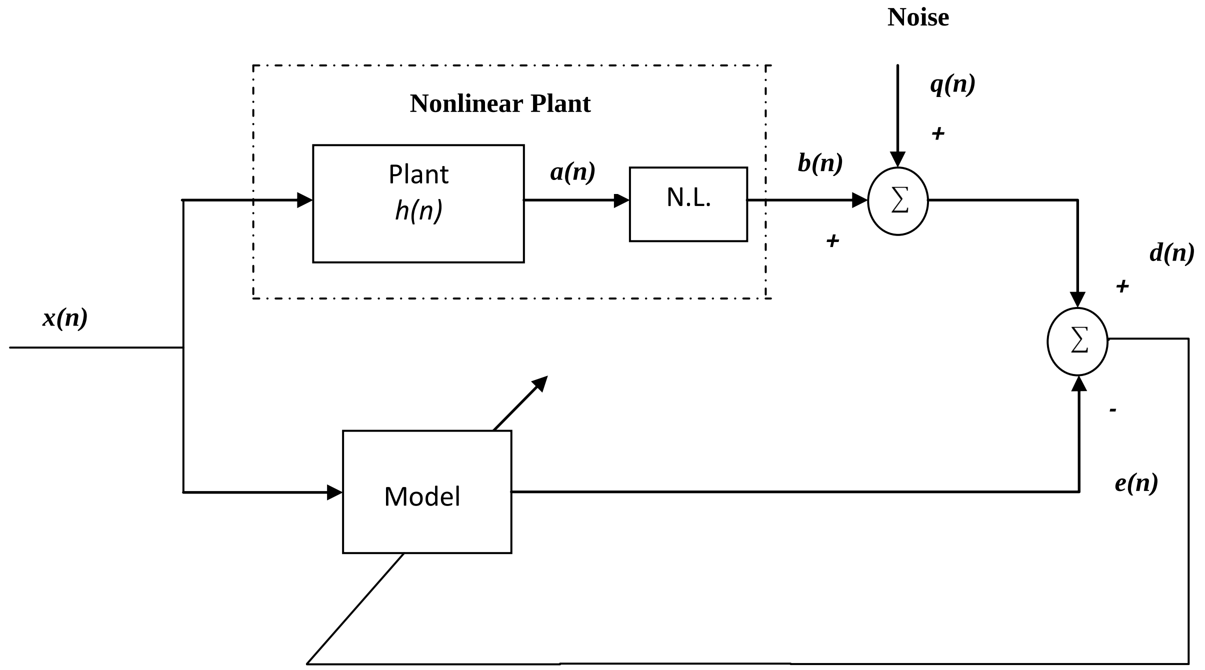


Fig.1.1. Block diagram of system identification

A system identification structure is shown in Fig.1.1. The model is placed parallel to the nonlinear plant and same input is given to the plant as well as the model. The impulse response of the linear segment of the plant is represented by $h(n)$ which is followed by nonlinearity(NL) associated with it. White Gaussian noise $q(n)$ is added with nonlinear output accounts for measurement noise. The desired output $d(n)$ is compared with the estimated output $y(n)$ of the identifier to generate the error $e(n)$ which is used by some adaptive algorithm for updating the weights of the model. The training of the filter weights is continued until the error becomes minimum and does not decrease further. At this stage the correlation between input signal and error signal is minimum. Then the training is stopped and the weights are stored for testing. For testing purpose new samples are passed through both the plant and the model and their responses are compared.

System identification [15] is the experimental approach to process modeling. System identification includes the following steps

- ***Experiment design*** Its purpose is to obtain good experimental data and it includes the choice of the measured variables and of the character of the input signals.

- ***Selection of model structure*** A suitable model structure is chosen using prior knowledge and trial and error.
- ***Choice of the criterion to fit***: A suitable cost function is chosen, which reflects how well the model fits the experimental data.
- ***Parameter estimation*** An optimization problem is solved to obtain the numerical values of the model parameters.
- ***Model validation***: The model is tested in order to reveal any inadequacies.

Modeling and system identification is a very broad subject, of great importance in the fields of control system, communications, and signal processing. Modeling is also important outside the traditional engineering discipline such as social systems, economic systems, or biological systems. An adaptive filter can be used in modeling that is, imitating the behavior of physical systems which may be regarded as unknown “black boxes” having one or more inputs and one or more outputs.

The essential and principal property of an adaptive system is its time-varying, self-adjusting performance. The adaptive systems have following characteristics

1) They can automatically adapt (self-optimize) in the face of changing (non-stationary) environments and changing system requirements.
2) They can be trained to perform specific filtering and decision making tasks.
3) They can extrapolate a model of behavior to deal with new situations after trained on a finite and often small number of training signals and patterns.
4) They can repair themselves to a limited extent.
5) They can be described as nonlinear systems with time varying parameters.

The adaptation is of two types

(i) open-loop adaptation

The open-loop adaptive process is shown in Fig.1.2.(a). It involves making measurements of input or environment characteristics, applying this information to a formula or to a computational algorithm, and using the results to set the adjustments of the adaptive system. The adaptation of process parameters don’t depend upon the output signal.

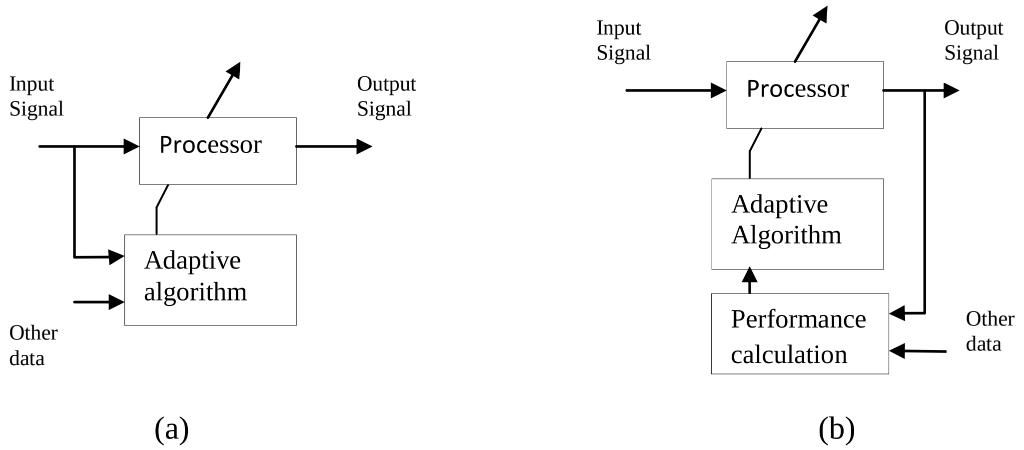


Fig.1.2. Type of adaptations (a) Open-loop adaptation and (b) Closed-loop adaptation

(ii) closed-loop adaptation

Close-loop adaptation (as shown in Fig. 1.2(b)) on the other hand involves the automatic experimentation with these adjustments and knowledge of their outcome in order to optimize a measured system performance. The latter process may be called adaptation by "performance feedback". The adaptation of process parameters depends upon the input as well as output signal.

System identification techniques are two types

A. Direct Modeling (System Identification)

In this type of modeling the adaptive model is kept parallel with the unknown plant. Modeling a single-input, single-output system is illustrated in Fig.1.3. Both the unknown system and adaptive filter are driven by the same input. The adaptive filter adjusts itself in such a way that its output is match with that of the unknown system. Upon convergence, the structure and parameter values of the adaptive system may or may not resemble those of unknown systems, but the input-output response relationship will match. In this sense, the adaptive system becomes a model of the unknown plant

Let *d(n)* and *y(n)* represent the output of the unknown system and adaptive model with *x(n)* as its input

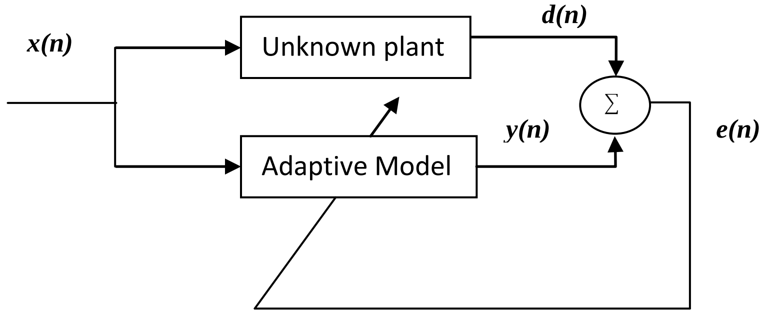


Fig.1.3 Direct Modeling

Here, the task of the adaptive identifier is to accurately represent the signal *d(n)* at its output. If $y(n) = d(n)$, then the adaptive identifier has accurately modeled or identified the portion of the unknown system that is driven by *x(n).*

Since the model typically chosen for the adaptive identifier is a linear identifier, the practical goal of the adaptive identifier is to determine the best linear model that describes the input-output relationship of the unknown system. Such a procedure makes the most sense when the unknown system is also a linear model of the same structure as the adaptive identifier, as it is possible that $y(n) = d(n)$ for some set of adaptive filter parameters. For ease of discussion, let the unknown system and the adaptive filter both be FIR filters, such that

$$d(n) = W_{OPT}^{T}(n)X(n) \tag{1.1}$$

where $W_{OPT}(n)$ is an optimum set of filter coefficients for the unknown system at time *n.* In this problem formulation, the ideal adaptation procedure would adjust *W(n)* such that $W(n) = W_{OPT}(n)$ as n . In practice, the adaptive filter can only adjust *W(n)* such that *y(n)* closely $\infty \rightarrow$approximates *d(n)* over time.

The system identification task is at the heart of numerous. We list several of these applications here [3].

- Echo Cancellation for Long-Distance Transmission
- Acoustic Echo Cancellation
- Adaptive Noise Canceling
- Adaptive control Design.

B. Inverse Modeling

We now consider the general problem of inverse modeling, as shown in Fig.1.4. In this diagram, a source signals *s(n)* is fed into a plant that produces the input signal *x(n)* for the adaptive identifier. The output of the adaptive identifier is subtracted from a desired response signal that is a delayed version of the source signal, such that

$$d(n) = s(n - \Delta) \tag{1.2}$$

Where Δ is a positive integer value. The goal of the adaptive identifier is to adjust its characteristics such that the output signal is an accurate representation of the delayed source signal.

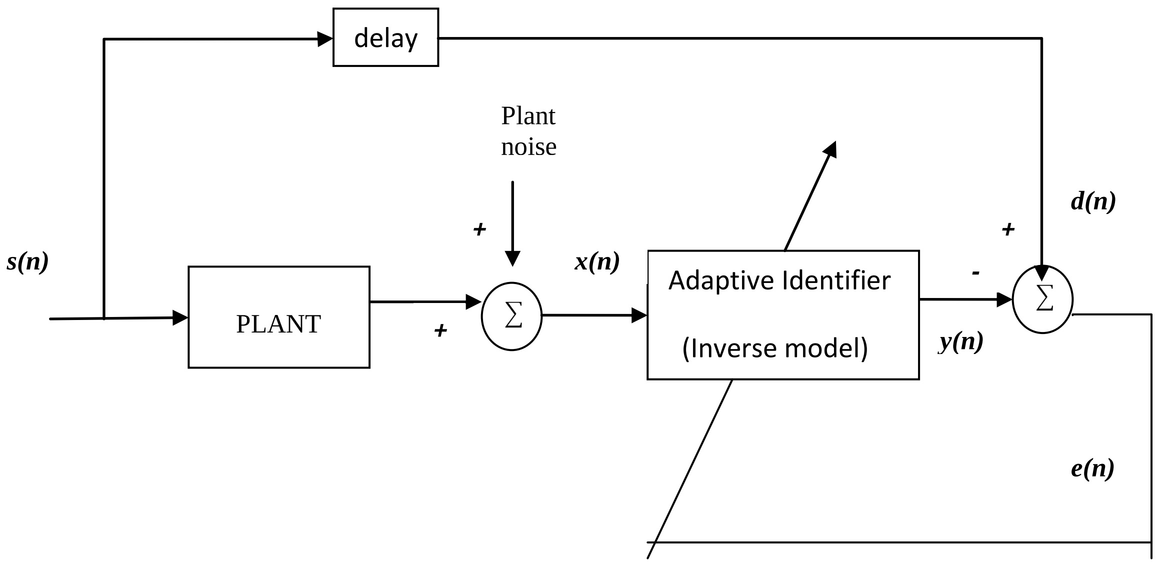


Fig 1.4 Inverse Modeling Structure

Channel equalization is an important application of Inverse Modeling. In channel equalization the inverse model of the channel is modeled and the channel effects of multi-path and inter symbol interference (ISI) are reduced.

1.3. MOTIVATION

Adaptive Identifier has proven to be useful in many contexts such as linear prediction, channel equalization, noise cancellation, and system identification. The adaptive filter attempts to iteratively determine an optimal model for the unknown system, or "plant", based on some function of the error between the output of the adaptive Identifier and the output of the plant. The optimal model or solution is attained when this function of the error is minimized. The adequacy of the resulting model depends on the structure of the adaptive Identifier, the algorithm used to update the adaptive Identifier parameters, and the characteristics of the input signal. When the parameters of a physical system are not available or time dependent it is difficult to obtain the mathematical model of the system. In such situations, the system parameters should be obtained using a system identification procedure. The purpose of system identification is to construct a mathematical model of a physical system from input-output. Studies on linear system identification have been carried out for more than three decades [2]. However, identification of nonlinear systems is a promising research area. Nonlinear characteristics such as saturation, dead-zone, etc. are inherent in many real systems. In order to analyze and control such systems, identification of nonlinear system is necessary. Hence, adaptive nonlinear system identification has become more challenging and received much attention in recent years.

1.4 LITERATURE REVIEW

In literature most of the work was carried out on dynamic systems as most of real life problems are dynamic in sense. Single layer neural network for linear system identification using gradient descent technique is reported by Bhama and Singh [9]. The problem of nonlinear dynamical system identification using MLP structure trained by Back Propagation algorithm was proposed by Narendra and Parthasarathy [1][10].

It has been reported that even if only the outputs are available for measurement, under certain assumptions, it is possible to identify the dynamic system form the delayed inputs and outputs using an multilayer Perceptron (MLP) [6]. Nguyen and Widrow have shown that satisfactory results can be obtained in the case of identification and control of highly nonlinear Truck-Backer-Upper system using MLP [8].

Originally, the Functional Link ANN (FLANN) was proposed by Pao [12]. He has shown that, this network may be conveniently used for function approximation and pattern classification with faster convergence rate and lesser computational load than an MLP structure.

The FLANN is basically a flat net and the need of the hidden layer is removed and hence, the Back Propagation learning algorithm used in used in this network becomes very simple. The functional expansion effectively increases the dimensionality of the input vector and hence the hyper-planes generated by the FLANN provide greater discrimination capability in the input pattern space. Pao have reported identification and control of nonlinear systems using FLANN [13].

Chen and Billings [6] have reported nonlinear system modeling and identification using ANN structures. They have studied this problem using an MLP structure and a radial basis function network and have obtained satisfactory results with networks.

Several research works have been reported on system identification using MLP networks in [5],[9] and [14] and using RBF networks [6] in and [7] . Recently, Yang and Tseng [5] have reported function approximation with an orthonormal ANN using Legendre functions. Besides system identification, FLANN is used in some digital communication problems.

Chen and Billings [6] have utilized a FLANN structure with polynomial expansion in terms of outer product of the elements of the input vector for this purpose, and the output node has linear characteristics. In this thesis, the performance of the FLANN structure with trigonometric polynomials for function expansion has been compared with that of an MLP structure with simulation by taking system model examples of Narendra and Parthasarathy [1].

In this thesis, Heating, Ventilating and Air conditioning (HVAC) System is Identified by using different non linear structures such as MLP, FLANN and ANFIS.

1.5 PROBLEM FORMULATION

The single-zone thermal system model shown in Fig. 2.4 is chosen for our analysis [21]. The system represents a simplification of an overall building climate control problem, but retains the distinguishing characteristics of an HVAC system. When the plant behavior is completely unknown, it may be characterized using certain model and then, its identification may be carried out with some artificial neural networks(ANN) like Multilayer Perceptron (MLP) or functional link artificial neural network(FLANN) using some learning rules such as back propagation (BP) algorithm. So in this thesis Heating Ventilating and Air conditioning System is identified with different techniques. The Neural identification model is developed to mimic the dynamics of the system. In this thesis we considered only forward modeling scheme.

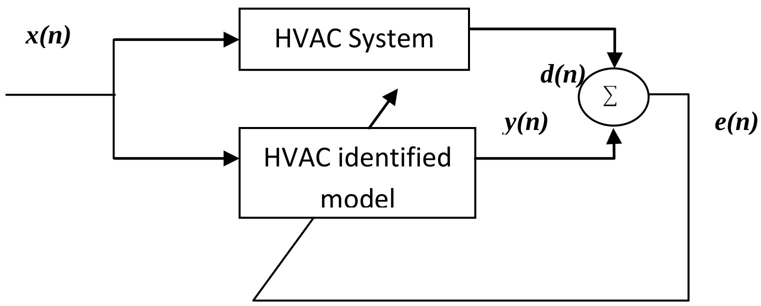


Fig 1.5 Implementation of System Identification Technique

In this thesis, the problem of system identification was extensively studied, analyzed and viewed The input signal *x(n)* is passed to the HVAC Plant and the HVAC Identified Model , the error *e(n)* generated from the difference between the desired signal *d(n)* and estimated signal *e(n)*. Using some adaptive algorithm the weights of the Model are updated by using the error generated. The process is continued until error becomes minimum. This is the main problem on which the entire thesis is worked on. The system identification problem of some standard plants are taken form Narendra and Parthasarathy [1] and solved. Unlike in most of the research works the thesis has focused in implementing the system identification algorithms. The HVAC System is identified by using different techniques such as MLP-BP, MLP-Emotional BP, FLANN-BP and Neuro-Fuzzy (ANFIS) using MATLAB R2008a. And compared these MATLAB R2008a simulated results.

1.6 IMPLEMENTATION APPROACHES

The major approaches used in this thesis are

- MATLAB simulations

MATLAB R2008a is used for the system identification process. The codes are written in the Matlab m-file and simulated. All the problems discussed in this thesis are simulated and graphs obtained are given.

1.7 CONTRIBUTIONS OF THE THESIS

The major contribution of this thesis is

- Review of different Nonlinear system identification techniques such as MLP-BP, FLANN-LMS, MLP-MBP and Neuro-fuzzy.
- MATLAB implementation of BP method of system identification.
- System Identification Using Neural Networks.
- Implementation of Neural Network structures for system identification.

1.8 THESIS LAYOUT

In ***chapter 2*** gives the theory of heating ventilating and air conditioning system basically it is mechanical system. It is non-linear system and this HVAC system model shown and explained.

In ***Chapter 3***, the theory, structure and algorithms of (Multi-layer Perceptron) MLP and Functional link Neural Network (FLANN) are discussed. Learning technique for the above networks is also discussed. Simulation results are carried out for comparisons of FLANN structure over MLP for different nonlinear condition. Simulation results are carried out in MATLAB R2008a.

In ***Chapter 4*** gives an introduction to modified back propagation technique and discusses in details. In this chapter Back propagation is used for weight updating of FLANN structure in efficient nonlinear system identification. Simulation results are carried out in MATLAB R2008a for different nonlinear condition.

In ***chapter 5*** gives the theory of Adaptive Neuro-Fuzzy Inference System (ANFIS) and using this ANFIS structure and identified the HVAC System States.

In ***Chapter 6*** summarizes the work done in this thesis work and points to possible directions for future work.

CHAPTER 2

HEATING, VENTILATING AND AIR-CONDITIONING (HVAC) SYSTEM MODEL

2.1 INTRODUCTION

Heating, Ventilating, and Air Conditioning (HVAC) Systems are a permanent part of everyday life in industrial society. HVAC systems include a range from the simplest hand-stoked stove, used for comfort heating, to the extremely reliable total air-conditioning systems found in submarines and space shuttles. Cooling equipment varies from the small domestic unit to refrigeration machines that are 10,000 times the size, which are used in industrial processes. Depending on the complexity of the requirements, the HVAC designer must consider many more issues than simply keeping temperatures comfortable.

The objectives of HVAC systems are to provide an acceptable level of occupancy comfort and process function, to maintain good indoor air quality (IAQ), and to keep system costs and energy requirements to a minimum.

Commercial heating, ventilating, and air conditioning (HVAC) systems provide the people working inside buildings with "conditioned air" so that they will have a comfortable and safe work environment. People respond to their work environment in many ways and many factors affect their health, attitude and productivity. "Air quality" and the "condition of the air" are two very important factors. By "conditioned air" and "good air quality," we mean that air should be clean and odor-free and the temperature, humidity, and movement of the air will be within certain acceptable comfort ranges. ASHRAE, the American Society of Heating, Refrigerating and Air Conditioning Engineers, has established standards which outline indoor comfort conditions that are thermally acceptable to 80% or more of a commercial building's occupants. Generally, these comfort conditions, sometimes called the "comfort zone," are between 68°F and 75°F for winter and 73°F to 78°F during the summer. Both these ranges are for room air at approximately 50% relative humidity and moving at a slow speed (velocity) of 30 feet per minute or less.

2.2 WORKING OF AN HVAC SYSTEM

An HVAC system is designed to provide conditioned air to the occupied space, also called the "conditioned" space, to maintain the desired level of comfort. To begin to explain how an HVAC system works let's set some design conditions. First, we clean rooms. Examples of negative rooms are commercial kitchens, hospital intensive care units (ICU) and fume hood laboratories.

Air Volume Using the roof top air handling unit as an example, the volume of air required to heat, ventilate, cool and provide good indoor air quality is calculated based on the heating, cooling and ventilation loads. The air volumes are in units of cubic feet per minute (cfm). The total volume of air for this roof top unit (RTU) is calculated to be 5250 cfm. Constant volume supply air and return air fans (SAF and RAF) circulate the conditioned air to and from the occupied conditioned space. The total volume of return air back to the air handling unit is 4200 cfm. The difference between the amount of supply air (5250 cfm) and the return air (4200 cfm) is 1050 cfm. This is the ventilation air. It is used in the conditioned space for make-up air (MUA) for toilet exhaust and other exhaust systems. Ventilation air is also used for positive pressurization of the conditioned space, and for “fresh” outside air to maintain good indoor air quality for the occupants. The return air, 4200 cfm, goes into the mixed air chamber (plenum). The return air is then mixed with 1050 cfm, which is brought in through the outside air (OA) dampers into the mixed air plenum. This 1050 cfm of outside air is the minimum outside air required for this system. It is 20% of the supply air (1050/5250). It mixes with the 4200 cfm of return air (80%, 4200/5250) to give mixed air (MA, 100%). Next, the 5250 cfm of mixed air then travels through the filters and into the coil sections. If more outside air than the minimum is brought into the system, perhaps for air-side economizer operation, any excess air is exhausted through exhaust air dampers (EA) to maintain the proper space pressurization. For example, if 2050 cfm is brought into the system through the OA dampers and 4200 cfm comes back through the return duct into the unit then 1000 cfm is exhausted through the exhaust air dampers (EA). This maintainsthe total supply cfm (5250) into the space and maintains the proper space pressurization. The airflow diagram looks like this:

Fig. 2.1 Air flow diagram

Where cfm $\longrightarrow$ cubic feet per minute.

RA (return air)

EA (exhaust air)

MA (mixed air)

OA (outside air)

SA (supply air)

2.3 HVAC SYTEM MODEL

The single-zone thermal system model shown in Fig. 2.2 is chosen for our analysis[21]. The system represents a simplification of an overall building climate control problem, but retains the distinguishing characteristics of an HVAC system.

Fresh air enters the system at temperature $T_0(t)$ and volumetric flow rate $f_0(t)$ and is mixed with recirculated air at temperature $T_5(t)$ and flow rate $f_5(t)$. Air with temperature $T_1(t)$ and flow rate f(t). passes through the heat exchanger, where an amount of heat given by $q_{he}(t)$ (positive for heating and negative for cooling) is exchanged with the air. The air and heat exchanger are assumed to have some capacitance, so that the resulting temperature $T_2(t)$ has a transient response. In addition, perfect mixing in the heat exchanger is assumed, so that the air temperature within and exiting the heat exchanger is $T_2(t)$.

After being conditioned in the heat exchanger, the air passes into the thermal space. The capability of applying a space thermal load is included as $q_l(t)$. The temperature $T_3(t)$ of the space has a transient response due to the capacitance of the air and the thermal space. Perfect mixing in the thermal space is assumed, so that the air temperature within and exiting the space is $T_3(t)$. Air leaving the thermal space is drawn through the fan, after which a portion may be recirculated to mix with the fresh air and the remainder may be exhausted from the system. HVAC System model shown below

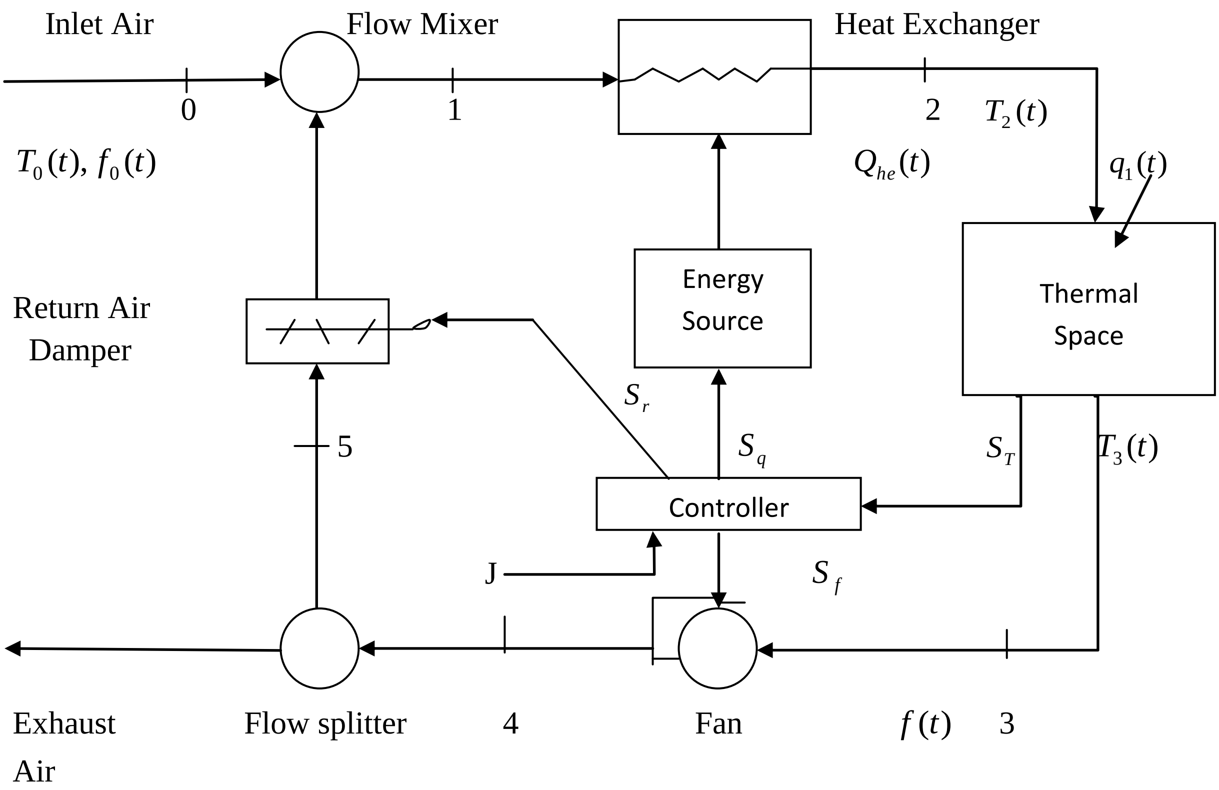


Fig. 2.2 HVAC System model

The conditions within the system are regulated by a controller that provides signals to control the heat input in the heat exchanger, the volumetric airflow rate, and the position of the return air damper. The controller signals are depicted as thin lines and are denoted by S_q, S_f and S_r. The signal S_T denotes the temperature in the thermal space, while J denotes a cost associated with the performance of the system. Thermal losses between components are neglected and, thus, temperatures $T_4(t)$ and $T_5(t)$ are equal to the temperature of the air exiting the thermal space. In addition, infiltration and exfiltration effects are neglected and, thus, flow rates at locations *2–4* are equal to f(t).The humidity of the air is not considered, and transient effects in the flow splitter, mixer, fan, and heat exchanger are neglected.

The system equations are derived from the conservation of energy principles and are given by

$$\rho c_p V_{he} \frac{dT_2}{dt} = f\rho c_p (T_1 - T_2) + Q_{he} \tag{2.1}$$

$$\rho c_p V_{ts} \frac{dT_3}{dt} = f\rho c_p (T_2 - T_3) + Q_l \tag{2.2}$$

Where the parameters and variables are as described below.

c_p = constant pressure specific heat or air (J/kg ^{o}C).

f = volumetric airflow rate (m^3/s).

Q_{he} =heat input in the heat exchanger (W).

Q_l = thermal load on the room (W).

t = time (s).

T_{ref} = desired thermal space temperature (^{o}C).

T_i = air temperature at location i (^{o}C).

V_{he} = effective heat exchanger volume (m^3).

V_{ts} = effective thermal space volume (m^3).

ρ = air density (kg/m^3).

A lumped capacitance assumption is made, implying that the capacitance of the heat exchanger and the thermal space are accounted for in the effective heat exchanger and thermal space volumes. Statements of the conservation of mass and energy applied at the flow mixer yield

$$T_1 = T_3 + (T_0 - T_3)/r \tag{2.3}$$

where

$$r = f / f_0 \tag{2.4}$$

is the system-to-fresh-air volumetric flow-rate ratio. For r=1, there is no recirculation and a once-through system is considered. The position of the return air damper as described by r is obtained from the values of f and f_0 which are computed explicitly by the controller.

Denoting $x=[T_2\ T_3]^T$ and making the appropriate system equations

$$\dot{x}_1 = \frac{1}{V_{he}}\left[(T_0 - X_2)u_3 + (X_2 - X_1)u_2 + \frac{u_1}{\rho c_p}\right] \tag{2.5}$$

$$\dot{x}_2 = \frac{1}{V_{ts}}\left[(X_1 - X_2)u_2 + \frac{Q_l}{\rho c_p}\right] \tag{2.6}$$

Where $u = [Q_{he}, f, f_0]^T$.

2.4 SIMULATION RESULTS

The Heating, Ventilating, and Air-Conditioning (HVAC) Systems are a permanent part of everyday life in our industrialized society. The single-zone thermal system model shown in Fig. 2.2 is chosen for our analysis [21]. The system represents a simplification of an overall building climate control problem, but retains the distinguishing characteristics of an HVAC system.

The HVAC system state equations shown above (2.5 and 2.6) are solved by Range-Kutta method. For solving these system equations we considered the different variables and parameters have taken such as thermal load on the room (Q_l), air density (ρ) and etc. Here the states x1 and x2 are in ^{0}C with respect to time. These two states are identified by using different structures such as MLP, FLANN and ANFIS. All the simulations are carried out using MATLAB R2008a. The two desired states x1 and x2 shown in Fig.2.3.

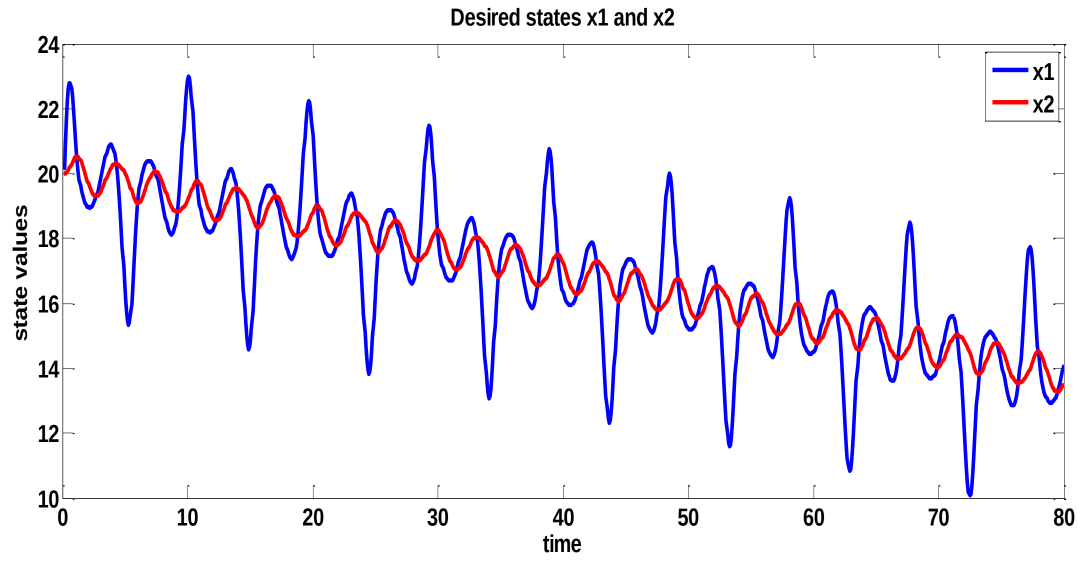


Fig.2.3 HVAC System States in ^{0}C

For the purposes of comfort and hygiene, the minimum allowable value of u_3, the outside air volumetric flow rate, is set at 0.0354 m^3/ s[22].

The equilibrium states of the system are

$$x_{1EQ} = x_{2EQ} = \frac{u_3 T_0 + \frac{u_1}{\rho c_p}}{u_3} \tag{2.7}$$

Since this is an underdetermined case, an infinite number of combinations of u_1 and u_2 provide the same steady-state output and the system does not possess a unique inverse.

The ranges of the control variables are defined as

$$Q_{he}=€[-4000,4000]W \tag{2.8}$$

and

$$f,\ f_0€[0.0354,2]m^3/s. \tag{2.9}$$

The value of u_3 can never exceed the value of u_2 , due to conservation of mass principles. Thus, the controller must command values for these inputs that satisfy the following condition:

$$u_2 \geq u_3. \tag{2.10}$$

The operating ranges of the system states and outside air temperature are assumed to be

$$x_1\ €[5,35]\ ^0C \quad \text{or} \quad [41,95]\ ^0F \tag{2.11}$$

$$x_2,T_0\ €[10,30]\ ^0C \quad \text{or} \quad [50,86]\ ^0F \tag{2.12}$$

and the range of the reference temperature is assumed be

$$T_{ref} \in [17,23]\ ^0C \quad \text{or} \quad [62.6, 73.4]\ ^0F \tag{2.13}$$

In order to most effectively use $u_{3,}$ the controller must have information as to whether the outside air temperature is higher or lower than the desired room temperature. Thus, an additional input variable called T_{diff} is introduced,
Where

$$T_{diff} = T_{ref} - T_0 \tag{2.14}$$

It is assumed that T_0 can be measured accurately with an inexpensive temperature sensor. In order to determine the ranges of the changes in the states over a sample period of T_s=10 s, the state equations (3.5) and (3.6) are integrated from 0–10 s, using 1000 random initial conditions satisfying (3.8)–(3.12). Histograms for Δx_1 and Δx_2. Based on the extreme values of Δx_1 and Δx_2. The ranges for the changes in the states are assumed to be

$$\Delta x_1 \in [-13.0, 13.0]\ ^0C \tag{2.15}$$

$$\Delta x_2 \in [-1.5, 1.5]\ ^0C \tag{2.16}$$

The range of control signals using assumptions (2.11)–(2.13), (2.15), and (2.16) will be used to train the neural network to learn the HVAC thermal dynamics.

2.5 HEATING AND COOLING

Heat is energy in the form of molecules in motion. Heat flows from a warmer substance to a cooler substance. Heat energy flows downhill! Heat does not raise, heated air rises!
Temperature is the level of heat (energy).
The lowest temperature is minus 460°F.
The sun’s temperature is approximately 27,000,000°F.
The temperatures associated with most HVAC systems range from 0°F to 250°F.
Most people feel comfortable if the indoor air temperature is between 68°F and 78°F.

2.5.1 Standard Temperatures on the Fahrenheit and Celsius Scales

Freezing point of (pure) water is:

32 degrees Fahrenheit (32°F) and zero degrees Celsius (0°C).

Boiling point of (pure) water is:

212 degrees Fahrenheit (212°F) and 100 degrees Celsius (100°C).

Temperature Conversions for Fahrenheit and Celsius

°C = (°F - 32) ÷ 1.8

°F = 1.8 (°C) + 32

The following is a quick reference for estimating and converting everyday temperatures from Celsius to Fahrenheit:

0°C is 32°F

16°C is approximately 61°F

28°C is approximately 82°F

37°C is 98.6°F

100°C is 212°F

Absolute Temperatures

The Fahrenheit absolute scale is the Rankine (°R) scale.

The Celsius absolute scale is the Kelvin (°K) scale.

Absolute zero is minus 460°F and 0°R, or minus 273°C and 0°K.

The Fahrenheit/Celsius and the Rankine/Kelvin scales are used interchangeably to describe equipment and fundamentals of the heating and air conditioning industry.

2.5.2 Heat and Temperature

Heat is energy in the form of molecules in motion. As a substance becomes warmer, its molecular motion and energy level (temperature) increases. Temperature describes the level of heat (energy) with reference to no heat. Heat is a positive value relative to no heat. Because all heat is a positive value in relation to no heat, cold is not a true value. It is really an expression of comparison. Cold has no number value and is used by most people as a basis of comparison only. Therefore, warm and hot are comparative terms used to describe higher temperature levels. Cool and cold are comparative terms used to describe lower temperature levels. The Fahrenheit scale is the standard system of temperature measurement used in the United States. However, the U.S. is one of the few countries in the world still using this system. Most countries use the metric temperature measurement system, which is the Celsius scale. The Fahrenheit and Celsius scales are currently used interchangeably in the U.S. to describe equipment and fundamentals in the heating, ventilating and air conditioning industry.

2.5.3 Heat Transfer

Heat naturally flows from a higher energy level to a lower energy level. In other words, heat travels from a warmer substance to a cooler substance. When there is a temperature difference between two substances, heat transfer will occur. In fact, temperature difference is the driving force behind heat transfer. The greater the temperature difference, the greater the heat transfer.

2.5.4 Types of Heat Transfer

The three types of heat transfer are conduction, convection and radiation.

Conduction

Conduction heat transfer is heat energy traveling from one molecule to another. A heat exchanger in an HVAC system or home furnace uses conduction to transfer heat. Your hand touching a cold wall is an example of heat transfer by conduction from your hand to the wall. However, heat does not conduct at the same rate in all materials. For example, all HVAC copper conducts at a different rate than iron or aluminum, etc.

Convection

Heat transfer by convection is when some substance that is readily movable such as air, water, steam, or refrigerant moves heat from one location to another. Compare the words "convection" (the action of conveying) and "convey" (to take or carry from one place to another). An HVAC system uses convection in the form of air, water, steam and refrigerants in ducts and piping to convey heat energy to various parts of the system. When air is heated, it rises; this is heat transfer by "natural" convection. "Forced" convection is when a fan or pump is used to convey heat in fluids such as air and water. For example, many large buildings have a central heating plant where water is heated and pumped throughout the building to the final heated space. Fans then move heated air into the conditioned space.

Radiation

Heat transferred by radiation travels through space without heating the space. Radiation or radiant heat does not transfer the actual temperature value. The first solid object that the heat rays encounter absorbs the radiant heat. A portable electric space heater that glows red-hot is an example of heat transfer by radiation. As the electric heater coil glows red-hot it radiates heat into the room. The space heater does not heat the air (the space)—instead it heats the solid objects that come into contact with the heat rays. Any heater that glows has the same effect. However, radiant heat diminishes by the square of the distance traveled; therefore, space heaters must be placed accordingly. Another good example of radiant heat is the sun; the sun heats the earth, but not the air around the earth. The sun is also a good example of diminishing heat. The earth does not experience the total heat of the sun because the sun is some 93 million miles from the earth.

2.5.5 Ventilating

The ventilation requirement is 1050 cfm. 1050 cfm of outside air is brought in through the outside air (OA) dampers into the mixed air plenum. This 1050 cfm of outside air mixes with the 4200 cfm of return air to form 5250 cfm of mixed air, which goes through the coil(s) and becomes supply air.

2.5.6 Cooling

For this system, the total heat given off by the people, lights and equipment in the conditioned space plus the heat entering the space through the outside walls, windows, doors, roof, etc., and the heat contained in the outside ventilation air will be approximately 154,000 Btu/hr. A ton of refrigeration (TR) is equivalent to 12,000 Btu/hr of heat. Therefore, this HVAC system requires a chiller that can provide approximately 13 tons of cooling (154,000 Btu/hr ÷ 12000 Btu/hr/ton = 12.83 TR) To maintain the proper temperature and humidity in the conditioned space the cooling cycle is this: The supply air (which is 20°F cooler than the air in the conditioned space) leaves the cool ing coil and goes through the heating coil (which is off), through the supply air fan, down the duct and into the conditioned space. The cool supply air picks up heat in the conditioned space. The warmed air makes its way into the return air inlets, then into the return air duct and back to the air handling unit. The return air goes through the return air fan into the mixed air chamber and mixes with the outside air. The mixed air goes through the filters and into the cooling coil. The mixed air flows through the cooling coil where it gives up its heat into the chilled water tubes in the coil. This coil also has fins attached to the tubes to facilitate heat transfer. The cooled supply air leaves the cooling coil and the air cycle repeats. The water, after picking up heat from the mixed air, leaves the cooling coil and goes through the chilled water return (CHWR) pipe to the water chiller's evaporator. The "warmed" water flows into the chiller's evaporator—sometimes called the water cooler—where it gives up the heat from the mixed air into the refrigeration system. The newly "chilled" water leaves the evaporator, goes through the chilled water pump (CHWP) and is pumped through the chilled water supply (CHWS) piping into the cooling coil to pick up heat from the mixed air and the water cycle repeats. The evaporator is a heat exchanger that allows heat from the chilled water return (CHWR) to flow by conduction into the refrigerant tubes. The liquid refrigerant in the tubes “boils off” to a vapor removing heat from the water and conveying the heat to the compressor and then to the condenser. The heat from the condenser is conveyed to the cooling tower through the condenser water in the condenser return (CWR) pipe. As the condenser water cascades down the tower, outside air is drawn across the cooling tower removing heat from the water through the process of evaporation. The “cooled” condenser water falls to the bottom of the tower basin and is pumped from the tower through the condenser water pump (CWP) and back to the condenser in the condenser water supply piping (CWS) and the cycle repeats.

2.6 HEATING SYSTEMS

For over 10,000 years, man has used fire to warm himself. In the beginning, interior heating was just an open fire, but comfort and health was greatly improved by finding a cave with a hole at the top. Later, fires were contained in hearths or sunken beneath the floor. Eventually, chimneys were added which made for better heating, comfort, health, and safety and also allowed individuals to have private rooms. Next, came stoves usually made of brick, earthenware, or tile. In the 1700s, Benjamin Franklin improved the stove, the first steam heating system was developed, and a furnace for warm-air heating used a system of pipes and flues and heated the spaces by gravity flow. In the 1800s, high speed centrifugal fans and axial flow fans with small, alternating current electric motors became available and high-pressure steam heating systems were first used. The 1900s brought the Scotch marine boiler and positive-pressure hydronic circulating pumps that forced hot water through the heating system. The heating terminals were hot water radiators, which were long, low, and narrow, as compared to steam radiators, and allowed for inconspicuous heating. Centrifugal fans were added to furnaces in the 1900s to make forced-air heating systems.

2.7 VENTILATING SYSTEMS

In occupied buildings, carbon dioxide, human odors and other contaminants such as volatile organic compounds (VOC) or odors and particles from machinery and the process function need to be continuously removed or unhealthy conditions will result. Ventilation is the process of supplying “fresh” outside air to occupied buildings in the proper amount to offset the contaminants produced by people and equipment. In many instances, local building codes, association guidelines, or government or company protocols stipulate the amount of ventilation required for buildings and work environments. Ventilation systems have been around for a long time. In 1490, Leonardo da Vinci designed a water driven fan to ventilate a suite of rooms. In 1660, a gravity exhaust ventilating system was used in the British House of Parliament. Then, almost two hundred years later, in 1836, the supply air and exhaust air ventilation system in the British House of Parliament used fans driven by steam engines. Today, ventilation guidelines are approximately 15 to 25 cfm (cubic feet per minute) of air volume per person of outside air (OA) for non-smoking areas, 50 cfm for smoking areas. Ventilation air may also be required as additional or "make-up" air (MUA) for kitchen exhausts, fume hood exhaust systems, and restroom and other exhaust systems. Maintaining room or conditioned space pressurization (typically +0.03 to +0.05 inches of water gage) in commercial and institutional buildings is part of proper ventilation.

Figure 4-10 shows 20% of the total supply air is ventilation outside air (OA) and 80% is return air (RA). The outside air is brought (or forced) into the mixed air plenum by the action of the supply air fan. The outside air coming through the outside damper is mixed with the return air from the conditioned space. The return air dampers control the amount of return air. If the room pressure is too high, the exhaust air (EA) dampers open to let some of the return air escape to the outside, which relieves some of the pressure in the conditioned space. Exhaust air dampers are also called relief air dampers.

2.8 AIR CONDITIONING SYSTEMS

Brooklyn, New York, was the place, and 1902 was the year the first truly successful air conditioning system for room temperature and humidity control was placed into operation. But first it took the engineering innovations of Willis Carrier to advance the basic principles of cooling and humidity control and design the system. Cooling air had already been done successfully but it was only part of the air conditioning problem. The other part was how to regulate space humidity. Carrier recognized that drying the air could be accomplished by saturating it with chilled water to induce condensation. In 1902, Carrier built the first air conditioner to combat both temperature and humidity. The air conditioning unit was installed in a printing company and chilled coils were used in the machine to cool the air and lower the relative humidity to 55%. Four years later, in 1906, Carrier was granted a patent for his air conditioner the "Apparatus for Treating Air." However, Willis Carrier did not invent the very first system to cool an interior structure nor interestingly, did he come up with the term "air conditioning." It was Stuart Cramer, a textile engineer, who coined the term "air conditioning.” Mr.Cramer used “air conditioning” in a 1906 patent for a device that added water vapor to the air. In 1911, Mr. Carrier, who is called the “father of air conditioning,” presented his “Rational Psychrometric Formulae” to the American Society of Mechanical Engineers. Today, the formula is the basis in all fundamental psychometric calculations for the air conditioning industry. Though Willis Carrier did not invent the first air conditioning system, his cooling and humidity control system and psychrometric calculations started the science of modern psychrometrics and air conditioning. As already mentioned, air “cooling” was only part of the answer. The big problem was how to regulate indoor humidity. Carrier’s air conditioning invention addressed both issues and has made many of today’s products and technologies possible. In the 1900s, many industries began to flourish with the new ability to control the indoor environmental temperature and humidity levels in both occupied and manufacturing areas. Today, air conditioning is required in most industries and especially in ones that need highly controllable environments, such as clean environment rooms (CER) for medical or scientific research, product testing, and sophisticated computer and electronic Component manufacturing.

CHAPTER 3

SYSTEM IDENTIFICATION USING ARTIFICIAL NEURAL NETWORKS

3.1 INTRODUCTION

Nonlinear system identification of a complex dynamic plant has potential applications in many areas such as control, communication, power system, instrumentation, pattern recognition and classification. Because of the function approximation properties and learning capability, Artificial Neural Networks (ANN's) have become a powerful tool for these complex applications. The ANN's are capable of generating complex mapping between the input and the output space and thus, arbitrarily complex nonlinear decision boundaries can be formed by these networks.

An artificial neural network basically consists a number of computing elements, called neurons that perform the weighted sum of the input signal and the connecting weight. The sum is added with the bias or threshold and the resultant signal is then passed through a non-linear element such as $\tanh(.)$ type. Each neuron is associated with three parameters on whose learning of neuron can be adjusted; these are the connecting weights, the bias and the slope of the non-linear function. From the structural point of view, a neural network (NN) may be single layer or it may be multi-layer. In multi-layer structure, there may be more than one hidden layers and there is one or many artificial neurons in each layer and for a practical case there may be a number of layers. Each neuron of one layer is connected to each and every neuron of the next layer.

A neural network is a massively parallel distributed processor made up of simple processing unit, which has a natural property for storing experimental knowledge and making it available for use. It resembles the brain in two types

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

Artificial Neural Networks (ANN) has emerged as a powerful learning technique to perform complex tasks in highly nonlinear dynamic environments. Some of the prime advantages of using ANN models are their ability to learn based on optimization of an appropriate error function and their excellent performance for approximation of nonlinear function [3]. At present, most of the work on system identification using neural networks are based on multilayer feed-forward neural networks with back propagation learning or more efficient variations of this algorithm [18] ,[1].On the otherhand the Functional link ANN(FLANN) originally proposed by Pao [12] is a single layer structure with functionally mapped inputs. Wang and Chen [19] have presented a fully automated recurrent neural network (FARNN) that is capable of self-structuring its network in a minimal representation with satisfactory performance for unknown dynamic system identification and control.

3.2 NEURON STRUCTURE

In 1958, Rosenblatt demonstrated some practical applications using the perceptron [20]. The perceptron is a single level connection of McCulloch-Pitts neurons sometimes called single-layer feed-forward networks. The network is capable of linearly separating the input vectors into pattern of classes by a hyper plane. A linear associative memory is an example of a single-layer neural network. In such an application, the network associates an output pattern (vector) with an input pattern (vector), and information is stored in the network by virtue of modifications made to the synaptic weights of the network.

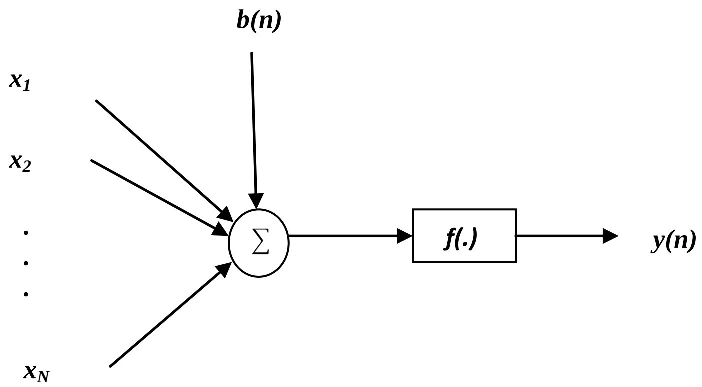


Fig 3.1 Neuron Structure

The structure of a single neuron is presented in Fig. 3.1. An artificial neuron involves the computation of the weighted sum of inputs and threshold [3]. The resultant signal is then passed through a non-linear activation function. The output of the neuron may be represented as,

$$y(n) = f\left[\sum_{j=1}^{N} w_j(n)x_j(n) + b(n)\right] \tag{3.1}$$

where, $b(n)$ = threshold to the neuron is called as bias, $w_j(n)$ = weight associated with the j^{th} input, and N = no. of inputs to the neuron.

3.2.1 Activation Functions and Bias

The perceptron internal sum of the inputs is passed through an activation function, which can be any monotonic function. Linear functions can be used but these will not contribute to a non-linear transformation within a layered structure, which defeats the purpose of using a neural filter implementation. A function that limits the amplitude range and limits the output strength of each perceptron of a layered network to a defined range in a non-linear manner will contribute to a nonlinear transformation. There are many forms of activation functions, which are selected according to the specific problem. All the neural network architectures employ the activation function [3, 27] which defines as the output of a neuron in terms of the activity level at its input (ranges from -1 to 1 or 0 to 1). Table 3.1 summarizes the basic types of activation functions. The most practical activation functions are the sigmoid and the hyperbolic tangent functions. This is because they are differentiable.

NAME	**MATHEMATICAL REPRESENTATION**
Linear	$f(x) = kx$
Step	$f(x) = \begin{cases} \alpha, & if\ x \geq k \\ \beta, & if\ x < k \end{cases}$
Sigmoid	$f(x) = \dfrac{1}{1 + e^{-\alpha x}}\ , \alpha > 0$
Hyperbolic Tangent	$f(x) = \dfrac{1 - e^{-\gamma x}}{1 + e^{-\gamma x}}, \gamma\ > 0$
Gaussian	$f(x) = \dfrac{1}{\sqrt{2\pi\sigma^2}} e^{\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]}$

Table 3.1 Types of Activation Functions

The bias gives the network an extra variable and the networks with bias are more powerful than those of without bias. The neuron without a bias always gives a net input of zero to the activation function when the network inputs are zero. This may not be desirable and can be avoided by the use of a bias.

3.2.2 Learning Technique:

The property that is of primary significance for a neural network is that the ability of the network to learn from its environment, and to improve its performance through learning. The improvement in performance takes place over time in accordance with some prescribed measure. A neural network learns about its environment through an interactive process of adjustments applied to its synaptic weights and bias levels. Ideally, the network becomes more knowledgeable about its environment after each iteration of learning process. Hence we define learning as:

"It is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded."

The processes used are classified into two categories as described in [3]:

(i) Supervised Learning (Learning With a Teacher)

(ii) Unsupervised Learning (Learning without a Teacher)

(i) Supervised Learning:

We may think of the teacher as having knowledge of the environment, with that knowledge being represented by a set of input-output examples. The environment is, however unknown to neural network of interest. Suppose now the teacher and the neural network are both exposed to a training vector, by virtue of built-in knowledge, the teacher is able to provide the neural network with a desired response for that training vector. Hence the desired response represents the optimum action to be performed by the neural network. The network parameters such as the weights and the thresholds are chosen arbitrarily and are updated during the training procedure to minimize the difference between the desired and the estimated signal. This updation is carried out iteratively in a step-by-step procedure with the aim of eventually making the neural network emulate the teacher. In this way knowledge of the environment available to the teacher is transferred to the neural network. When this condition is reached, we may then dispense with the teacher and let the neural network deal with the environment completely by itself. This is the form of supervised learning.

By applying this type of learning technique, the weights of neural network are updated by using LMS algorithm. The update equations for weights are derived as LMS [3]:

$$w_j(n+1) = w_j(n) + \mu \Delta w_j(n) \tag{3.2}$$

(ii) Unsupervised Learning:

In unsupervised learning or self-supervised learning there is no teacher to over-see the learning process, rather provision is made for a task independent measure of the quantity of representation that the network is required to learn, and the free parameters of the network are optimized with respect to that measure. Once the network has become turned to the statistical regularities of the input data, it develops the ability to form the internal representations for encoding features of the input and thereby to create new classes automatically. In this learning the weights and biases are updated in response to network input only. There are no desired outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into some classes.

3.3 MULTILAYER PERCEPTRON

In the multilayer neural network or multilayer perceptron (MLP), the input signal propagates through the network in a forward direction, on a layer-by-layer basis. This network has been applied successfully to solve some difficult and diverse problems by training in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm [3]. The scheme of MLP using four layers is shown in Fig.3.2. $x_i(n)$ represents the input to the network, f_j and f_k represent the output of the two hidden layers and $y_i(n)$ represents the output of the final layer of the neural network. The connecting weights between the input to the first hidden layer, first to second hidden layer and the second hidden layer to the output layers are represented by respectively

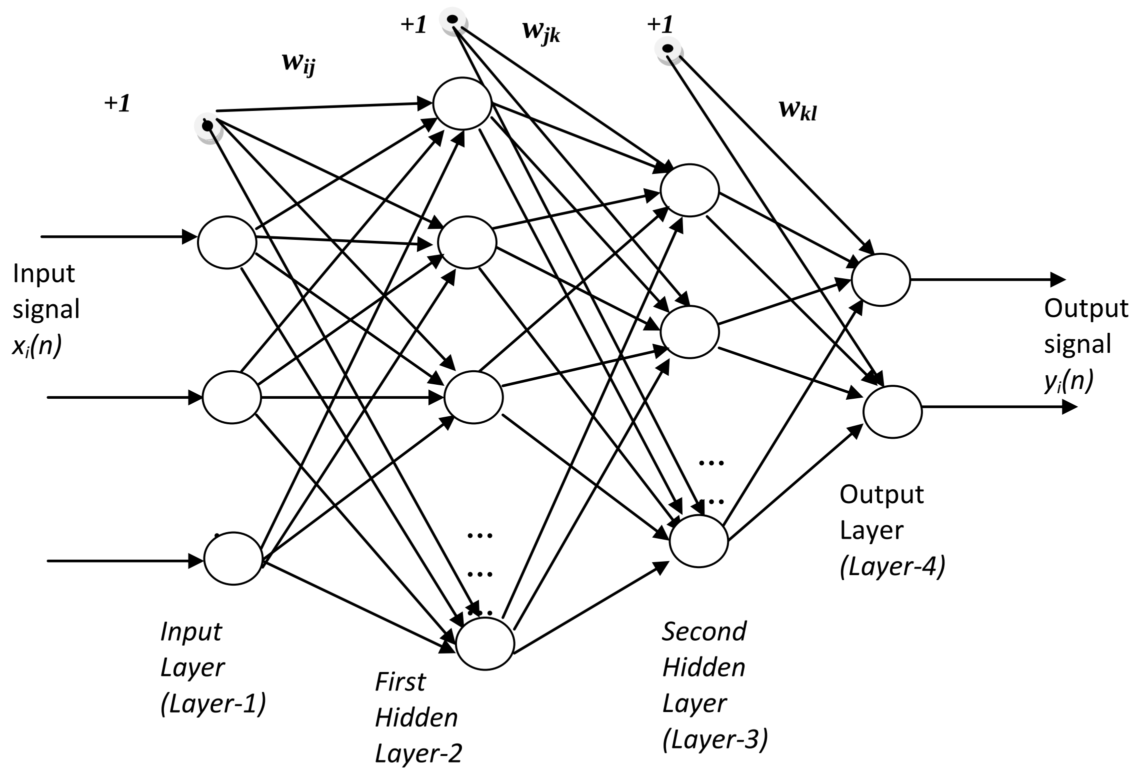


Fig 3.2 Structure of Multilayer Perceptron

If P_1 is the number of neurons in the first hidden layer, each element of the output vector of first hidden layer may be calculated as,

$$f_j = \varphi_j\left[\sum_{i=1}^{N} w_{ij}\, x_i(n) + b_j\right], i = 1,2, \dots N, j = 1,2, \dots P_1 \tag{3.3}$$

where b_j is the threshold to the neurons of the first hidden layer, N is the no. of inputs and φ is the nonlinear activation function in the first hidden layer chosen from the Table 3.1. The time index n has been dropped to make the equations simpler. Let P_2 be the number of neurons in the second hidden layer. The output of this layer is represented as, f_k and may be written as

$$\varphi_k\left[\sum_{j=1}^{P_1} w_{jk}\, f_j + b_k\right], k = 1,2, \dots . P_2 \tag{3.4}$$

where, b_k is the threshold to the neurons of the second hidden layer. The output of the final output layer can be calculated as

$$y_l(n) = \varphi_l\left[\sum_{k=1}^{P_2} w_{kl}\, f_k + b_l\right], l = 1,2, \dots P_3 \tag{3.5}$$

where, b_l is the threshold to the neuron of the final layer and P_3 is the no. of neurons in the output layer. The output of the MLP may be expressed as

$$y_l(n) = \varphi_l\left[\sum_{k=1}^{P_2} w_{kl}\left(\varphi_k\left[\sum_{j=1}^{P_1} w_{jk}\left(\varphi_j\left[\sum_{i=1}^{N} w_{ij}\, x_i(n) + b_j\right]\right) + b_k\right]\right) + b_l\right] \tag{3.6}$$

3.3.1 Back Propagation Algorithm

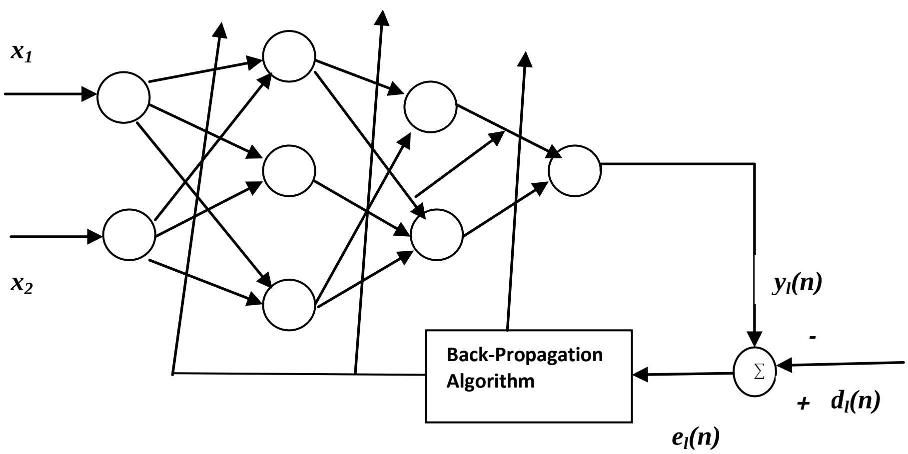


Fig 3.3 Neural Network with Back Propagation Algorithm

An MLP network with 2-3-2-1 neurons (2, 3, 2 and 1 denote the number of neurons in the input layer, the first hidden layer, the second hidden layer and the output layer respectively) with the back-propagation (BP) learning algorithm, is depicted in Fig.3.3. The parameters of the neural network can be updated in both sequential and batch mode of operation. In BP algorithm, initially the weights and the thresholds are initialized as very small random values. The intermediate and the final outputs of the MLP are calculated by using (3.3), (3.4), and (3.5.) respectively. The final output $y_l(n)$ at the output of neuron l, is compared with the desired output $d(n)$ and the resulting error signal $e(n)$ is obtained as

$$e_l(n) = d(n) - y_l(n) \tag{3.7}$$

The instantaneous value of the total error energy is obtained by summing all error signals over all neurons in the output layer, that is

$$\xi(n) = \frac{1}{2} \sum_{l=1}^{P_3} e_l^2(n) \tag{3.8}$$

where P_3 is the no. of neurons in the output layer.

This error signal is used to update the weights and thresholds of the hidden layers as well as the output layer. The reflected error components at each of the hidden layers is computed using the errors of the last layer and the connecting weights between the hidden and the last layer and error obtained at this stage is used to update the weights between the input and the hidden layer. The thresholds are also updated in a similar manner as that of the corresponding connecting weights. The weights and the thresholds are updated in an iterative method until the error signal become minimum. For measuring the degree of matching, Squared error cannot be considered as the network may have multiple outputs and Root Mean Square Error (RMSE) cause over fitting of the model and the weights may not converge. So the Mean Square Error (MSE) is taken as a performance measurement.

The weights are using the following formulas,

$$w_{kl}(n+1) = w_{kl}(n) + \Delta w_{kl}(n) \tag{3.9}$$

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n) \tag{3.10}$$

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{3.11}$$

$$\Delta w_{kl}(n) = -2\mu \frac{\partial \xi(n)}{\partial w_{kl}(n)} = \mu e(n) \frac{dy_l(n)}{dw_{kl}(n)}$$

$$= \mu e(n) \varphi_l' \left[\sum_{k=1}^{P_2} w_{kl} f_k + b_l \right] f_k \tag{3.12}$$

where, μ is the convergence coefficient (0<μ<1). Similarly $\Delta w_{jk}(n)$ and $\Delta w_{ij}(n)$ the can be computed [3]. The thresholds of each layer can be updated in a similar manner, i.e.

$$b_l(n+1) = b_l(n) + \Delta b_l(n) \quad (3.13)$$

$$b_k(n+1) = b_k(n) + \Delta b_k(n) \quad (3.14)$$

$$b_j(n+1) = b_j(n) + \Delta b_j(n) \quad (3.15)$$

where, $\Delta b_l(n)$,$\Delta b_k(n)$ and $\Delta b_j(n)$ are the change in thresholds of the output, hidden and input layer respectively. The change in threshold is represented as,

$$\Delta b_l(n) = -2\mu \frac{\partial \xi(n)}{\partial b_l(n)} = \mu e(n) \frac{d y_l(n)}{d b_l(n)}$$

$$= \mu e(n) \varphi_l' \left[\sum_{k=1}^{P_2} w_{kl} f_k + b_l \right] \quad (3.16)$$

From the structural point of MLP, it is very complex and it there are more than two hidden layers the structure becomes more complex. As more number of weights are present when implemented in DSP or FPGA memory requirements are considered and during updation of weights in Back Propagation it becomes very complex thereby causing over burden on the processor used. So a very simple and powerful structure is required and thus FLANN is considered.

3.4 SIMULATION RESULTS

The MLP structure considered for simulation purpose is shown in Fig.3.2. A three-layer MLP structure with single hidden layer with three nodes and one input node and one output node was chosen for the purpose of identification. tanh(.) function is taken as an activation function for the given structure. The BP algorithm is used to adapt the weights of MLP structure. The input *u* is a uniform distributed signal, called volumetric air flow rate (m^3/sec), in the interval [0, 80] with 1000 samples. The convergence parameter set to 0.001 for MLP weight updating. 80 iterations are taken for structure updation, after which the weights of the ANN is stored for testing. For testing, the input signal is taken from the volumetric air flow rate (with 200) samples in the interval [20 40]. After the simulation, in the training part the error approached to zero as shown in the figures 3.5 and 3.7 for two states respectively. In these figure, the mean square error (MSE) is plotted over the 80 iterations. In the testing part, the estimated (MLP model) output is matched to desired (Plant) output. The graphs for response matching are shown in figures 3.4 and 3.6 for given two states (x1 and x2) testing samples, respectively.

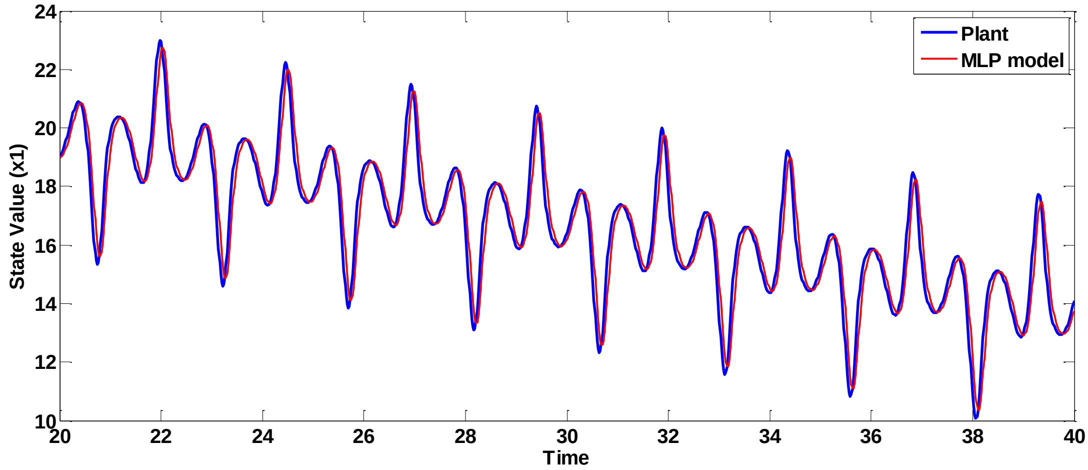


Fig. 3.4 HVAC System single (x1) state in ^{0}C

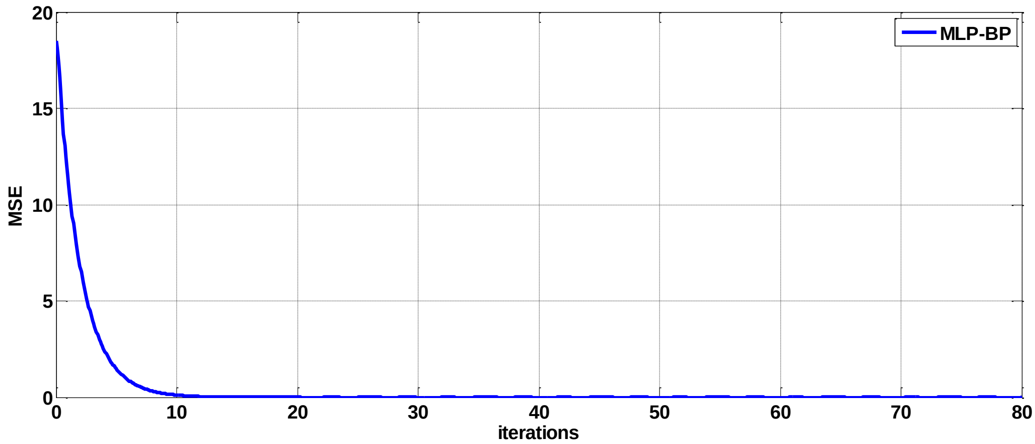


Fig.3.5. Mean square error of HVAC System x1 state.

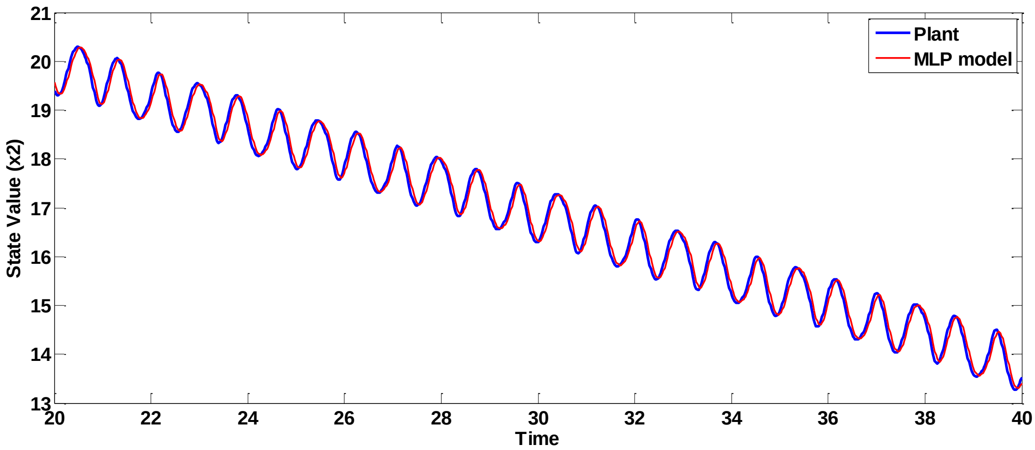


Fig. 3.6 HVAC System single (x2) state in ^{0}C

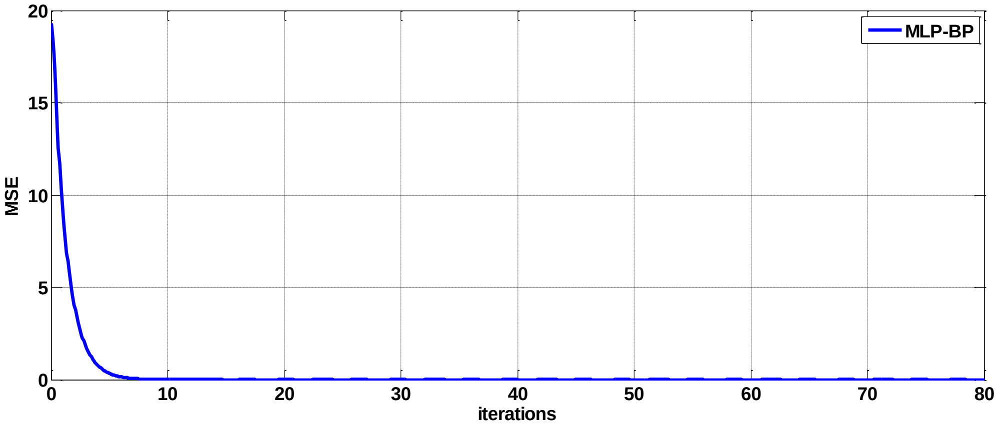


Fig.3.7 Mean square error of HVAC System x2 state.

3.5 FUNCTIONAL LINK ANN

Pao originally proposed FLANN and it is a novel single layer ANN structure capable of forming arbitrarily complex decision regions by generating nonlinear decision boundaries [12]. Here, the initial representation of a pattern is enhanced by using nonlinear function and thus the pattern dimension space is increased. The functional link acts on an element of a pattern or entire pattern itself by generating a set of linearly independent function and then evaluates these functions with the pattern as the argument. Hence separation of the patterns becomes possible in the enhanced space. The use of FLANN not only increases the learning rate but also has less computational complexity. Pao et al [20] have investigated the learning and generalization characteristics of a random vector FLANN and compared with those attainable with MLP structure trained with back propagation algorithm by taking few functional approximation problems. A FLANN structure with two inputs is shown in Fig. 3.4.

3.5.1 Learning Algorithm

Let **X** is the input vector of size N×1 which represents N number of elements; the kth element is given by:

$$X(k) = x_k\ , 1 \leq k \leq N \tag{3.17}$$

Each element undergoes nonlinear expansion to form M elements such that the resultant matrix has the dimension of N×M. The functional expansion of the element x_k by power series expansion is carried out using the equation given in (3.18)

$$s_i = \begin{cases} x_k\ for\ i = 1 \\ x_k^l\ for\ i = 2,3, \dots M \end{cases} \tag{3.18}$$

where l = 1,2,3, … M. For trigonometric expansion, the

$$s_i = \begin{cases} x_k \; for \; i = 1 \\ \sin(l\pi x_k) \; for \; i = 2,4,\dots,M \\ \cos(l\pi x_k) \; for \; i = 3,5,\dots,M+1 \end{cases} \tag{3.19}$$

where l = 1,2,3, … M. In matrix notation the expanded elements of the input vector E, is denoted by S of size N×(M+1). The bias input is unity. So an extra unity value is padded with the S matrix and the dimension of the S matrix becomes N×Q, where Q = M+2.

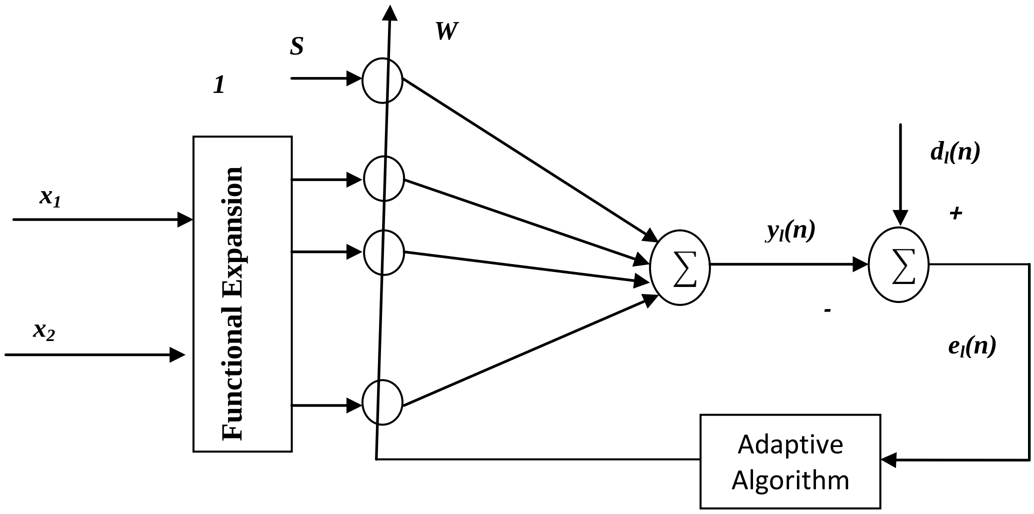


Fig. 3.8 Structure of FLANN

Let the weight vector is represented as **W** having Q elements. The output is given as

$$y = \sum_{i=1}^{Q} s_i w_i \tag{3.20}$$

In matrix notation the output can be,

$$Y = S.W^T \tag{3.21}$$

At n^th^ iteration the error signal $e(n)$ can be computed as

$$e(n) = d(n) - y(n) \tag{3.22}$$

Let $\xi(n)$ denotes the cost function at iteration k and is given by

$$\xi(n) = \frac{1}{2} \sum_{j=1}^{P} e_j^2(n) \tag{3.23}$$

where P is the number of nodes at the output layer. The weight vector can be updated by least mean square algorithm, as

$$w(n+1) = w(n) - \frac{\mu}{2}\hat{\Delta}(n) \tag{3.24}$$

where $\hat{\Delta}(n)$ is an instantaneous estimate of the gradient $\xi(n)$ of with respect to the weight vector $w(n)$. Now

$$\hat{\Delta}(n) = \frac{\partial \xi}{\partial w} = -2e(n)\frac{\partial y(n)}{\partial w} = -2e(n)\frac{\partial [w(n)s(n)]}{\partial w}$$

$$= -2e(n)s(n) \tag{3.25}$$

Substituting the value of (4.25) in (4.24) we get

$$w(n+1) = w(n) - \mu e(n)s(n) \tag{3.26}$$

where μ denotes the step-size $(0 \leq \mu \leq 1)$ which controls the convergence speed of the LMS algorithm.

The functions used for Functional Expansion is linearly independent and this may be achieved by the use of suitable orthogonal polynomials for functional expansion. The trigonometric polynomial basis functions provide a compact representation of the function in the mean square sense. However, when the outer product terms were used along with the trigonometric polynomials for functional expansion, better results were obtained in the case of learning of a two-variable function.

3.6 SIMULATION RESULTS

For the simulation purpose FLANN structure with single input node and single output node is taken. In this structure, the input pattern is expanded by using trigonometric polynomials, i.e., by using $\cos(n\pi u)$ and $\sin(n\pi u)$, for n = 1, 2. One bias and one direct input are also taken in the function expansion. Thus, it has only 6 weights in the structure which are to be updated in each iteration. Least square method is used for weight updation. The input u is a uniform distributed signal, called volumetric air flow rate (m^3/sec), in the interval [0, 80] with 1000 samples. 80 iterations are taken for structure updation, after which the weights of the ANN is stored for testing. For testing, the input signal is taken from the volumetric air flow rate (with 200) samples in the interval [0 80]. After the simulation, in the training part the error approached to zero as shown in the figures 3.10 and 3.12 for two states (x1 and x2) respectively. In these figures, the mean square error (MSE) is plotted over the 80 iterations. In the testing part, the estimated output is matched to desired output. The graphs for response matching are shown in figures 3.9 and 3.11 for given two states testing samples, respectively.

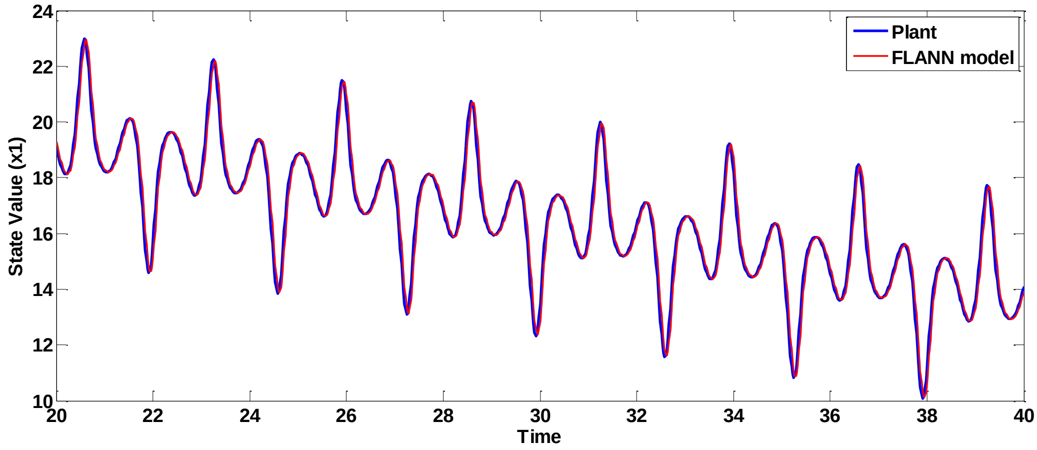


Fig. 3.9 HVAC System x1 state in ^{0}C

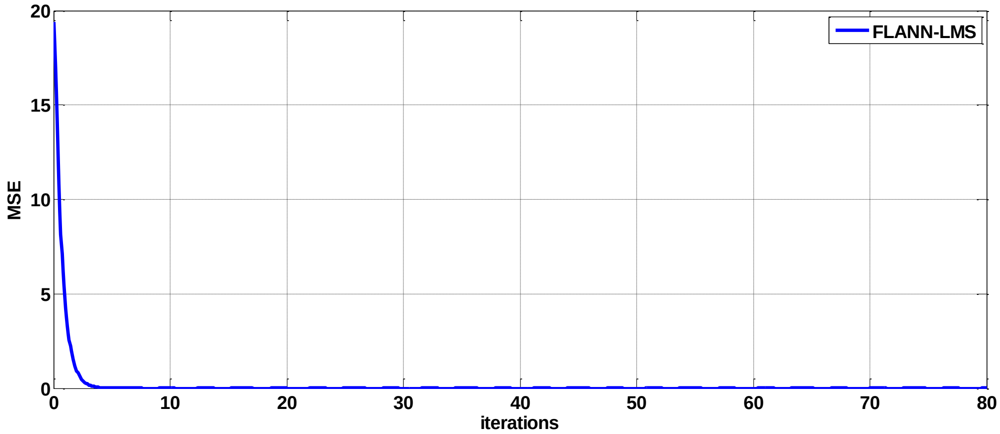


Fig.3.10. Mean square error of HVAC System x1 state.

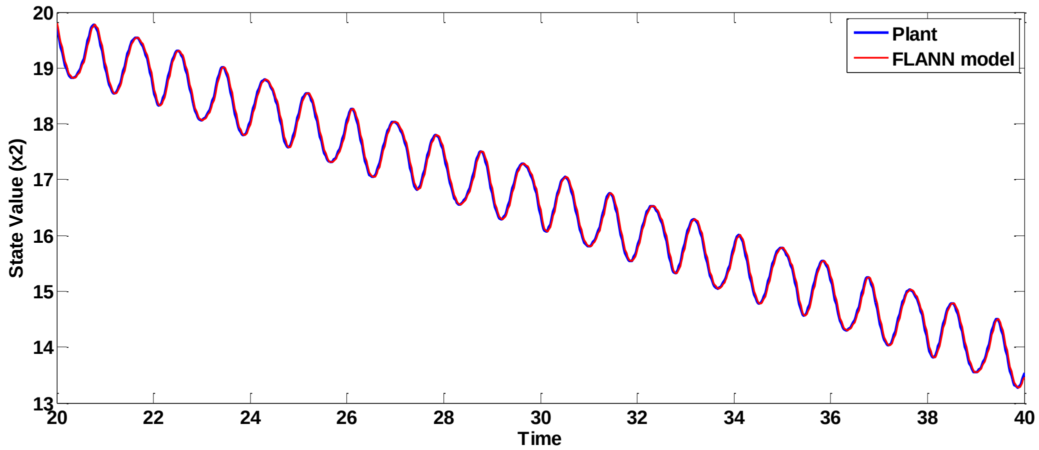


Fig. 3.11 HVAC System x2 state in ^{0}C

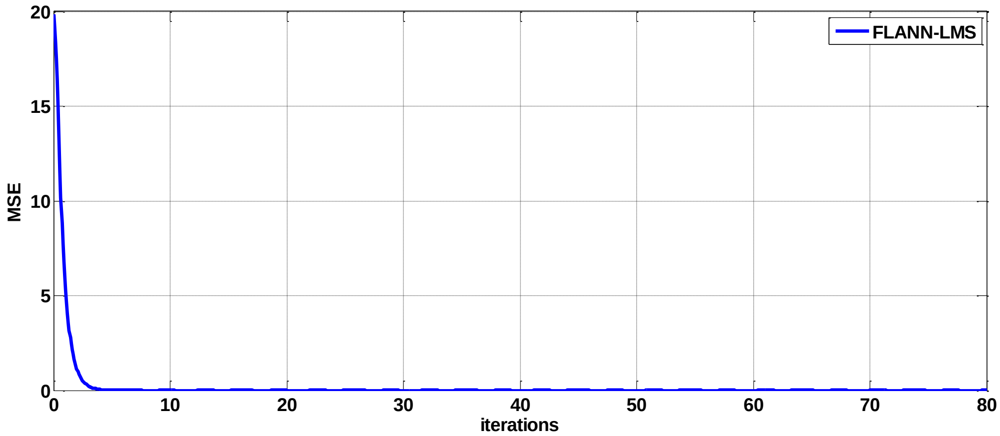


Fig.3.12. Mean square error of HVAC System x2 state.

CHAPTER 4

MODIFIED BP AND BP ALGORITHMS

4.1 INTRODUCTION

Emotion tends to be used in clinical terminology for what a person is feeling at a given moment. Joy, sadness, anger, fear, disgust, and surprise are often considered the six most basic emotions, and other well-known human emotions (e.g., pride, shame, regret, elation, etc.) are often treated as elaborations or specializations of these six to complex social situations. Recent definitions of emotion have either emphasized the external stimuli that trigger emotion, or the internal responses involved in the emotional state, when in fact emotion includes both of those things and much more [23]. According to Perlovsky [24], [25] emotions refer to both exaggeratedly expressive communications and to internal states related to feelings. Love, hate, courage, fear, joy, sadness, pleasure, and disgust can all be described in both psychological and physiological terms. Emotion is the realm where thought and physiology are inextricably entwined, and where the self is inseparable from individual perceptions of value and judgment toward others and ourselves. Emotions are sometimes regarded as the antithesis of reason. A distinctive and challenging fact about human beings is a potential for both opposition and entanglement between will, emotion, and reason.

Recently, Abu Maria and Abu Zitar [29] proposed and implemented a regular and an emotional agent architecture, which is supposed to resemble some of the human behaviors. They noticed that artificial emotions can be used in different ways to influence decision making. Moreover, Gobbini and Haxby [30] proposed a model for distributed neural systems that participate in the recognition of familiar faces, highlighting that this spatially distributed process involves not only visual areas but also areas that primarily have cognitive and social functions such as person knowledge and emotional responses.

In summary, many researchers have attempted incorporating emotions into AI for different aims and reasons. Perhaps the common question among all these works and also the work that is presented within this paper is as follows: *Should we, and can we, develop machines with feelings?*

The answer to the first part is yes, we should have emotional and intelligent machines. Several researchers (e.g., [24] and [31]) suggested that passion, emotion, or feeling can add backing to an argument, even one based primarily on reason, and that typically there is no thought based "purely" on intellectual logic or "purely" on emotion—most decisions and cognitions are founded on a mixture of both. In fact decisions and cognitions can be greatly influenced by the emotional state, as described in [27]: "The specific effects on attention and cognition of a number of affective states have been studied extensively (e.g. anxiety and fear, anger and frustration, positive and negative affect, etc.). These effects include altering the nature of attentional processing (e.g. changes in attention capacity, speed and bias); helping to activate (or inhibit) particular perceptual and cognitive schemas that enhance (or limit) the perception and processing of specific stimuli." Therefore, having emotional machines not only gets us closer to modeling humans, but also aids in improving the decision making process of these machines.

The answer to the second part is *yes* and *no*. Yes we can have emotional intelligent machines, if we accept that their emotions are not exactly human, but rather simulation of some emotions that appear to model apparent human external emotions or their perception by other humans; and no, we cannot have emotional robots if we expect them to have human-like emotions and feelings— for the simple reason that we are still unsure about what constitutes the essence of emotions. The motivation for the work in this paper comes from our belief that we can have certain human emotions artificially modeled in machines. Previous works on modeling different emotions suggested that this is conceivable. However, with the existence of many emotions that vary in response from one human to another, even with similar input stimuli, we choose to model specific emotional parameters with the objective of improving the learning capability of a "nonhuman" system. The system here is based on a supervised neural network that uses the back propagation (BP) learning algorithm.

Therefore, our aim in this paper is to model simulated emotions within a simple supervised neural network structure, and to investigate the effect of the added emotional factors on the learning and decision making capabilities of the neural network.

We only consider two emotions (anxiety and confidence), which we believe have an effect on learning and decision making in humans. In our hypothesis (think of children learning new tasks), when we learn a new task, the anxiety level is high at the beginning and the confidence level is low. After time, practice and getting positive feedback, the anxiety level decreases while the confidence level increases. Once learning is achieved, we tend to be less anxious and more confident performing a task that we have already experienced. Therefore, anxiety and confidence are two dependent dimensions, where confidence is defined as the negative rate of change of anxiety.

Anxiety is a physiological state characterized by cognitive, somatic, emotional, and behavioral components. These components combine to create the feelings that we typically recognize as fear, apprehension, or worry. Anxiety is not always pathological or maladaptive: it is a common emotion along with fear, anger, sadness, and happiness.

Confidence is described as a state of being certain, either that a hypothesis or prediction is correct, or that a chosen course of action is the best or most effective given the circumstances. Confidence can be described as a subjective, emotional state of mind, but is also represented statistically as a confidence level within which one may be certain that a hypothesis will either be accepted or rejected.

In our work, we refer to anxiety and confidence as "emotions," however, one could argue whether they are genuine human emotions. The definition of anxiety describes it as a common emotion, however we may also consider it as an emotional state of mind or emotional response that may not be related to any biological processes in the brain. Similarly for confidence, it is considered as an emotional state of mind, an emotional response, or an emotion as we call it, because it has an emotional effect on the learning process.

In this paper, we propose a new emotional back propagation (EmBP) learning algorithm based on incorporating two essential emotions (anxiety and confidence) during the processes of learning and decision making. The distinctive, emotion-related elements of EmBP are twofold. First, there is pattern averaging, which attempts mimicking the tendency for human emotional judgments and preferences to be based on general impressions

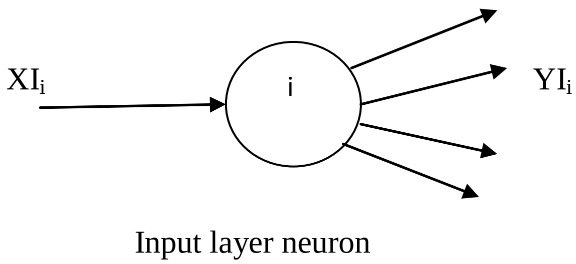


Fig 4.1 Input/output configuration of an input-layer neuron

rather than precise details of the objects being perceived. Second, there are the confidence and anxiety variables, which are influenced by the perceived objects: "Indeed, anger or fear can often be thought of as a systematic response to observed facts [24]." This paper suggests that these two emotional responses can be successfully simulated and used during the training of a supervised neural network with the purpose of providing more effective learning. The two emotional variables are dependent on each other, where confidence is measured as the difference between anxiety levels at two different iterations.

4.2 EMOTIONAL BACK PROPAGATION LEARNING ALGORITHM

In 1986, Rumelhart *et al.* proposed a generalized delta rule known as BP for training layered neural networks. This algorithm has been popularly used ever since due to its implementation simplicity and quick training, specially, when sufficient training database is available. In this section, the modification of this algorithm, by adding two emotional coefficients, provides the proposed EmBP, which will be explained in details according to the flow of information within the neural network, which consists of three layers: input layer with (4.2.1) neurons, hidden layer with (h) neurons, and output layer with (j) neurons.

4.2.1 Input-Layer Neurons

These are not processing neurons, thus, the output of each input-layer neuron is defined as

$$YIi=XI_i \tag{4.1)}$$

where XI_i and YIi are, respectively, the input and output values of neuron in the input layer. Fig. 4.1 shows the input and output configuration of an input-layer neuron.

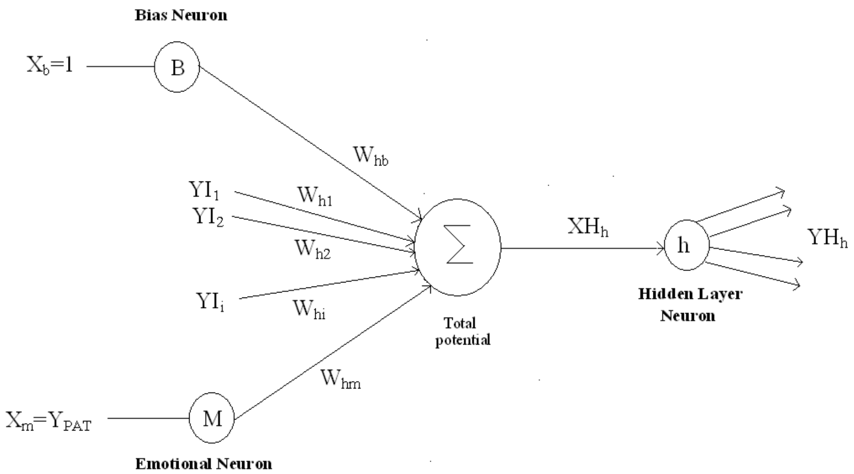


Fig. 4.2 Input/output configuration of a hidden-layer neuron

4.2.2 Hidden-Layer Neurons

These are processing neurons; therefore, the sigmoid activation function is used to activate each neuron in this layer. Here it is assumed that there is one hidden layer, however the same process can be applied for more than one hidden layer using the following algorithm. The output of each hidden-layer neuron is defined as

$$YH_h=\left(\frac{1}{1+\exp(-XH_h)}\right) \tag{4.2}$$

where XH_h and YH_h are the input and output values of neuron h in the hidden layer, respectively. The input to a hidden-layer neuron XH_h is calculated using the total potential (TP_h) of all input values coming into that neuron. The total potential is the sum of multiplications of input values and their associated weights. There are three different groups of inputs, and consequently, types of total potential, coming into a hidden-layer neuron. The first total potential (TP_{hc}) is the conventional total potential, which is obtained using the output values of the previous layer (input layer, in this case) and the conventional weight matrix. The second total potential (TP_{hb}) is obtained using the hiddenlayer bias neuron and its associated weights. The third total potential (TP_{hm}) is obtained using the hidden-layer emotional neuron and its associated weights. Therefore,the input to a hidden-layer neuron is defined as

$$XH_h = TP_{hc} + TP_{hb} + TP_{hm} \tag{4.3}$$

TP_{hc} is defined as

$$TP_{hc} = \sum_{i=1}^{r} W_{hi} \bullet YI_i \tag{4.4}$$

Where W_{hi} is the weight given by hidden neuron h to input Neuron i , and YI_i is the output of input neuron i.r is the maximum number of input-layer neurons. TP_{hb} is defined as

$$TP_{hb} = W_{hb} \bullet X_b \tag{4.5}$$

where W_{hb} is the weight given by hidden neuron h to the hidden-layer bias neuron b , X_b and is the input value to the bias neuron, which is set to 1(X_b=1).
TP_{hm} is defined as

$$TP_{hm} = W_{hm} \bullet X_m \tag{4.6}$$

where W_{hm} is the weight given by hidden neuron h to the hidden-layer emotional neuron m , and X_m is the input value to the emotional neuron. X_m represents the input pattern average value, which in our hypothesis affects the learning of the neural network. According to Baumgartner *et al.* “Most of the published neuroimaging papers examining emotional processes have used visual stimuli in order to evoke emotions (positive or negative).” Therefore, the global average of an input pattern is fed into the emotional neuron and the resulting total potential is used to calculate the output of the hidden layer.

X_m is calculated as

$$X_m = Y_{PAT} \tag{4.7}$$

Where Y_{PAT} is the global input pattern average value for an input Image P(x,y)

$$Y_{PAT} = \sum_{x=1,y=1}^{x_{max},y_{max}} P(x,y) / x_{max}.y_{max} \tag{4.8}$$

Where x_{max} and y_{max} are the highest number of pixels in the x and y directions of image P(x,y) , respectively. Fig.4.2 shows the input and output configuration of a hidden-layer neuron.

4.2.3 Output-Layer Neurons

These are also processing neurons, and similarly to the hidden layer, the sigmoid activation function is used to activate each neuron in this layer.

The output of each output-layer neuron is defined as

$$YJ_j = \left(\frac{1}{1+\exp(-XJ_j)} \right) \tag{4.9}$$

where XJ_j and YJ_j are the input and output values of neuron j in the output layer, respectively.

The input to an output-layer neuron XJ_j is also calculated using the total potential (TP_j) of all input values coming into that neuron from the previous hidden layer and the bias and emotional neurons.Therefore, the input to an output-layer neuron is defined as

$$XJ_j = TP_{jc} + TP_{jb} + TP_{jm} \tag{4.10}$$

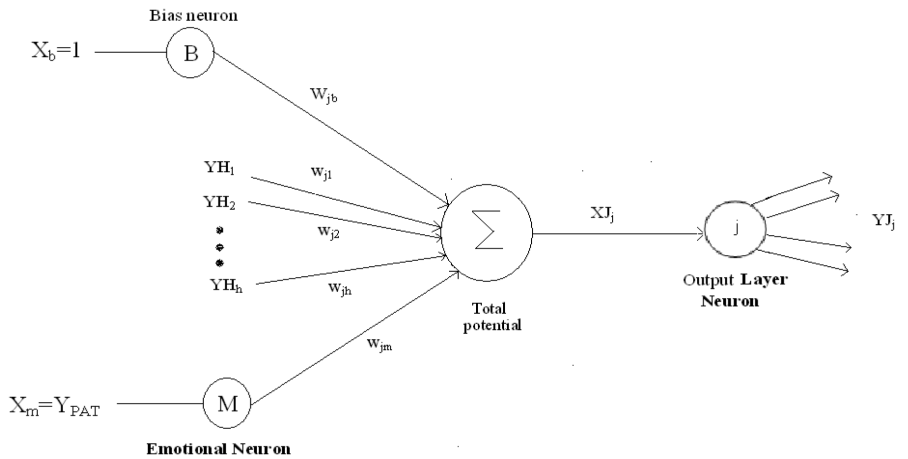


Fig 4.3 Input/Output configuration of an output-layer neuron

TP_{jc} is defined as

$$TP_{jc} = \sum_{h=1}^{l} W_{jh} \bullet YH_h \tag{4.11}$$

where W_{jh} is the weight given by output neuron j to hidden neuron h, and YH_h is the output of hidden neuron h .*l* is the maximum number of hidden-layer neurons.

TP_{jb} is defined as

$$TP_{jb} = W_{jb} \bullet X_b \tag{4.12}$$

where W_{jb} is the weight given by output neuron j to the outputlayer bias neuron b , and X_b is the input value to the bias neuron, which is set to $1(X_b=1)$.

TP_{jm} is defined as

$$TP_{jm} = W_{jm} \bullet X_m \tag{4.13}$$

where W_{jm} is the weight given by output neuron j to the outputlayer emotional neuron m, and X_m is the input value to the emotional neuron. X_m is calculated as in (4.7). Fig. 4.3 shows the input and output configuration of an output-layer neuron.

4.2.4 The Emotional Back propagation Parameters

Here the proposed emotional parameters are used together with the existing learning coefficient (η) and momentum rate (α) in order to adjust the neural network weights, based on error minimization.

The proposed emotional parameters are the *anxiety coefficient* (μ) and the *confidence coefficient* (k). According to our hypothesis, when we learn a new task, the anxiety level is high at the beginning and the confidence level is low. After time, practice, and getting positive feedback, the anxiety level decreases while the confidence level increases. Once learning is achieved, we tend to be less anxious and more confident doing a task that we have already learned. The proposed emotional neural network incorporates both emotional coefficients during the learning and the generalization processes. Both coefficients have values between “0” and “1.” In order to model the emotional factor in an artificial neural network, the following assumptions are made.

Assumption 1: The anxiety level is dependent on the input patterns, where new patterns cause higher anxiety. During the first iteration (new task learning), the initial anxiety coefficient value is set to “1.”

Assumption 2: The anxiety level is dependent on the difference (error) between the actual output of the neural network and the desired (target) output. This is a kind of feedback that the emotional neural network uses to measure how successful its learning is. Anxiety decreases with the minimization of the error.

Assumption 3: The confidence level increases with the decrease in anxiety level. During the first iteration (new task learning), the initial confidence coefficient value is set to "0." Based on the above assumptions, the anxiety coefficient (μ) value is defined as

$$\mu = Y_{AvPAT} + E \tag{4.14}$$

where Y_{AvPAT} is the average value of all presented patterns to the neural network in each iteration, which is defined as

$$Y_{AvPAT} = \sum_{p=1}^{N_p} Y_{PAT} \Big/ N \tag{4.15}$$

where p is pattern index from first to the last pattern N_p .Y_{PAT} is the average value of pattern p. The error feedback E is defined as

$$E = \sum_{j=1}^{N_j} (T_j - YJ_j)^2 \Big/ N_p \bullet N_j \tag{4.16}$$

where j is the output neuron index from first to the last neuron N_j and N_p is the total number of patterns. YJ_j and T_j are the actual and target output value for neuron j, respectively. The confidence coefficient (k) value is defined as

$$k = \mu_o - \mu_i \tag{4.17}$$

where (μ_0) is the anxiety coefficient value after the first iteration (exposure to new patterns) and (μ_i) is the anxiety coefficient value in at subsequent iteration i.

4.3 BACK PROPAGATION WEIGHT UPDATE RULE

This idea was first described by Werbos [32] and popularised by Rumelhart *et al.*[33].

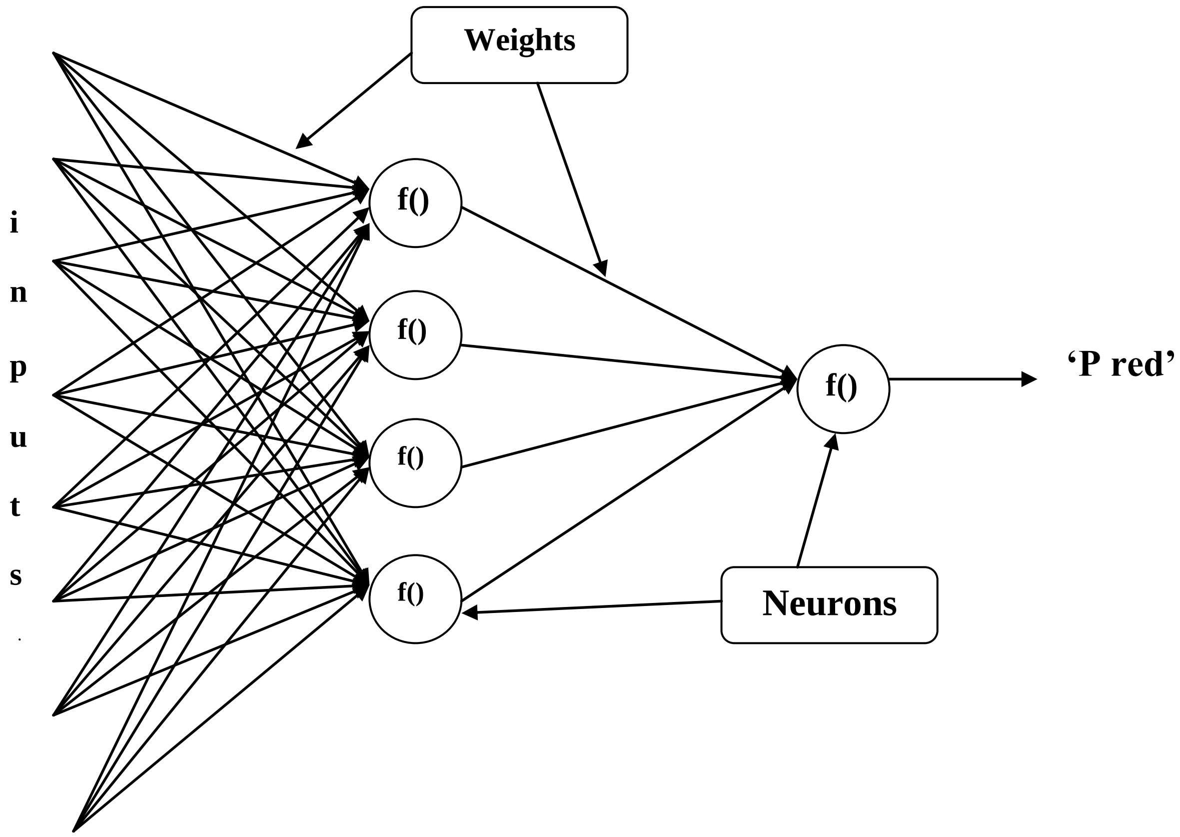


Fig 4.4 A multilayer perceptron

Consider the network above, with one layer of hidden neurons and one output neuron. When an input vector is propagated through the network, for the current set of weights there is an output *Pred*. The objective of supervised training is to adjust the weights so that the difference between the network output *Pred* and the required output *Req* is reduced. This requires an algorithm that reduces the absolute error, which is the same as reducing the squared error, where:

$$\text{Network Error} = Pred - Req$$

$$= E \qquad (4.18)$$

The algorithm should adjust the weights such that E^2 is minimised. Back-propagation is such an algorithm that performs a gradient descent minimisation of E^2.

In order to minimize E^2, its sensitivity to each of the weights must be calculated. In other words, we need to know what effect changing each of the weights will have on E^2. If this is known then the weights can be adjusted in the direction that reduces the absolute error.

The notation for the following description of the back-propagation rule is based on the diagram below.

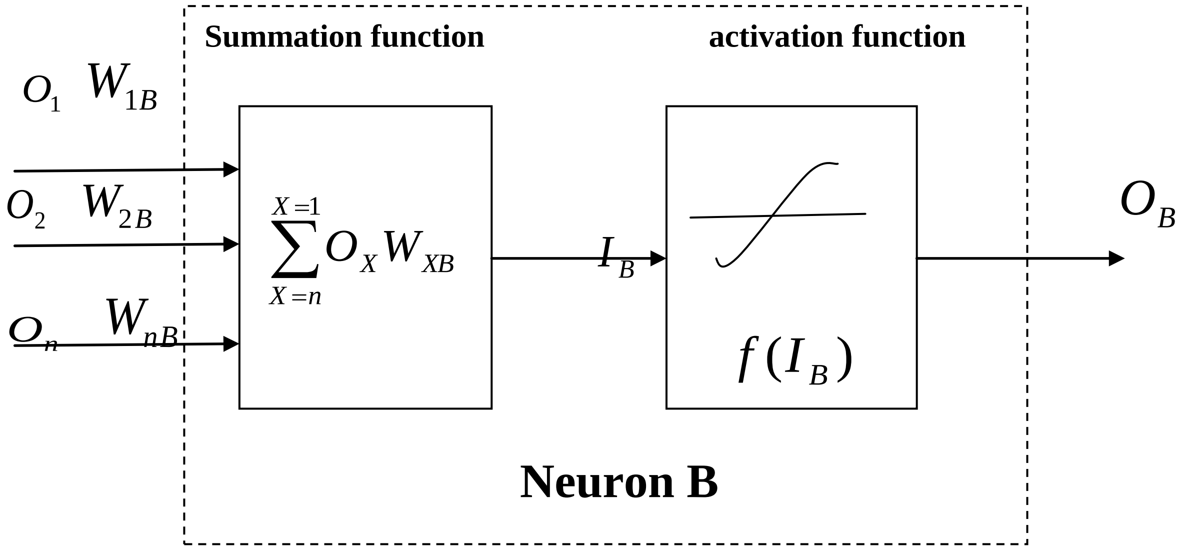


Fig 4.5 Notations for back propagation rule

The dashed line represents a neuron *B*, which can be either a hidden or the output neuron. The outputs of *n* neurons ($O_1 ... O_n$) in the preceding layer provide the inputs to neuron *B*. If neuron *B* is in the hidden layer then this is simply the input vector.

These outputs are multiplied by the respective weights ($W_{1B}...W_{nB}$), where W_{nB} is the weight connecting neuron *n* to neuron *B*. The summation function adds together all these products to provide the input, I_B, that is processed by the activation function f (**.**) of neuron *B*. $f(I_B)$ is the output, O_B, of neuron *B*.

For the purpose of this illustration, let neuron 1 be called neuron *A* and then consider the weight W_{AB} connecting the two neurons.

The approximation used for the weight change is given by the delta rule:

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial W_{AB}} \tag{4.19}$$

where η is the learning rate parameter, which determines the rate of learning, and

$$\frac{\partial E^2}{\partial W_{AB}}$$

is the sensitivity of the error, E^2, to the weight W_{AB} and determines the direction of search in weight space for the new weight $W_{AB(new)}$ as illustrated in the figure below.

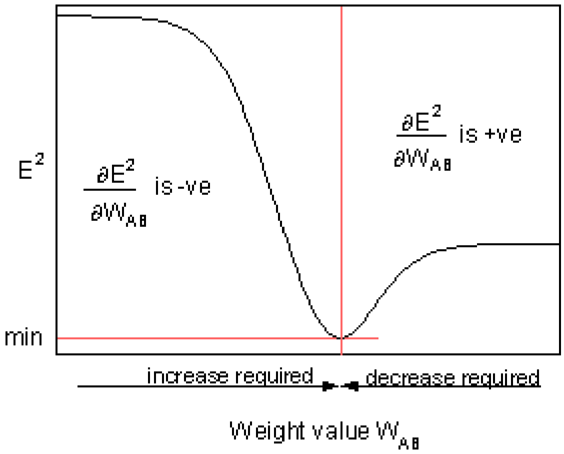


Fig 4.6 In order to minimize E^2 the delta rule gives the direction of weight change required

From the chain rule,

$$\frac{\partial E^2}{\partial W_{AB}} = \frac{\partial E^2}{\partial I_B}\frac{\partial I_B}{\partial W_{AB}} \tag{4.20}$$

and

$$\frac{\partial I_B}{\partial W_{AB}} = \frac{\partial \sum_{x=n}^{x=1} O_x W_{xB}}{\partial W_{AB}}$$

$$= \frac{\partial (O_A W_{AB})}{\partial W_{AB}} + \frac{\partial \sum_{X=n}^{x=2} O_x W_{xB}}{\partial W_{AB}}$$

$$= O_A \tag{4.21}$$

Since the rest of the inputs to neuron B have no dependency on the weight W_{AB}.Thus from eqns. (5.20) and (5.21), eqn. (5.19) becomes,

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A \tag{4.22}$$

and the weight change of W_{AB} depends on the sensitivity of the squared error, E^2, to the nput, I_B, of unit B and on the input signal O_A.

There are two possible situations:

1. B is the output neuron;

2. B is a hidden neuron.

Considering the first case:

Since B is the output neuron, the change in the squared error due to an adjustment of W_{AB} is simply the change in the squared error of the output of B:

$$\partial E^2 = \partial(\mathrm{Pr}\,ed - \mathrm{Re}\,q)^2$$

$$\frac{\partial E^2}{\partial I_B} = 2(\mathrm{Pr}\,ed - \mathrm{Re}\,q)\frac{\partial\,\mathrm{Pr}\,ed}{\partial I_B}$$

$$= 2E\frac{\partial f(I_B)}{\partial I_B}$$

$$= 2Ef'(I_B) \qquad (4.23)$$

Combining eqn. (4.22) with (4.23) we get,

$$W_{AB(new)} = W_{AB(old)} - \eta O_A 2Ef'(I_B) \qquad (4.24)$$

The rule for modifying the weights when neuron B is an output neuron. If the output activation functions, $f(.)$, is the logistic function then:

$$f(x) = \frac{1}{1+e^{-x}} = (1+e^{-x})^{-1} \qquad (4.25)$$

differentiating (4.25) by its argument x

$$f'(x) = -1(1+e^{-x})^{-2} - 1(e^{-x}) = \frac{e^{-x}}{(1+e^{-x})^2} \qquad (4.26)$$

But, $$f(x) = \frac{1}{1+e^{-x}} \qquad (4.27)$$

$$e^{-x} = (1-f(x))/f(x) \qquad (4.28)$$

Inserting (4.28) into (4.26) gives:

$$f'(x) = \frac{\dfrac{(1-f(x))}{f(x)}}{\dfrac{1}{(f(x))^2}}$$

$$= f(x) \times (1 - f(x)) \tag{4.29}$$

similarly for the tanh function,

$$f'(x) = (1 - f(x)^2)$$

or for the linear (identity) function,

$$f'(x) = 1$$

This gives:

$$W_{AB(new)} = W_{AB(old)} - \eta O_A 2 E O_B (1 - O_B) \text{............} (\log istic)$$

$$W_{AB(new)} = W_{AB(old)} - \eta O_A 2 E (1 - O_B{}^2) \text{............} (\tanh)$$

$$W_{AB(new)} = W_{AB(old)} - \eta O_A 2 E \text{.........................} (linear)$$

Considering the second case:

B is a hidden neuron.

$$\frac{\partial E^2}{\partial I_B} = \frac{\partial E^2}{\partial I_0} \frac{\partial I_0}{\partial O_B} \frac{\partial O_B}{\partial I_B} \tag{4.30}$$

where the subscript, *o*, represents the output neuron.

$$\frac{\partial O_B}{\partial I_B} = \frac{\partial f(I_B)}{\partial I_B} = f'(I_B) \tag{4.31}$$

$$\frac{\partial I_0}{\partial O_B} = \frac{\partial \sum_p O_p W_{p0}}{\partial O_B} \tag{4.32}$$

where p is an index that ranges over all the neurons including neuron B that provide input signals to the output neuron. Expanding the right hand side of equation (4.32),

$$\frac{\partial \sum_p O_p W_{p0}}{\partial O_B} = \frac{\partial O_B W_{B0}}{\partial O_B} + \frac{\partial \sum_p^{p=B} O_p W_{P0}}{\partial O_B} = W_{B0} \tag{4.33}$$

since the weights of the other neurons ,W_{pO} ($p!=B$) have no dependency on O_B.

Inserting (4.31) and (4.33) into (4.30),

$$\frac{\partial E^2}{\partial I_B} = \frac{\partial E^2}{\partial I_0} W_{B0} f'(I_B) \tag{4.34}$$

Thus $\frac{\partial E^2}{\partial I_B}$ is now expressed as a function of $\frac{\partial E^2}{\partial I_0}$, calculated as in (4.23).

The complete rule for modifying the weight W_{AB} between a neuron A sending a signal to a neuron B is,

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A \tag{4.35}$$

where, $\frac{\partial E^2}{\partial I_B} = 2Ef'_0 \; (I_B)$ -I_B is the output newron (4.36)

$\frac{\partial E^2}{\partial I_B} = \frac{\partial E^2}{\partial I_0} W_{BO} f'_k(I_B)$ -I_B is the hidden newron (4.37)

where $f_o(.)$ and $f_h(.)$are the output and hidden activation functions respectively.

4.4 SIMULATION RESULTS

The MLP structure considered for simulation purpose is shown in Fig.3.2. A three-layer MLP structure with single hidden layer with three nodes and one input node and one output node was chosen for the purpose of identification. tanh(.) function is taken as an activation function for the given structure. The Modified Back Propagation (MBP) algorithm is used to adapt the weights of MLP structure. The input *u* is a uniform distributed signal, called volumetric air flow rate (m^3/sec), in the interval [0, 80] with 1000 samples. The convergence parameter set to 0.001 for MLP weight updating. 80 iterations are taken for structure updation, after which the weights of the ANN is stored for testing. For testing, the input signal is taken from the volumetric air flow rate (with 200) samples in the interval [20 40]. After the simulation, in the training part the error approached to zero as shown in the figures 4.8 and 4.10 for two states respectively. In these figure, the mean square error (MSE) is plotted over the 80 iterations. In the testing part, the estimated (MLP model) output is matched to desired (Plant) output. The graphs for response matching are shown in figures 4.7 and 4.9 for given two states (x1 and x2) testing samples, respectively.

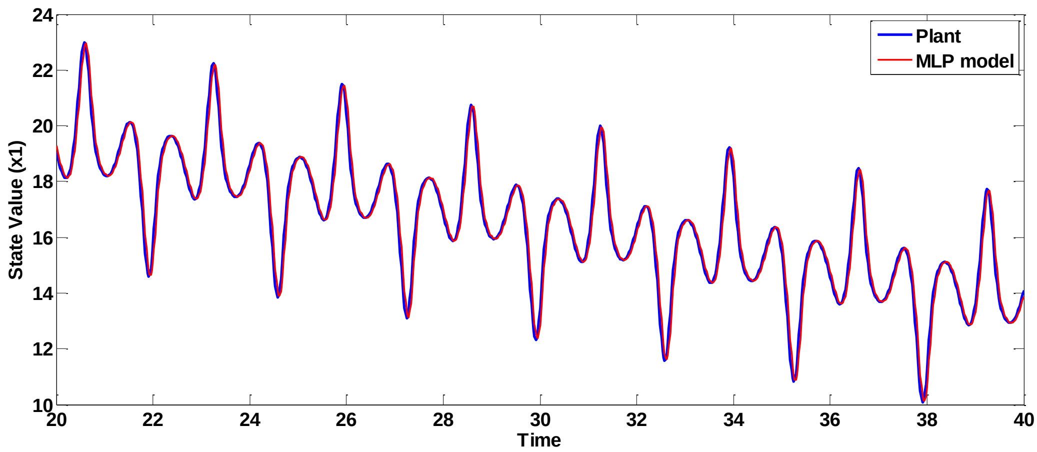


Fig.4.7 HVAC System x1 state in ^{0}C

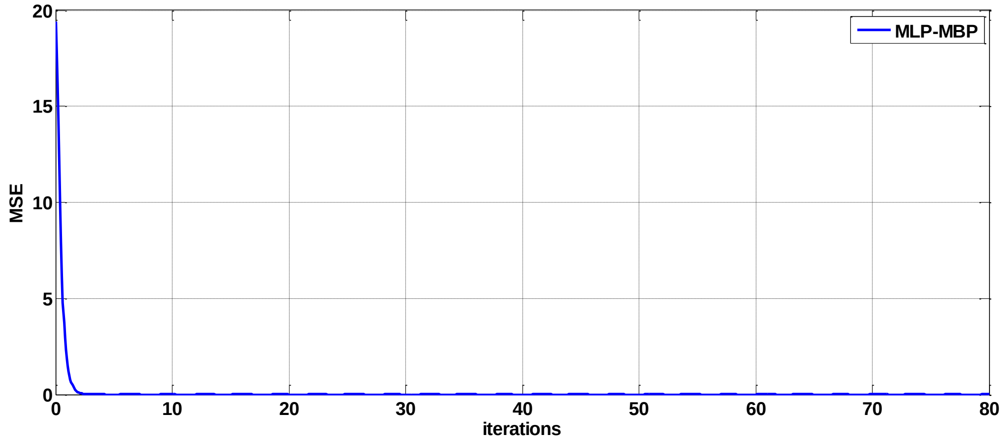


Fig.4.8 Mean square error of HVAC System x1 state.

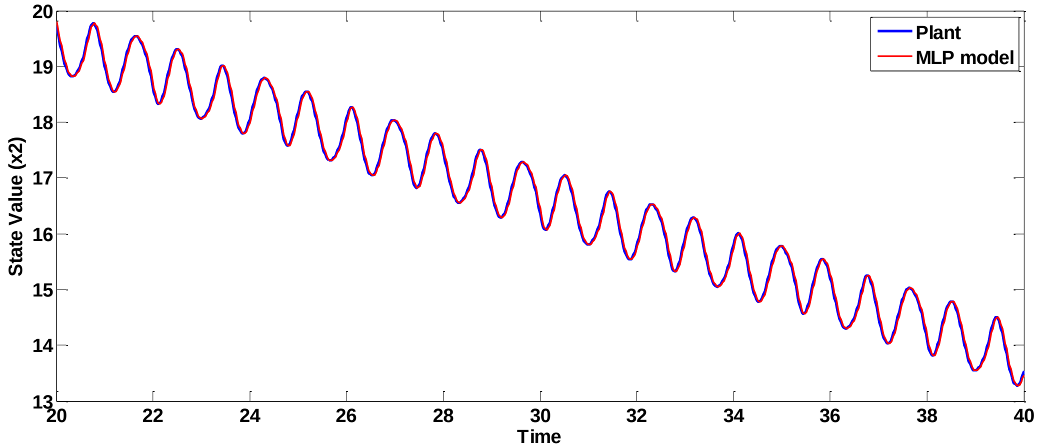


Fig.4.9 HVAC System x2 state in ^{0}C

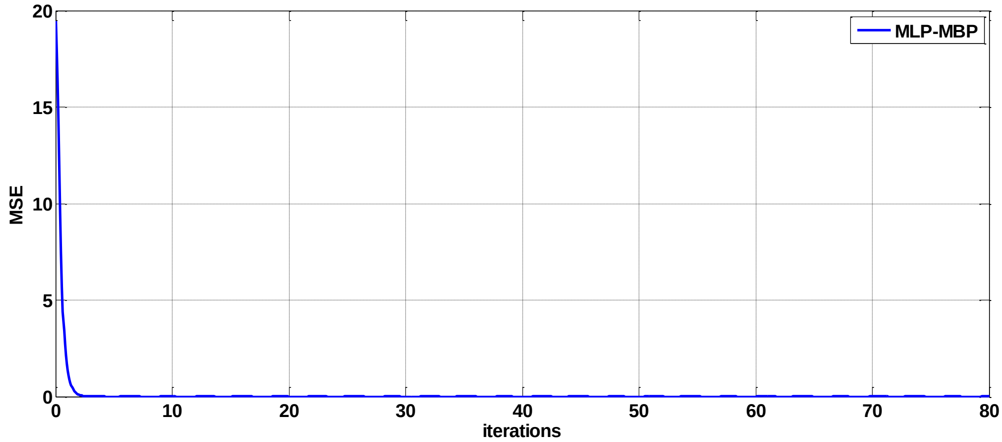


Fig. 4.10 Mean square error of HVAC System x2 state.

4.5 COMPARISON OF RESULTS

The Mean Square Errors (MSE) for HVAC system state x1 are compared for different ANN structures, and shown below in Fig.4.11. Among all these errors the MLP-MBP error is very fast converging comparing other techniques and it contains less error and less computation time shown in table No 4.1. The FLANN-LMS error is converging slowly with respect to MLP-MBP and fast converging with respect to MLP-BP and computational time value is in between these two techniques shown in table No 4.1. The MLP-BP error is very slowly converging, comparing MLP-BP and FLANN-LMS errors, and computational time also very high shown in table No 4.1. So in all these techniques the MLP-MBP technique is very good. All the simulations are carried out using MATLAB R2008a.

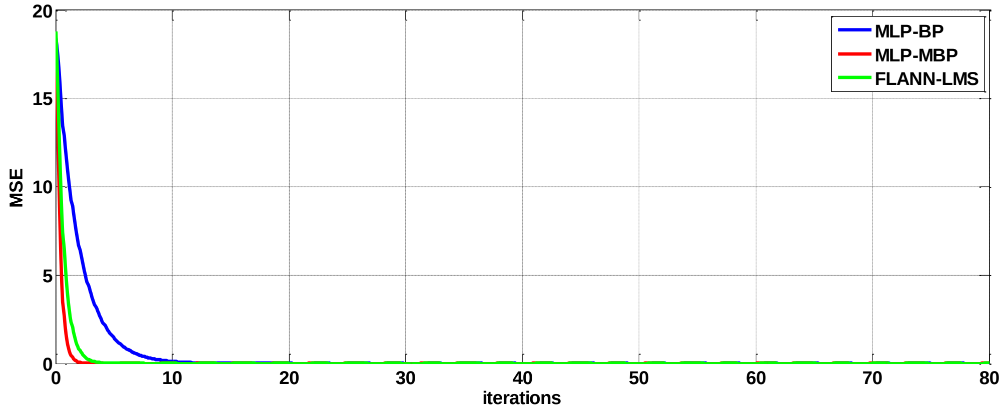


Fig.4.11. Mean square error of HVAC System x1 state.

The Mean Square Errors (MSE) for HVAC system state x2 are compared for different ANN structures, and shown below in Fig.4.12. Among all these errors the MLP-MBP error is very fast converging comparing other techniques and it contains less error and less computation time shown in table No 4.1. The FLANN-LMS error is converging slowly with respect to MLP-MBP and fast converging with respect to MLP-BP and computational time value is in between these two techniques shown in table No 4.1. The MLP-BP error is very slowly converging, comparing MLP-BP and FLANN-LMS errors, and computational time also very high shown in table No 4.1. So in all these techniques the MLP-MBP technique is very good. All the simulations are carried out using MATLAB R2008a.

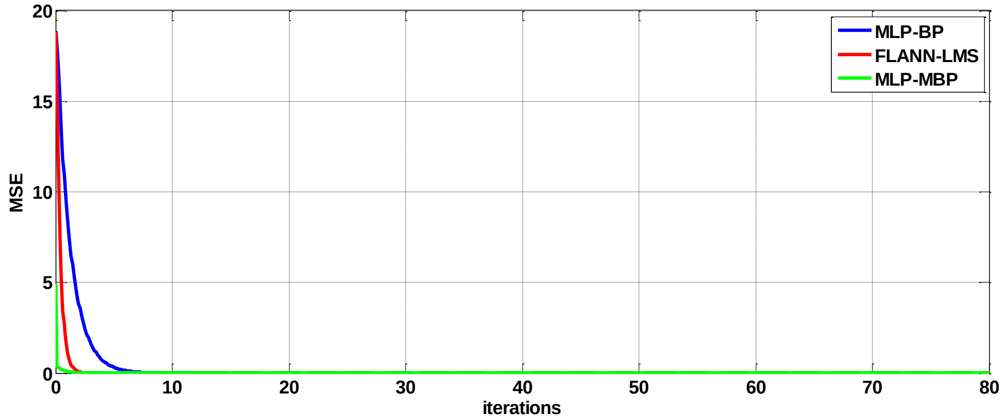


Fig.4.12 Mean square error of HVAC System x2 state.

4.6 PERFORMANCE OF DIFFERENT TECHNIQUES

For the evaluation of performance of different methods, we have taken same training input samples and testing input samples. For the MSE, we have taken same 80 iterations. As shown in the table (4.1), proposed MLP-MBP and ANFIS method are given min MSE as compared to MLP-BP and FLANN-LMS. MLP-MBP and ANFIS are also taken less computational time for the training.

Table 4.1

SYSTEM IDENTIFICATION TECHNIQUE	ERROR MIN (MSE)	FIG.NO.	COMPUTATIONAL TIME(sec)	PERFORMANCE
MLP-BP	0.0054	2.9	8.967	NORMAL
FLANN-LMS	0.0025	3.7	9.162	GOOD
MLP-MBP	0.0018	4.11	8.728	VERY GOOD
ANFIS	0.00012	5.7	3.592	EXCELLENT

CHAPTER 5

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

5.1 INTRODUCTION

System identification: is the process of constructing a model to predict the behavior of a target system. Conventional system identification techniques are mostly based on linear models with fast computation and rigorous mathematical support. On the other hand, neuro-fuzzy modeling represents nonlinear identification techniques that require massive computation but without mathematical proofs of convergence to global minima or the like.

System modeling based on conventional mathematical tools (e.g., differential equations) is not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy if then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This *fuzzy modeling* or *fuzzy identification*, first explored systematically by Takagi and Sugeno [40], has found numerous practical applications in control, prediction and inference [35, 36]. However, there are some basic aspects of this approach which are in need of better understanding. More specifically:

1. No standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system.
2. There is need for effective methods for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index.

In this perspective, the aim of this *Adaptive-Network-based Fuzzy Inference System*, or simply *ANFIS*, which can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. The next section introduces the basics of fuzzy if-then rules and fuzzy inference systems.

5.2 FUZZY IF-THEN RULES AND FUZZY INFERENCE SYSTEMS

A. Fuzzy If-Then Rules

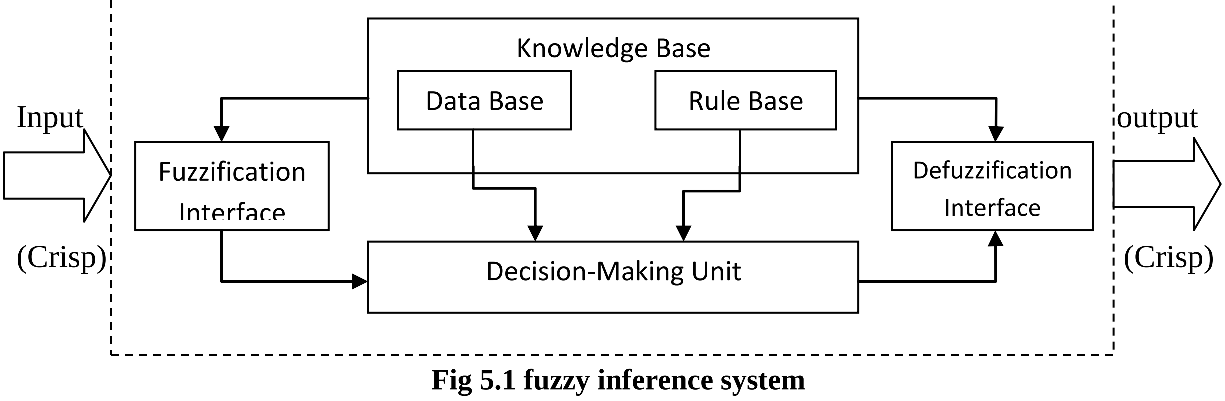


Fig 5.1 fuzzy inference system

Fuzzy if-then rules or *fuzzy conditional statements* are expressions of the form IF A THEN B, where A and B are labels of *fuzzy sets* characterized by appropriate membership functions. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision. An example that describes a simple fact is

if pressure is high, then volume is small

where *pressure* and *volume* are *linguistic variables*, *high* and *small* are *linguistic values* or *labels* that are characterized by membership functions. Another form of fuzzy if-then rule, proposed by Takagi and Sugeno [39], has fuzzy sets involved only in the premise part. By using Takagi and Sugeno's fuzzy if-then rule, we can describe the resistant force on a moving object as follows:

$$\textit{if velocity is high, then force} = k*(\textit{velocity})^2$$

where, again, *high* in the premise part is a linguistic label characterized by an appropriate membership function. However, the consequent part is described by a non fuzzy equation of the input variable, velocity. Both types of fuzzy if-then rules have been used extensively in both modeling and control. Through the use of linguistic labels and membership functions, a fuzzy if-then rule can easily capture the spirit of a "rule of thumb" used by humans. From another angle, due to the qualifiers on the premise parts, each fuzzy if-then rule can be viewed as a local description of the system under consideration. Fuzzy if-then rules form a core part of the fuzzy inference system to be introduced below.

B. Fuzzy Inference Systems

Fuzzy inference systems are also known as *fuzzy-rule-based systems*, *fuzzy models*, *fuzzy associative memories (FAM)*, or *fuzzy controllers* when used as controllers. Basically a fuzzy inference system is composed of five functional blocks (Figure 5.1):

- A **rule base** containing a number of fuzzy if-then rules;
- A **database** which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- A **decision-making unit** which performs the inference operations on the rules;
- A **fuzzification interface** which transforms the crisp inputs into degrees of match with linguistic values;
- A **defuzzification interface** which transform the fuzzy results of the inference into a crisp output.

Usually, the rule base and the database are jointly referred to as the *knowledge base*.

The steps of *fuzzy reasoning* (inference operations upon fuzzy if-then rules) performed by fuzzy inference systems are:

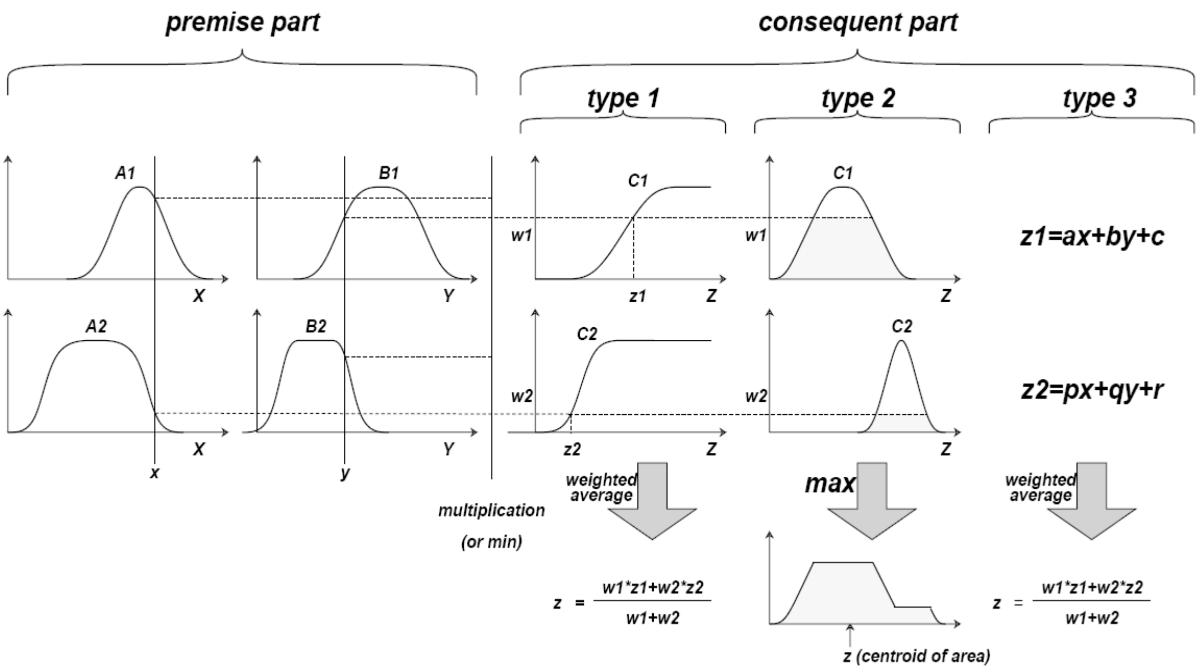


Figure 5.2 Commonly used fuzzy if-then rules and fuzzy reasoning mechanisms.

1. Compare the input variables with the membership functions on the premise part to obtain the membership values (or compatibility measures) of each linguistic label. (This step is often called *fuzzification*).

2. Combine (through a specific T-norm operator, usually multiplication or min.) the membership values on the premise part to get *firing strength* (*weight*) of each rule.

3. Generate the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength.

4. Aggregate the qualified consequents to produce a crisp output. (This step is called *defuzzification*) Several types of fuzzy reasoning [25, 26] have been proposed in the literature. Depending on the types of fuzzy reasoning and fuzzy if-then rules employed, most fuzzy inference systems can be classified into three types (Figure 5.2):

Type 1: The overall output is the weighted average of each rule’s crisp output induced by the rule’s firing strength (the product or minimum of the degrees of match with the premise part) and output membership functions. The output membership functions used in this scheme must be monotonically non-decreasing.

Type 2: The overall fuzzy output is derived by applying “max” operation to the qualified fuzzy outputs (each of which is equal to the minimum of firing strength and the output membership function of each rule). Various schemes have been proposed to choose the final crisp output based on the overall fuzzy output; some of them are center of area, bisector of area, mean of maxima, maximum criterion, etc [37, 38].

Type 3: Takagi and Sugeno's fuzzy if-then rules are used [39]. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output.

Figure 5.2 utilizes a two-rule two-input fuzzy inference system to show different types of fuzzy rules and fuzzy reasoning mentioned above. Be aware that most of the differences lie in the specification of the consequent part (monotonically non-decreasing or bell-shaped membership functions, or crisp function) and thus the defuzzification schemes (weighted average, centroid of area, etc) are also different.

5.3 ANFIS: ADAPTIVE-NETWORK-BASED FUZZY INFERENCE SYSTEM

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feed forward type. Due to these minimal restrictions, the adaptive network's applications are immediate and immense in various areas. In this section, we propose a class of adaptive networks which are functionally equivalent to fuzzy inference systems. The proposed architecture is referred to as *ANFIS*, standing for *Adaptive-Network-based Fuzzy Inference System*. We describe how to decompose the parameter set in order to apply the hybrid learning rule. Besides, we demonstrate how to apply the Stone-Weierstrass theorem to ANFIS with simplified fuzzy if-then rules and how the radial basis function network relate to this kind of simplified ANFIS.

A. ANFIS architecture

For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type [39]:

Rule 1: *If x is A_1 and y is B_1, then* $f_1=p_1x+q_1y+r_1$,

Rule 1: *If x is A_2 and y is B_2, then* $f_2=p_2x+q_2y+r_2$.

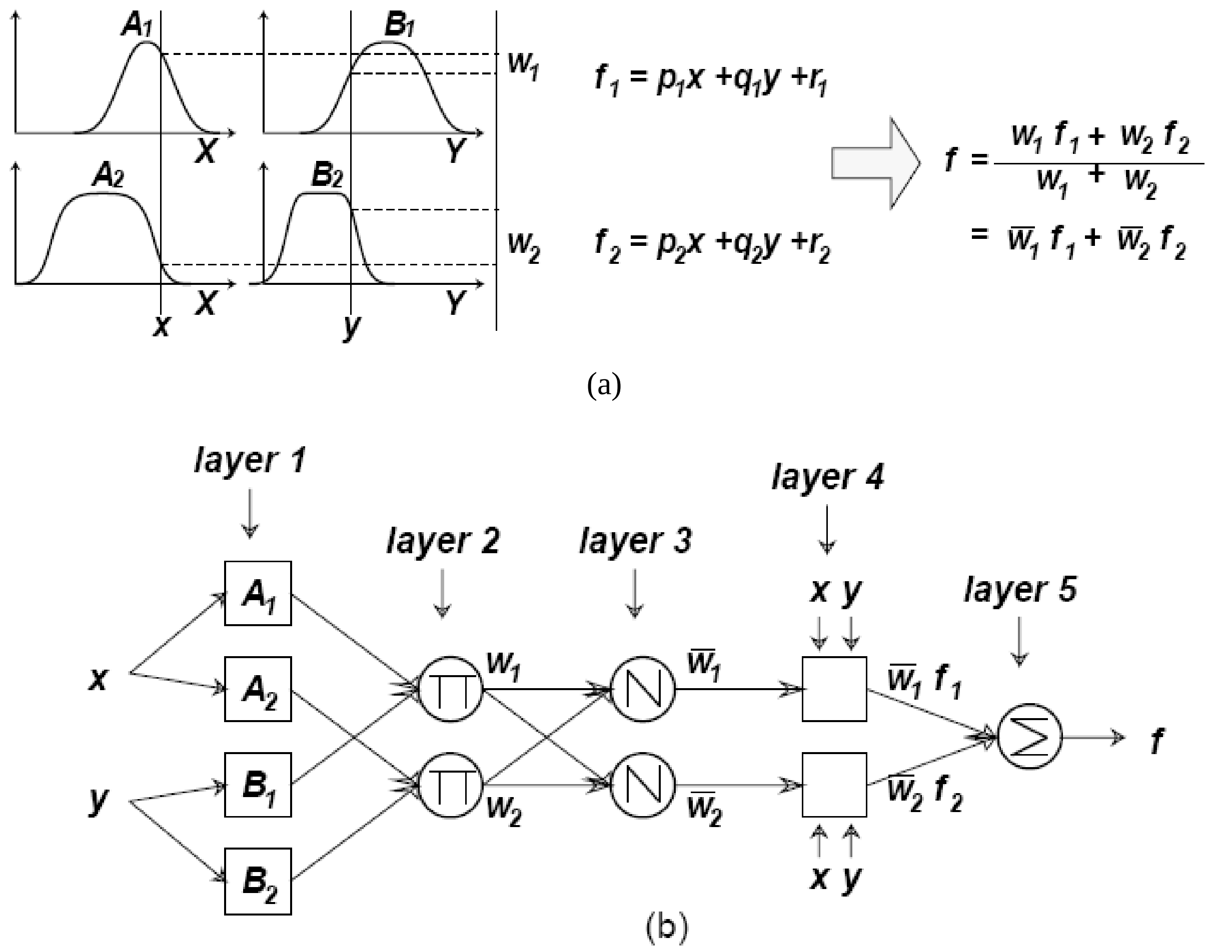


Figure 5.3. (a) Type-3 fuzzy reasoning; (b) Equivalent ANFIS (type-3 ANFIS) (Basic Structure of ANFIS).

Then the type-3 fuzzy reasoning is illustrated in Figure 5.3(a), and the corresponding equivalent ANFIS architecture (*type-3 ANFIS*) is shown in Figure 5.3(b). The node functions in the same layer are of the same function family as described below:

Layer 1 Every node i in this layer is a square node with a node function

$$O_i^1 = \mu A_i(x)$$

Where x is the input to node i, and A_i is the linguistic label (small, large, etc.) associated with this node function. In other words, $O^1{}_i$ is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we choose $\mu A_i(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}$$

or the Gaussian function

$$\mu A_i(x) = \exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right]$$

where {a_i, b_i, c_i} (or {a_i, c_i} in the later case) is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred to as *premise parameters*.

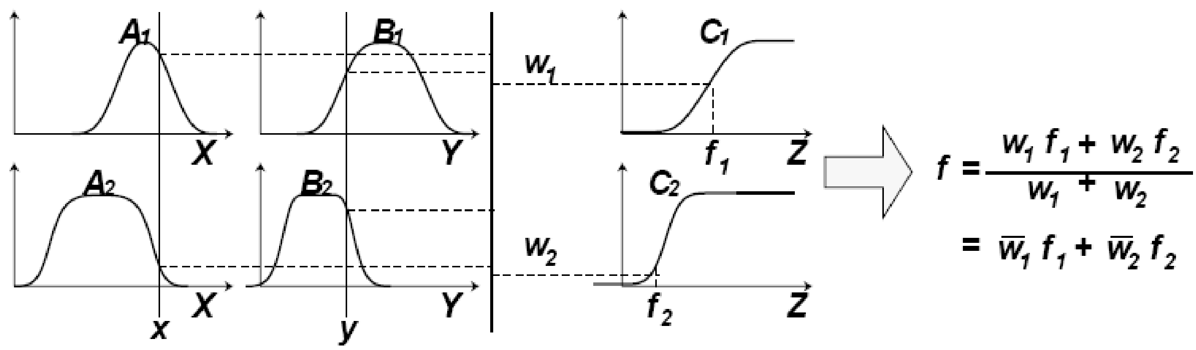
Layer 2 Every node in this layer is a circle node labeled □ □ which multiplies the incoming signals and sends the product out. For instance,

$$w_i = \mu A_i(x) \times \mu B_i(y), \text{ i=1,2.}$$

Each node output represents the firing strength of a rule. (In fact, other *T-norm* operators that perform generalized AND can be used as the node function in this layer.)

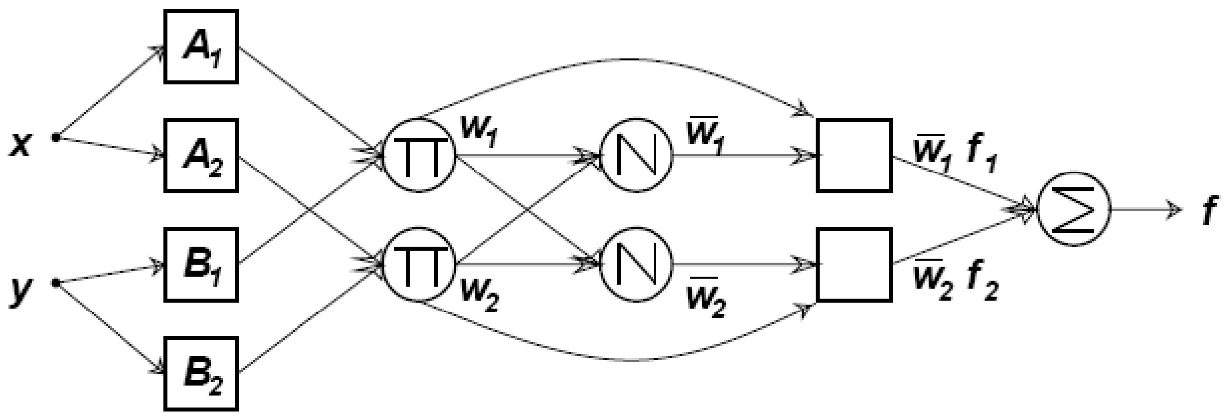
Layer 3 Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \text{ i=1,2.}$$



(a)

Figure 5.4. (a) Type-1 fuzzy reasoning



(b)

Figure 5.4 (b) equivalent ANFIS (type-1 ANFIS).

For convenience, outputs of this layer will be called *normalized firing strengths*.

Layer 4 Every node i in this layer is a square node with a node function.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

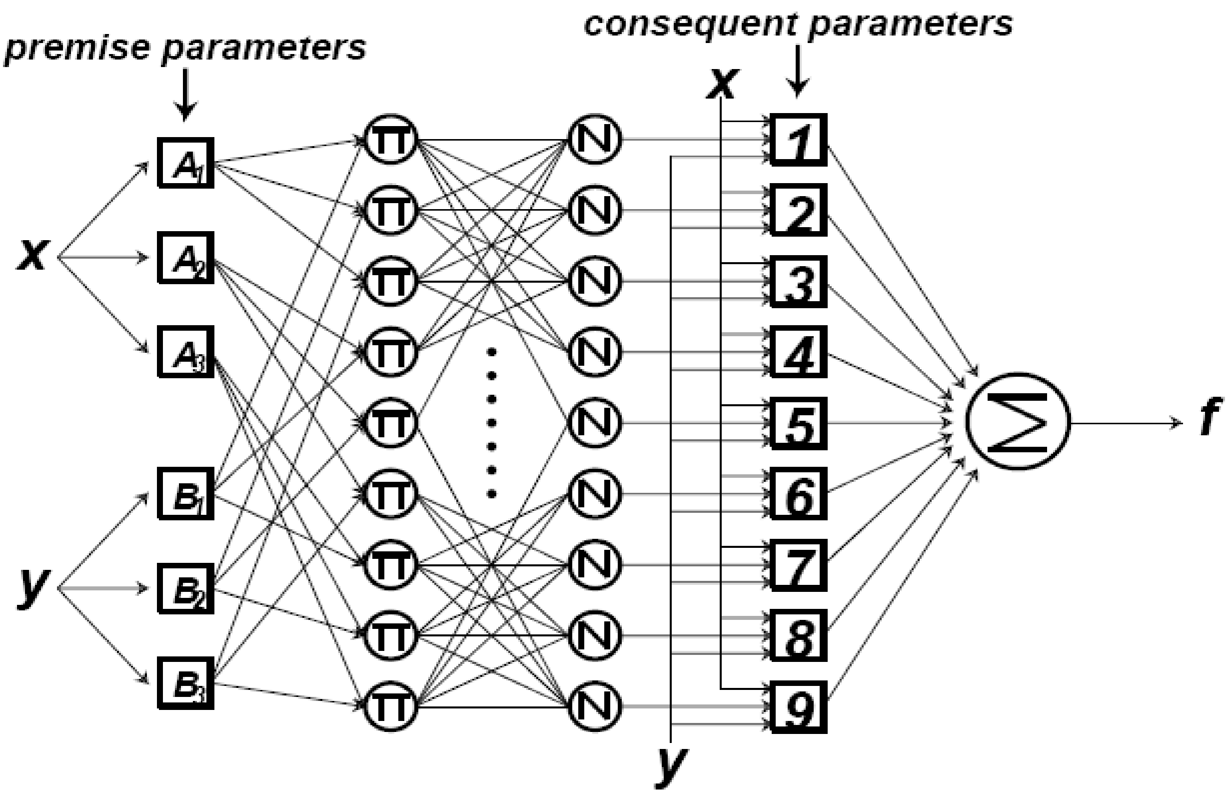
where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as *consequent parameters*.

Layer 5 The single node in this layer is a circle node labeled   that computes the overall output as the summation of all incoming signals, i.e.,

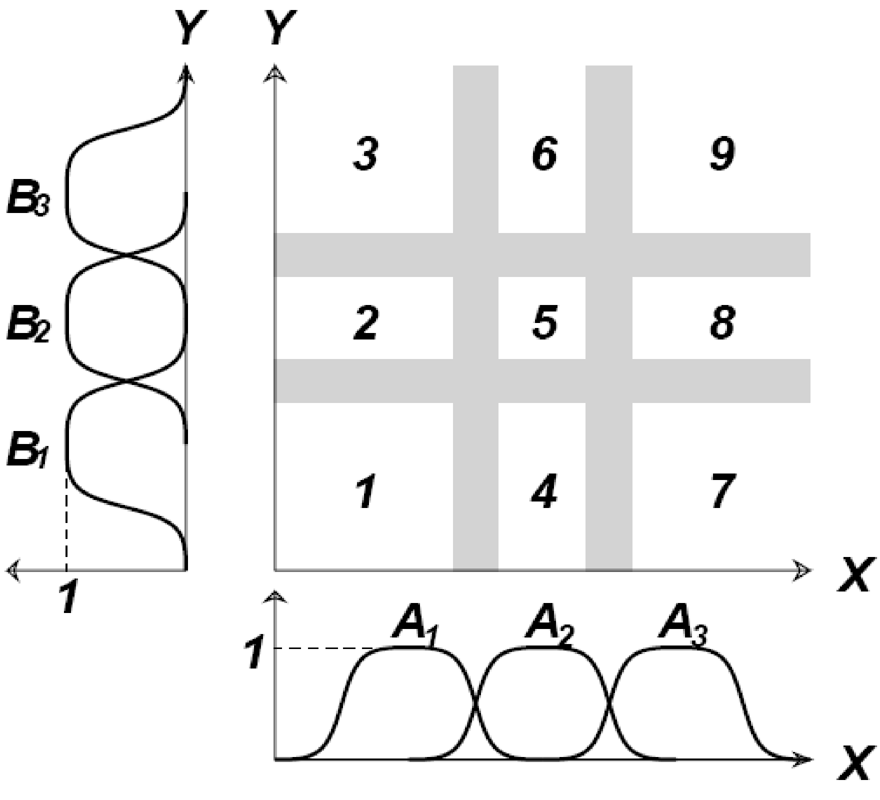
$$O_i^5 = \text{overall output} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Thus we have constructed an adaptive network which is functionally equivalent to a type-3 fuzzy inference system. For type-1 fuzzy inference systems, the extension is quite straightforward and the type-1 ANFIS is shown in Figure 5 where the output of each rule is induced jointly by the output membership funcion and the firing strength. For type-2 fuzzy inference systems, if we replace the centroid defuzzification operator with a discrete version which calculates the approximate centroid of area, then type-3 ANFIS can still be constructed accordingly. However, it will be more complicated than its type-3 and type-1 versions and thus not worth the efforts to do so.

Other example of ANFIS is 2-input, type-3 ANFIS with 9 rules can be shown in Fig 5.5. Three membership functions are associated with each input, so the input space is partitioned into 9 fuzzy subspaces, each of which is governed by fuzzy if-then rules. The premise part of a rule defines a fuzzy subspace, while the consequent part specifies the output within this fuzzy subspace.



(a)



(b)

Figure5.5. (a) 2-input type-3 ANFIS with 9 rules (ANFIS Architecture with nine rules).

(b) Corresponding fuzzy subspaces

5.4 ANFIS LEARNING ALGORITHM

From the proposed ANFIS architecture above (Figure 5.4), the output *f* can be defined as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

$$f = \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2)$$

$$f = (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2$$

Where p_1, q1, r1, p2, q2, and r_2 are the linear consequent parameters. The methods for updating the parameters are listed as below:

1. *Gradient decent only*: All parameters are updated by gradient decent back propagation.

2. *Gradient decent and One pass of Least Square Estimates (LSE)*: The LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient descent takes over to update all parameters.

3. *Gradient and LSE*: This is the hybrid learning rule. Since the hybrid learning approach converges much faster by reducing search space dimensions than the original back propagation method, it is more desirable. In the forward pass of the hybrid learning, node outputs go forward until layer 4 and the consequent parameters are identified with the least square method. In the backward pass, the error rates propagate backward and the premise parameters are updated by gradient descent.

5.5 SIMULATION RESULTS

In this section ANFIS model is used for identify the HVAC System states. All the simulations are carried out using MATLAB R2008a.

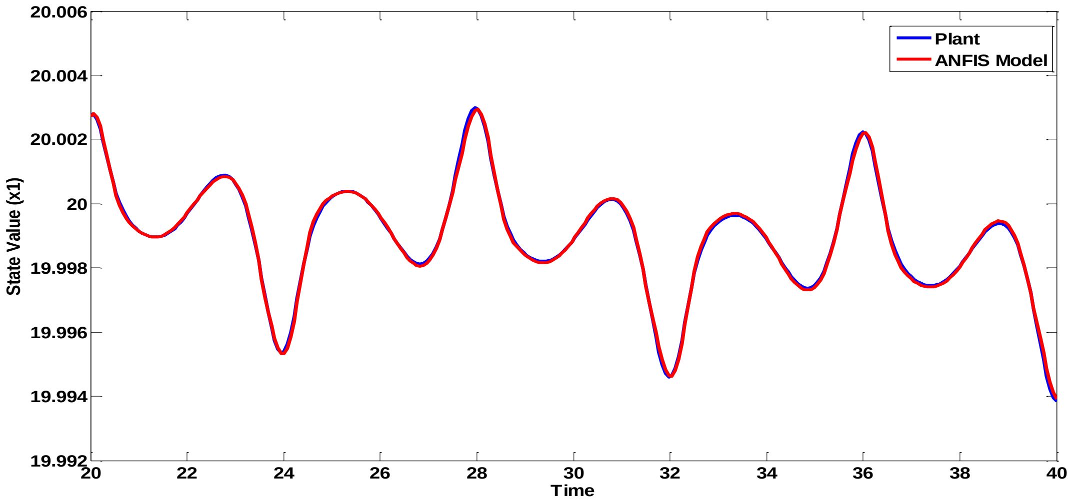


Fig.5.6 HVAC System x1 state in ^{0}C

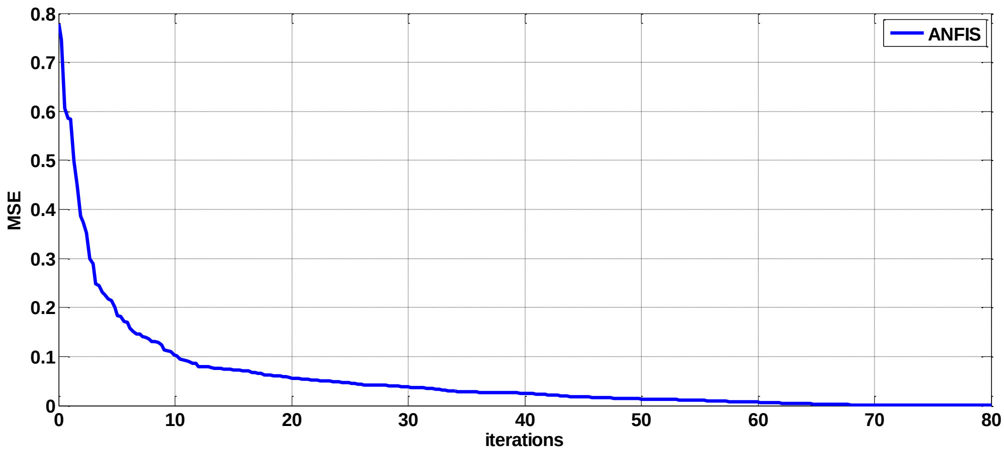


Fig.5.7 Mean square error of HVAC System x1 state.

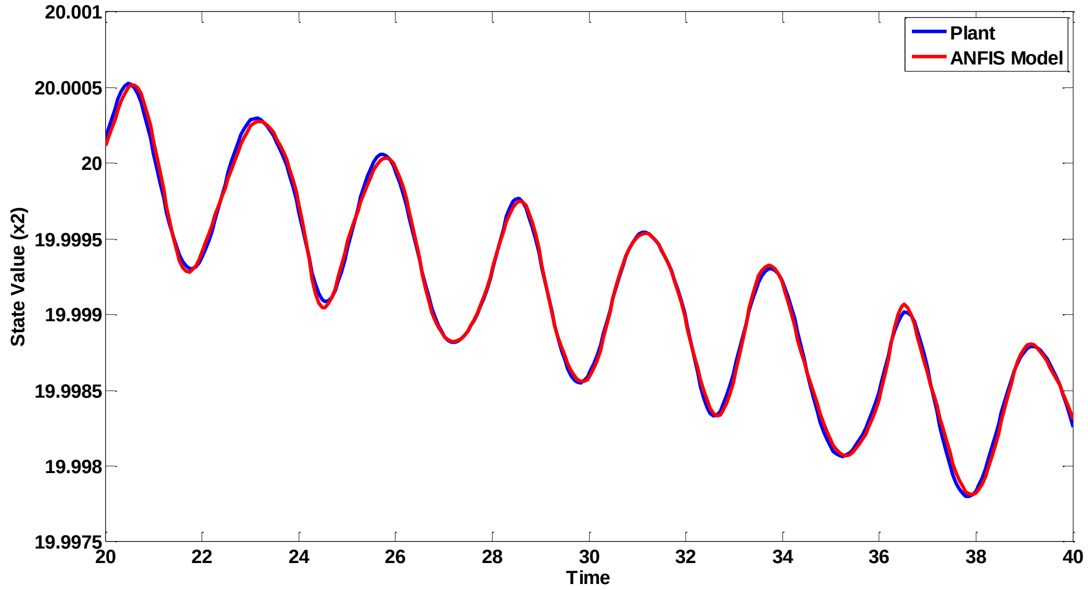


Fig.5.8 HVAC System x2 state in ^{0}C

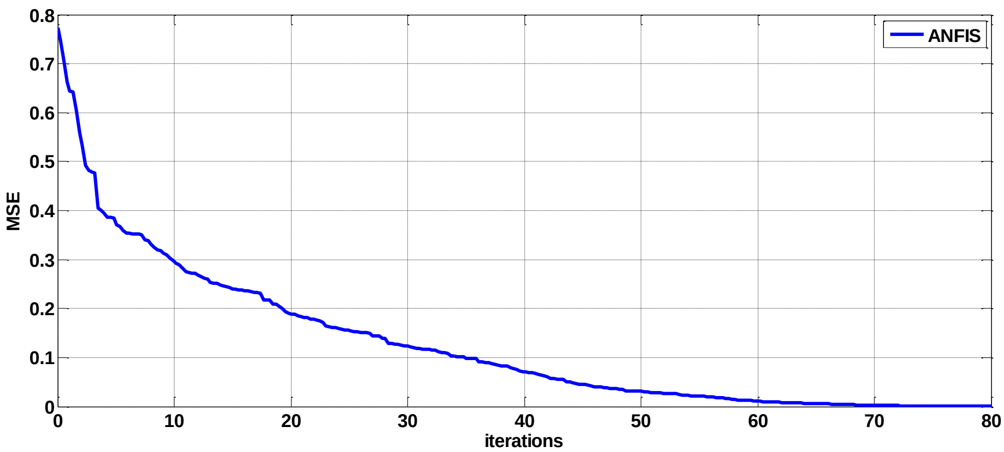


Fig.5.9 Mean square error of HVAC System x2 state.

CHAPTER 6

CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

6.1 CONCLUSIONS

The aim of this thesis is to find a proper artificial neural network (ANN) model for adaptive nonlinear static and dynamic system identification. The prime advantages of using ANN models are their ability to learn based on optimization of an appropriate error function and their excellent performance of nonlinear functions. In MLP identifier, as the convergence is slow and as the non-linearity associated with the system increases MLP structure requires more hidden layers, realizing a very complex structure and it is seen that computational time required is also increasing and cannot be applied for on-line applications. On the other hand FLANN, having a single layer structure with functionally mapped inputs, with the absence of hidden layer the structural complexity is reduced and the processor burden is also reduced as the number of addition and multiplications are decreased with this structure. In FLANN, the initial representation of the pattern is enhanced by using nonlinear function and thus the pattern dimension space is increased. The functional link acts as an element of a pattern or entire pattern itself by generating a set of linearly independent function and then evaluates these functions with the pattern as the argument. Hence separation of the patterns becomes possible in the enhanced space. It also seen that FLANN has taken less computational time for all the systems simulated and performed well and it can be applied for on-line application. And also hvac system is identified by using neuro-fuzzy model (ANFIS) and compared the results in Table (4.1).In this thesis HVAC system is identified with different techniques and compared the results using MATLAB R2008a.

6.2. SUGGESTIONS FOR FUTURE WORK

Other System Identification methods will be applied for efficiently modeling the HVAC system such as

1. RBF.
2. RNN.
3. Evolutionary Computing techniques such as Differential Evolutionary will be combined with Neural Network.
4. Comparative study of all these methods.
5. Controller design for HVAC System.

The case study on channel equalization, which is very important application of Inverse modeling is discussed and simulated in this thesis. So research can be carried out on more practical channels.

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