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of

### MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING

by

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#91172#

**DEDICATED TO MY PARENTS** 

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### ABSTRACT

Boiler is the heart of the chemical process industries like fertilizer manufacturing plant. Automatic boiler control system is desirable for safe, economic and reliable operation of the industry. Conventional three elements Proportional plus Integral plus Derivative (PID) controller are generally used in the different control loops of the boiler. Main drawback of the use of this type of the controller is the adjustment of controller's parameters such as gain, reset time and dead time due to change of operating point of the process. However, the application of Self Tuning Controller (STC) and Model Reference Adaptive Controllers (MRAC) can overcome this drawback in the case of linear process plant. The boiler plant is highly nonlinear plant. Thus a neural network based integrated control system is proposed to control an industrial boiler. A 120 ton per hour capacity boiler of the Zia Fertilizer Company Limited (ZFCL), Ashuganj, Bangladesh is taken as reference boiler for the case study. *Boiler To produce Start Start* 

The process inverse dynamic modelling technique is applied to design the proposed controller. A multilayer feedforward and diagonal recurrent neural network is trained to identify the unknown inverse dynamic model of the boiler plant by general backpropagation and dynamic back propagation training algorithm respectively. The training data was collected from the computer data bank of the reference boiler. After investigating the performance of both network, the feedforward network architecture is selected for the proposed controller. Using the weights of the network a new software controller is then developed for integrated control system of the ZFCL boiler. The developed controller is tested by using the boiler input - output data that are not used during the training. The output response of the developed controller is compared with that of the existing PID controller. Both responses are very close to each other. The developed controller output is then converted into signal using pulse width control technique. These signals can then be used for on-line regulation of the control valves through parallel port of the computer. The average value of the pulse indicates the percentage of the valve opening.

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## **LIST OF ABBREVIATIONS**

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ANN	Artificial Neural Network
BP	Backpropagation
DBP	Dynamic Backpropagation
DIM	Direct Inverse Modeling
DRN	Diagonal Recurrent Network
FFN	Feedforward Network
FT	Flow Transmitter
FIC	Flow Indicating Controller
GBP	General Backpropagation
LT	Level Transmitter
LIC	Level Indicating Controller
MIMO	Multi Input Multi Output
MRAC	Model Reference Adaptive Controller
NN	Neural Network
NNC	Neural Network Controller
PID	Proportional plus Integral plus Derivative
PT	Pressure Transmitter
PIC	Pressure Indicating Controller
PWC	Pulse Width Control
RSP	Remote Setpoint
STC	Self Tuning Controller
SISO	Single Input Single Output
SQRT	Square Root Extractor
TT	Temperature Transmitter
TIC	Temperature Indicating Controller
ZFCL	Zia Fertilizer Company Limited

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## **CHAPTER - ONE**

### INTRODUCTION



- □ INTRODUCTION
- □ LITERATURE REVIEW ON RECENT DEVELOPMENT IN ANN BASED CONTROL
- □ THE AIM AND OBJECTIVE OF THE THESIS
- □ THESIS LAYOUT

### **1.0 INTRODUCTION**

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A urea fertilizer manufacturing plant is an arrangement of processing units such as reformer, shift converter, absorber, desorber, methanator, ammonia converter, compressor, and urea reactor in a systematic and rational way. Steam is required for chemical process of the plant as well as for generating electricity for the plant. The valuable raw material such as natural gas and chemically treated water is being used to produce steam by an industrial boiler. Thus, one of the major production cost of the urea fertilizer depends on the cost of steam generation. This cost can be reduced by proper operation of the boiler plant which can be ensured by a sophisticated boiler control system.

Designing a control system for a boiler plant is very complicated as it involves a large number of theoretical and practical considerations such as the optimum controller response, stability, reliability, safety, operation, range of control and cost of the control system. The difficulties are aggravated by the fact that boiler plant is highly nonlinear, imprecisely known, multivariable systems with many interactions. Thus it is always desirable that an automatic control system for a boiler plant must be able to handle a wide range of unmeasurable disturbances, measurement noise, interactions from other control loops, actuators limitations and process dead time [1].

Rapid technological developments in digital computing systems coupled with significant reduction in their cost have had a profound effect on how process plants can be controlled. High speed computations along with the large information storage capacity possessed by digital computers provides virtually unlimited intelligence which allows the use of quite advance control techniques such as adaptive, inferential, multivariable and supervisory control [1],[2].

Automatic boiler control system is desirable for safe, economic and reliable operation of the industry. In the early days steam pressure, steam temperature, drum water level of

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boiler were controlled independently by Single Input Single Output (SISO) controller. But as boilers grew bigger in capacity, with correspondingly increased pressure levels, the SISO independent control schemes were ineffective in maximizing the boiler performance [3],[4].

Conventional three elements Proportional plus Integral plus Derivative (PID) controllers are generally used to control of the boiler plant. These types of controllers often require gain, reset time and dead time adjustment according to change of process for satisfactory performance at a particular operating condition [5]-[8].

With the progress of control theories, adaptive control system such as Model Reference Adaptive Control (MRAC) [5],[9] and Self Tuning Control (STC) [7],[9] have been developed to tune the controller's parameters automatically which is generally used in linear process plant. Boiler plant behaviors are usually non -linear [10]. Classical adaptive control systems had problems when dealing with non-linear plants or plants with unknown model. Moreover for adaptive controller, its response speed is the main determining factor for its successful application in practice. The parameter identification and optimization procedure requires a lot of computational time especially when a higher order discrete model is used to represent the control system. This problem is more often is encountered in Multi Input Multi Output (MIMO) cases like boiler plant [11]. To solve these problem a new emerging tool is the Artificial Neural Network (ANN) which tries to mimic the biological brain neural networks into mathematical model. The ANN offers more intelligent control than conventional adaptive control theories, which makes a framework for non-linear modeling, identification and control of plant by its learning, adaptation, self-organization, non-linear function approximation and massively parallel processing capabilities [10]-[12]. Thus, in this thesis work an attempt has been made to control a multivariable nonlinear plant like industrial boiler plant, using a ANN based integrated controller.

### 1.1 LITERATURE REVIEW ON RECENT DEVELOPMENT IN ANN BASED CONTROL

The application of ANN in different control systems such as supervised control [13],[14] direct inverse control (off-line) [15]-[20], indirect inverse control [21]-[24], self learning control [25]-[29], dynamic optimization [27] and backpropagation through time[30] have been reported by many researchers. The ANN based each control technique is briefly described in the following paragraphs.

In *Supervised control*, a Neural Network (NN) learns the mapping from sensor inputs to desired actions by adapting to a training set of examples of what it should do [14]. In this system, the more difficult task is to build a correct database of proper action, which usually comes from an expert operator. This type of control is feasible for complex and poorly defined processes for which no suitable conventional controller is available.

In Self learning control, a NN trains to find and optimise a control strategy, without guidance of exemplar training patterns [25], [26]. In most cases, the training is carried out on a model of the process. Moreover, the training involves assuming a set parameters for a given controller network and evaluating a performance measure for the set. A performance measure is used as the training signal. The network inputs are, generally, current and past value of the plant inputs and outputs. Thus, the accuracy of this type of control system is determined by the accuracy of the model used for training.

In *direct inverse control*, a NN is trained by using process input-output data so that it is able to extract the inverse mapping between the output and the control input. A multi layered Neural Network Controller proposed by D.Psaltis *et al.*[18], was trained by plant input-output data to get the inverse dynamics of the control plant. The training data was obtained from the plant input output relationship through time. The off-line learning of the NN was carried out to minimize the overall squared error  $(E^2)$  which is the difference

between desired and network predicted input. Controller was then designed by using the connection weights between the layers obtained from the learning process. This type of control was employed by J. L. Dirion *etal.* [19] for temperature control of an experimental semi-batch pilot reactor. The same technique was also used by J.Savkovic-Stevanovic [20] to control the product composition of an industrial distillation plant. The use of Neural Net Controller (NNC) proposed by the researcher [21] for controlling a complex system requires a long training time because of the use of large amount of off-line input/output data of the plant.

In order to overcome the off-line learning problems as described in the previous paragraph, P. Rasiskila *etal.* [23] developed the on-line specialized learning structure. In this method, the NN was trained in region of interest only. The reference value was the input signal for the NN. The network was then trained to find out the plant output that drived the system output to the reference value. The weights of the NN were adjusted so that the error between the actual system output and the reference value could be decreased in every iteration. However, this method of control may be initially unstable during learning because the network controls the system directly by itself. Thus in order to avoid the instability, it is necessary to prepare the initial value of the weights for the NN, which may be acquired by prior off-line learning.

The comprehensive review shows that Direct Inverse Modeling (DIM) technique is very easier and fast to design a controller[24]. In this thesis work this design technique is chosen to develop a NNC for industrial boiler.

#### **1.2 THE AIM AND OBJECTIVE OF THE THESIS**

Boiler plant is the heart of the process industries like fertilizer, refinery and steam power plant. The Boiler plant is highly nonlinear, imprecisely known, multivariable systems with many interactions. The conventional single input single output controller is ineffective in maximizing the performance of multivariable nonlinear boiler plant[2][3]. A single architecture multi input multi output nonlinear controller may be capable of maximizing the performance of a boiler. Thus this thesis was aimed at developing a NN based integrated control systems for the 120 ton per hour capacity boiler (which is presently controlled by nine conventional PID controllers) of Zia Fertilizer Company Limited at Ashuganj, Bangladesh.

To fulfill the aim the following objectives were envisaged.

- Identification of unknown inverse dynamic of the boiler plant from the training of a multilayer neural network.
- Implementation of general backpropogation and dynamic backpropagation training algorithm for feedforward network and diagonal recurrent networks respectively to investigate the convergence rate, minimum error and neural net controller output response.
- Selection of the best ANN architecture which provides the fastest convergence with minimum error and desired output response.
- Development of software controller for ZFCL boiler using weights of the selected trained ANN.
- Conversion of the controller output into signals which can be used for on-line regulation of the control valves.

### **1.3 THESIS LAYOUT**

Chapter 2 describes the existing conventional boiler control system of ZFCL. The theory and training algorithm of ANN is briefly described in chapter 3. In chapter 4, the ANN based control system of boiler plant is presented. Test results, comparison and performance of the controller are also given in chapter 4. On-line operation of the neural network based controller is described in chapter 5. Chapter 6 contains the conclusion and recommendation for further research.

## **CHAPTER - TWO**

BOILER CONTROL SYSTEM OF ZFCL

 $\Box$  INTRODUCTION

□ COMBUSTION CONTROL

□ DRUM LEVEL CONTROL

□ TEMPERATURE CONTROL

### 2.0 INTRODUCTION

Two high pressure boilers are being used to generate steam at ZFCL. One of the boilers known as BABCOCK boiler generates steam 195 ton/hr at 100% load. Another boiler known as SD Boiler generates 120 ton per hour steam at 100% load. A single line diagram of steam generation and distribution system of ZFCL is shown in Fig. 2.1.

To supply constant thermal energy to the process, it requires to maintain a constant pressure and temperature at common header from where the steam is distributed at various units of the plant. Thus it is desirable a boiler control system to provide steam at the desired pressure, temperature and quantity as demanded by the process.

Boiler control system of ZFCL consists of three control loops : (i) Combustion control (ii) Drum level control and (iii) Temperature control. In the case of BABCOCK boiler, combustion control and temperature control are performed manually whereas the drum level control is done automatically. Thus this boiler generates steam at a fixed rate. On the other hand, in the case of SD boiler, all controls are performed automatically except temperature control which is done manually.

The plant common steam header pressure and temperature are being maintained at a desired set point by only controlling the SD boiler. Nine microprocessor based PID controller are being used for automatic combustion and drum level control of the SD boiler. Combustion control, drum level control and temperature control system of SD boiler at ZFCL are described in the following sections.

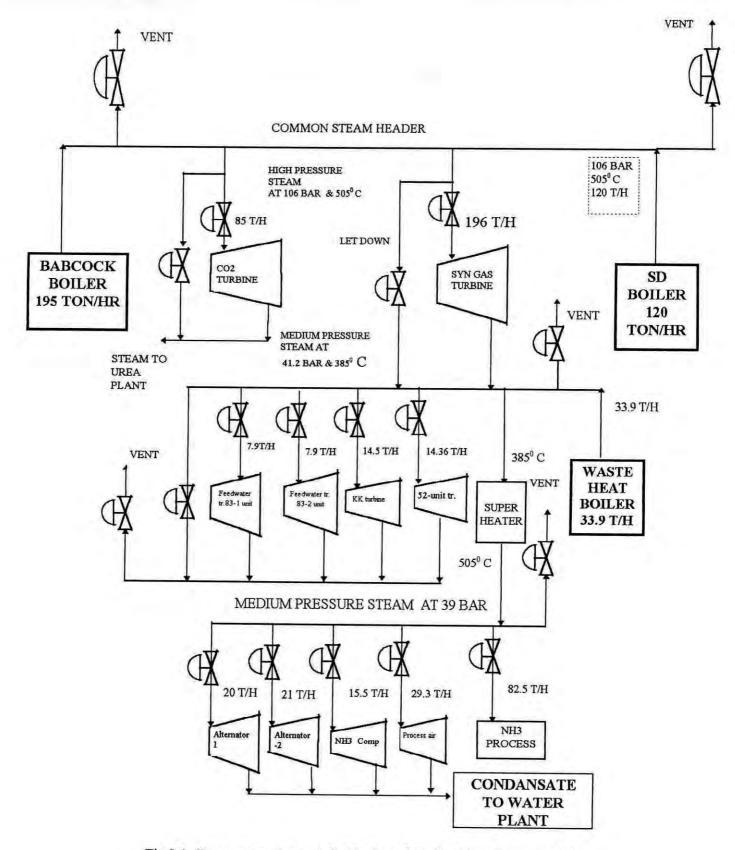


Fig.2.1. Steam generation and distribution of Zia Fertilizer Company Ltd.

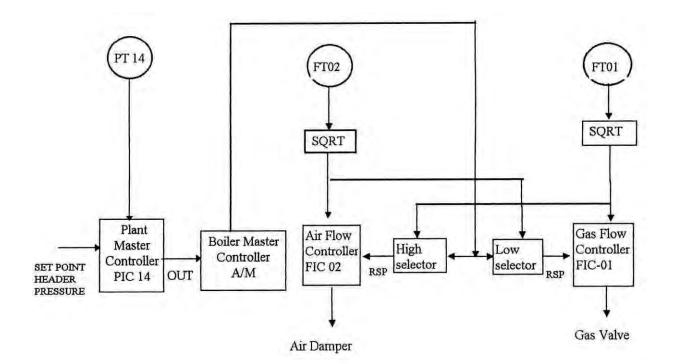
### 2.1 COMBUSTION CONTROL

The combustion control loop regulates the heat input to the boiler. This means that the control loop must regulates both fuel and air in order to maintain the best combustion efficiency under varying load conditions [31],[32].

Basically there are two methods of combustion control: (i) direct positioning control and (ii) metering control. In the direct positioning combustion control, the firing rate demand signal from plant master controller of the combustion control loop is transmitted directly to the fuel control valve and the combustion air fan damper. Thus this technique is referred to as open loop control as the fuel and air are not measured.

In a metering combustion control system, close loop control is used instead of open loop control. There are three types of metering combustion controls: (i) series metering control (ii) parallel metering with high-low selector. The first two methods are well described in the literature [31], [32]. The third method of control is used for combustion control of SD boiler of ZFCL. A schematic block diagram of the third method is shown in Fig 2.2.

The pressure transmitter PT14 transmits common steam header pressure to plant master controller. The Master controller computes the error between the actual steam header pressure and its desired set point. The output of master controller is fed as firing rate demand signal to auto/manual station which is used in the combustion loop to modulate the fuel and air to the boiler in order to maintain the steam header pressure at its desired set point.



PT 14 = Plant steam header pressure transmitter, FT 01 = Gas flow transmitter FT 02 = Air flow transmitter, RSP = Remote set point, SQRT= Square root extractor A/M = Auto/Manual station

Fig. 2.2. Combustion control system of boiler,

The firing rate demand signal from auto/manual station is fed to both fuel and air controller. A low signal selector is positioned in set point signal line to the fuel flow controller while a high signal selector is positioned in the set point signal line to the air flow controller. The low signal selector and high signal selector is also fed by measured air flow signal and measured fuel flow signal respectively. Both high and low selectors ensure the immediate increasing of the air flow for high steam demand and decreasing of fuel flow for the low steam demand. Finally gas and air control valve operates according to the deviation between above remote set point signal and measured flow signal of gas and air which are measured by FT-01 and FT-02 flow transmitter respectively.

#### 2.2 DRUM LEVEL CONTROL

The drum level control system is designed to provide continuous mass balance i.e. for every pound of steam produced a pound of water is added to the drum. In the drum, boiler water is a combination of steam bubbles and water which depends on drum pressure. Increasing in steam demand causes a temporary drop of pressure in the drum. Thus steam bubbles and water will be increased, tending to make water swell and raising the water level. At the same time the increasing in load requires the increased flow of feed water. This feed water is comparatively cool in comparison with the near saturation temperature of water available in the drum. Increase in feed water flow cools the water in the drum and causes the level to shrink or fall [31][32].

There are three types of drum level control system such as

- (i) Single element type control where only drum level is measured and is controlled by adding feedwater to compensate for water losses.
- (ii) Two element type control where the feedwater flow for controlling the drum level is influenced by the steam flow and drum level.
- (iii) Three element type control system where the feedwater valve position is influenced by three variables such steam flow, feedwater flow and drum level.

The third method is used to control the drum level at ZFCL. A schematic diagram of the drum level control system is shown in Fig 2.3. This type of control system is designed to regulate the flow of feed water and steam in such a manner as to hold the level of water at desired limit and can be compensated for swell and shrink effects. The steam flow can be measured by using the orifice or nozzle. Load changes in the form of steam flow change is measured by the FT-05 whose signal is transmitted to feed water flow

calculator (FY-03). The level transmitter LT-06 transmits the drum level signal to the drum level controller which produces the necessary corrective signal to maintain drum level at its set point. The controller output is then transmitted to the feed water flow calculator which computes the signal A as given in equation (2.1). The signal A is known as remote set point of feedwater flow controller.

$$A = L + S - B \tag{2.1}$$

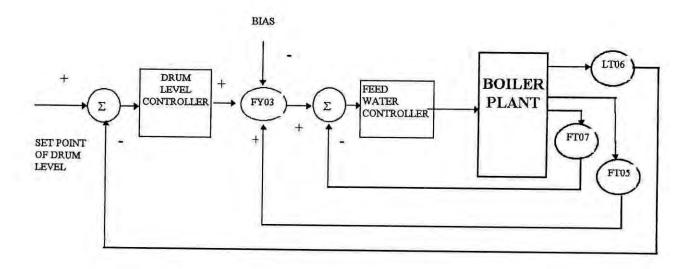
Where,

L = Level controller output (%)

S = Steam flow

B = Bias is selected as level controller output signal for 50% drum level.

Finally feed water control valve operates according to deviation between remote set point signal and measured feed water flow signal.

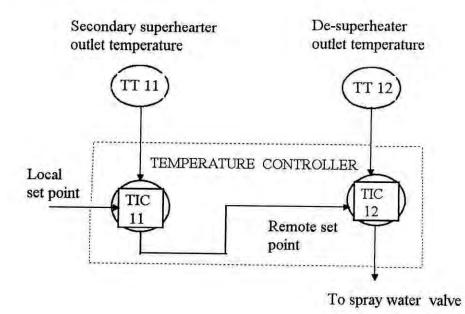


LT06 - LEVEL TRANSMITTER, FT05-STEAM FLOW TRANSMITTER, FT07 - WATER FLOW TRANSMITTER

Fig. 2.3 Three elements drum level control.

### 2.3 TEMPERATURE CONTROL

Two element steam temperature control loop shown in Fig.2.4 uses a cascade control to maintain the final superheated outlet temperature at desired value. The primary controller TIC11 receives a final steam temperature signal from temperature transmitter TT11. The received signal is compared with the local set point of TIC11. An error which is the difference between the measured temperature and the local set point causes a change in the control output which acts as a set point of the secondary controller TIC12. This controller also receives a signal from temperature transmitter TT12 which measures the steam temperature at the outlet of the desuperheater of the boiler. Increase in the final steam temperature will cause a decrease in the set point signal of the secondary controller. The controller output then adjusts the spray water flow in order to reduce the desuperheater outlet steam temperature for maintaining the desired temperature.



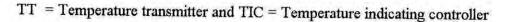


Fig.2.4 Steam temperature control system of boiler.

## **CHAPTER - THREE**

### ARTIFICIAL NEURAL NETWORKS

□ INTRODUCTION

- □ ARTIFICIAL NEURAL NETWORKS
- □ GENERAL BACKPROPAGATION WITH MULTI LAYER FEEDFORWARD NETWORK
- DYNAMIC BACKPROPAGATION WITH MULTI LAYER DIAGONAL RECURRENT NETWORK

### **3.0 INTRODUCTION**

Among the various intelligent system ANN is one of the potential tools. It has attracted significant attention in several disciplines such as signal processing, pattern recognition, and control [13]. The success of this tool is mainly attributed due to the unique feature of the Neural Networks, such as:

(i) Learning ability by adjusting their network interconnection weights and biases based on a learning algorithm.

(ii) Parallel structure with distributed storage and processing of information.

Challenges in modern control system design are characterized by large dimentionality, computational complexity, nonlinearity, and uncertainty. Neural networks can be a very powerful tool in dealing with such requirements[13]. The following sections describe the basic theory of ANN and learning algorithms.

### 3.1 ARTIFICIAL NEURAL NETWORKS

The ANN is an information-processing system that has certain performance characteristics in common with biological neural networks of human brain. The basic element of biological model of the human brain is called neuron and shown in Fig. 3.1. A biological neuron has three types of components such as dendrites, soma and axon. Many inputs enter the neuron with different synaptic weights through dendrites. Soma or cell body of the neuron process these information. The output of the cell body is transmitted through axon to another neuron. Humans are born with as many as 100 billion neurons. Each neuron has an average 10,000 connections to its neighbors, so that the human neocotrex has about  $10^{15}$  connections[33]. The massive parallelism in

human brain serves a strong motivation for the idea of building an intelligent machine modelled after biological neurons, which is known as artificial neural networks[33],[34].

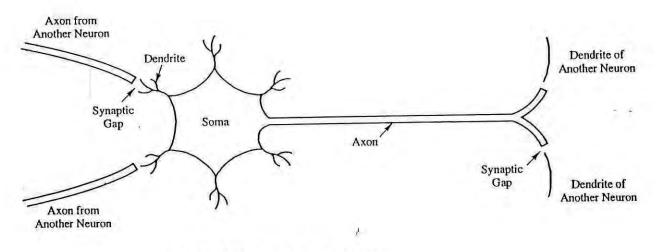
To simulate artificial neural networks, a simplified mathematical model can be extracted from biological is neuron which is shown in Fig. 3.2. The model is based on the following assumptions:

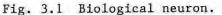
- (i) Information processing occurs at many simple elements called neurons.
- (ii) Signals are passed between neurons over connection links.
- (iii) Each connection link has associated weight, which in a typical neural net, multiplies the signal transmitted.
- (iv) Each neuron applies an activation function (usually nonlinear) to its net input (sum of the weighted input signals) to determine its output signal.

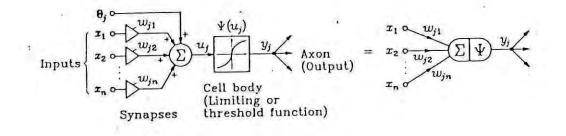
Generally, a neural network is characterized by

- (i) The connection between the neurons known as architecture,
- (ii) Activation function and
- (iii) Learning algorithm.

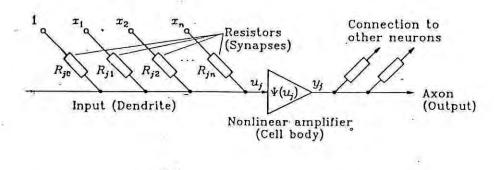
Existing neural network architecture can be divided into three basic categories: feedforward, recurrent, and self-organizing neural networks[34]. In feedforward networks the signals flow from the input units to the output units in a forward direction. But in recurrent network the output signal of a neuron is fed back to its input. In a self - organizing neural network, neighboring units compete in their activation by means of mutual lateral interactions, and develop adaptively into specific







(a)



(b)

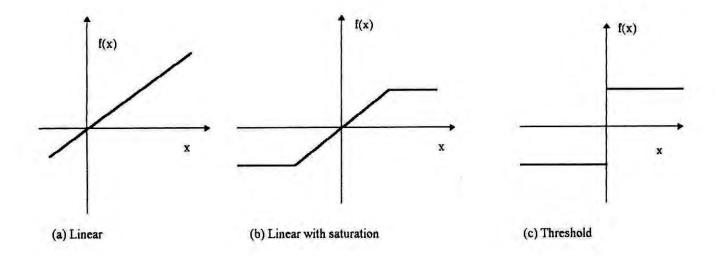
Fig. 3.2 (a) Mathmatical model of Biological Neuron(b) Electronic analog model of biological Neuron.

detectors of different signal patterns. Again each categories can subdivided as single layer and multilayer connection. A single layer net has one layer of connection weight whereas a multilayer net has one or more layers of nodes (called hidden units) between the input units and the output units. Multilayer nets can solve more complicated problems than single layer nets, but training may be more difficult. However, in some cases training may be more successful, because it is possible to solve a problem that a single layer net can not be trained to perform correctly at all [34],[35].

Several types of activation functions are linear, linear with saturation, threshold, and nonlinear sigmoid function. All types of function shown in Figure 3.3. In order to achieve the advantage of multilayer nets, nonlinear activation functions are required. Because the results of feeding a signal through multilayer net with linear activation functions are no different from what can be obtained using a single layer. There are three general learning schemes in neural networks such as (i) supervised learning in which the correct output signal for each input vector to be specified, (ii) unsupervised or self organising learning in which the network self-adjusts its parameters and structure to capture the regularities of input vector, without receiving explicit information from external environment, and (iii) reinforcement or graded learning in which the network receives implicit scalar evaluations of previous inputs[34].

Among these three learning schemes, supervised learning is used for real-time learning controller function, nonlinear mappings and process parameter identification for adaptive and intelligent control of dynamic systems. The most useful learning algorithm of supervised learning is backpropagration technique.

Multi layered feedforward and diagonal recurrent network architecture has been chosen for the present work. The nonlinear sigmoid function is used as an activation function of the hidden neurons in both network. For output neurons of the feedforward network, the



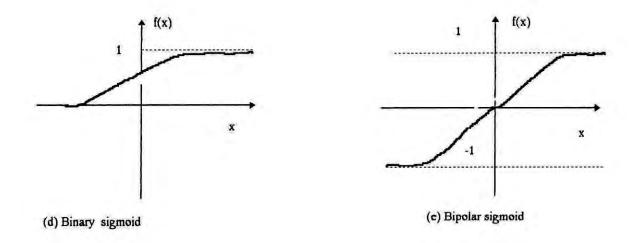


Fig. 3.3 Different activation function of a neuron.

nonlinear sigmoid function is used as an activation function whereas linear activation function is used for output neuron of diagonal recurrent network. The General Back Propagation(GBP) and Dynamic Back Propagation(DBP) algorithm has been chosen as learning algorithm for feedforward and diagonal recurrent network respectively. The mathematical background of each algorithm has been described in the following sections.

# 3.2 GENERAL BACK PROPAGATION ALGORITHM WITH MULTI LAYER FEEDFORWARD NETWORK

The backpropagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual computed output and the desired output [32],[34]. The training of a network by backpropagation involves three stages (i) to propagate the training pattern and calculate the actual output of the network (ii) backpropagate the associate error and (iii) the adjustments of weights.

A three layer Feed Forward Network (FFN) architecture is shown in Figure 3.4. The layers are fully interconnected. When signals are applied to the input layer of the network, it propagates towards the output layer through the interconnections of the middle layer, known as hidden layer. The propagated signal will finally produce a output. This output is then compared with the desired output for each node. The error signals (which are the difference between the desired output and computed output) are transmitted backward from the output layer to each node in the intermediate layer. Each unit in the intermediate layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process repeats, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error signal received, connection weights are then updated.

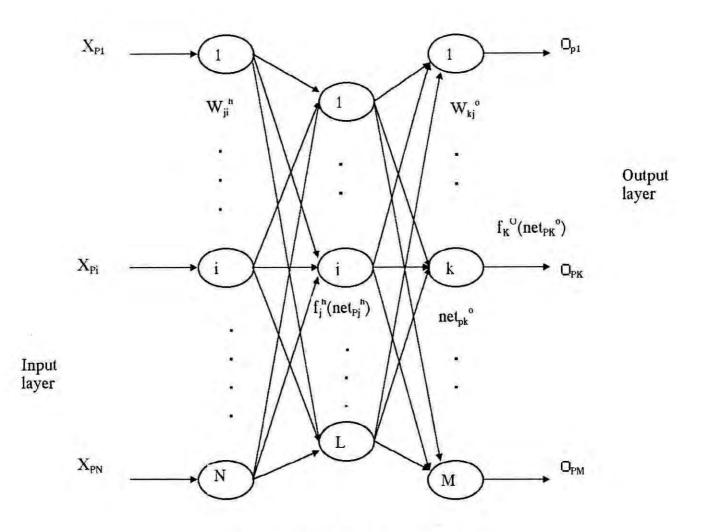


Fig. 3.4. Three layer feed forward network,

Let us consider an input vector,  $X_P = (x_{P1}, x_{P2}, \dots, x_{PN})$ , is applied to the input layer of the network. The subscript "P" refers to the p-th training vector. The input units distribute the values to the hidden layer units.

The net input to the j-th hidden unit is given as

$$\operatorname{net}_{Pj}^{h} = \sum_{i=1}^{h} w_{ji}^{h} \cdot x_{Pi}^{h} + \theta_{j}^{h}$$
 (3.1)

where  $w_{ji}^{h}$  is the weight on the connection from the i-th input unit to the j-th hidden unit, and  $\theta_{j}^{h}$  is the bias term. The superscript "h" refers to quantities on the hidden layer. Assuming that the activation of this node is equal to the net input, the output of this node becomes

$$\mathbf{i}_{\mathbf{P}\mathbf{j}} = \mathbf{f}_{\mathbf{j}}^{\mathbf{h}}(\mathbf{net}_{\mathbf{P}\mathbf{j}}^{\mathbf{h}}) \tag{3.2}$$

Where the function  $f_j^h(.)$  is refered to as an activation function. The equations for the output nodes can be written as

$$\operatorname{net}_{Pk}^{\circ} = \sum_{j=1}^{L} w_{kj}^{\circ} \cdot i_{Pj} + \theta_{k}^{\circ}$$
(3.3)

$$O_{pk} = f_k^{\circ}(net_{Pk}^{\circ})$$
(3.4)

where subscript "O"refers to quantities on the output layer.

The error value  $\delta_{Pk}$  at a single output unit "k" is defined as

$$\delta_{\mathbf{Pk}} = (\mathbf{y}_{\mathbf{Pk}} - \mathbf{O}_{\mathbf{pk}}) \tag{3.5}$$

where the subscript "k" refers to an output unit,  $y_{Pk}$  is the desired output value and  $O_{pk}$  is the actual output from the kth unit.

The error to be minimized is the sum of the squares of the errors of all the output units.

$$E_{\rm P} = \frac{1}{2} \sum_{k=1}^{\rm M} \delta_{\rm Pk}^2 \tag{3.6}$$

The mean-square error function  $E_P$  can be reduced by changing the weights of the network. In the gradient method, the change of weight is proportional to the negative gradient of the  $E_P$ . Thus the update rule of the weights of the network becomes as

$$W(t+1) = W(t) + \eta (-\partial E_p / \partial W)$$
(3.7)

where n is learning rate.

#### 3.2.1 Updates of Output Layer Weights

The negative gradient of  $E_P$  ( $\Delta E_P$ ) with respect to the weights,  $w_{kj}$  determines the direction in which to change the output layer weight.

From Eq. (3.5) and (3.6), the E<sub>P</sub> can be written as

$$E_{\rm P} = \frac{1}{2} \sum_{k} (y_{\rm Pk} - O_{\rm pk})^2$$
(3.8)

The derivative of  $E_P$  with respect to  $w_{kj}$  gives

$$\frac{\partial E_{p}}{\partial w_{kj}^{0}} = -(y_{pk} - O_{pk}), \frac{\partial f_{k}^{0}}{\partial (net_{pk}^{0})}, \frac{\partial (net_{pk}^{0})}{\partial w_{kj}^{0}}$$
(3.9)

The last term of Eq. (3.9) can be expressed as

$$\frac{\partial(\operatorname{net}_{\operatorname{Pk}}^{\circ})}{\partial w_{kj}^{\circ}} = \frac{\partial}{\partial w_{kj}^{\circ}} \sum_{j=1}^{L} w_{kj}^{\circ} \cdot i_{pj} = i_{pj}$$
(3.10)

Substituting Eq(3.10) into Eq.(3.9) gives,

$$-\frac{\partial E_{\mathbf{p}}}{\partial w_{\mathbf{k}j}^{\mathbf{o}}} = (\mathbf{y}_{\mathbf{p}\mathbf{k}} - \mathbf{O}_{\mathbf{p}\mathbf{k}}) \cdot \mathbf{f}_{\mathbf{k}}^{\mathbf{o}} (\operatorname{net}_{\mathbf{p}\mathbf{k}}^{\mathbf{o}}) \cdot \mathbf{i}_{\mathbf{p}j}$$
(3.11)

From Eq.(3.7) the weights of the output layer are than updated as

$$w_{kj}^{o}(t+1) = w_{kj}^{o}(t) + \Delta_{P} \cdot w_{kj}^{o}(t)$$
(3.12)

where 
$$\Delta_{p.} w_{kj}^{o} = \eta (y_{Pk} - O_{pk}) f_{k}^{o'} (net_{Pk}^{o}) i_{Pj}$$
 (3.13)

Output layer error term  $\delta_{Pk}^{0}$ , is defined as

$$\delta_{Pk}^{0} = (y_{Pk} - O_{Pk}) f_{k}^{o\prime} (net_{Pk})$$
$$= \delta_{Pk} f_{k}^{o\prime} (net_{Pk}^{o})$$
(3.14)

By combining the Eq. (3.13) and (3.14) the weight update equation becomes as

$$w_{ki}^{o}(t+1) = w_{ki}^{o}(t) + \eta \cdot \delta_{Pk}^{o}, i_{Pi}$$
(3.15)

#### 3.2.2 Updates of Hidden Layer Weights

The change of hidden layer weight can be obtained by taking the negative gradient with respect to the hidden layer weights  $w_{kj}$ . Derivative of the  $E_P$  with respect to  $w_{kj}$  gives:

$$\frac{\partial E}{\partial w} \frac{P}{ji} = \frac{1}{2} \sum_{k} \frac{\partial}{\partial w} \frac{h}{ji} (y_{Pk} - O_{Pk})^{2}$$

$$= -\sum_{k} (y_{Pk} - O_{Pk}) \cdot \frac{\partial O_{Pk}}{\partial (net_{Pk}^{\circ})} \cdot \frac{\partial (net_{Pk}^{\circ})}{\partial i_{Pj}} \cdot \frac{\partial (net_{Pj}^{h})}{\partial (net_{Pj}^{h})} \cdot \frac{\partial (net_{Pj}^{h})}{\partial w_{ji}^{h}}$$

$$= \sum_{k} (y_{Pk} - O_{Pk}) \cdot f_{k}^{\circ} (net_{Pk}^{\circ}) \cdot w_{kj}^{\circ} \cdot f_{j}^{h} (net_{Pj}^{h}) \cdot x_{Pi}$$
(3.16)
(3.16)

The hidden layer weights is updated in proportion to negative of the Eq. (3.17)

$$\Delta_{\rm P}.w_{\rm ji}^{\ h} = \eta.f_{\rm j}^{\rm h}({\rm net}_{\rm Pj}^{\ h}).x_{\rm Pi} \sum_{\rm k} (y_{\rm Pk} - O_{\rm Pk}).f_{\rm k}^{\rm o}({\rm net}_{\rm Pk}^{\rm o}).w_{\rm kj}^{\rm o}$$
(3.18)

Substituting Eq.(3.14) in the Eq.(3.18) gives

$$\Delta_{\mathbf{P}}.\mathbf{w}_{ji}^{\ h} = \eta.f_{j}^{\ h'}(\operatorname{net}_{Pj}^{\ h}).\mathbf{x}_{Pi}.\sum_{\mathbf{k}}\delta_{P\mathbf{k}}^{\ o}.\mathbf{w}_{kj}^{\ o}$$
(3.19)

Every weight update on the hidden layer depends on all the error signal terms,  $\delta_{Pk}^{\circ}$ , on the output layer. The known errors on the output layer are propagated back to the hidden layer to determine the appropriate weight changes on that layer.

By defining hidden layer error signal term  $\delta_{Pj}^{h}$  as

$$\delta_{Pj}^{\ h} = f_j^{\ h'}(net_{Pj}^{\ h}). \sum_k \delta_{Pk}^{\ o}, w_{kj}^{\ o}$$
(3.20)

The equation updating the weights of the hidden layer becomes:

$$w_{ji}^{h}(t+1) = w_{ji}^{h}(t) + \eta \cdot \delta_{Pj}^{h} \cdot x_{Pi}$$
(3.21)

#### **3.2.3 Improved Weights Updates Equations**

Error convergence is sometimes faster if a momentum term is added to the weight update equation [34]. In this procedure, the weight changes in a direction that is a combination of the current gradient and previous gradient. In order to use momentum, weights from one or more previous training patterns must be saved. The simplest form of backpropagation with moment, the new weights for training step of the (t+1)th are based on the weights at the training steps of the (t)th and (t-1)th. The weight update equations (3.15) and (3.21) for general backpropagation with momentum term is added to the weight of the simplest form as :

$$w_{kj}^{o}(t+1) = w_{kj}^{o}(t) + \eta \cdot \delta_{Pk}^{o} \cdot i_{Pj} + \alpha \left( w_{kj}^{o}(t) - w_{kj}^{o}(t-1) \right)$$
(3.22)

$$w_{ji}^{h}(t+1) = w_{ji}^{h}(t) + \eta \cdot \delta_{Pj}^{h} \cdot x_{Pi} + \alpha \left( w_{ji}^{h}(t) - w_{ji}^{h}(t-1) \right)$$
(3.23)

where  $\alpha$  is momentum factor.

## 3.2.4 Implementation of GBP for multi layer FFN

A series of equations to implement the GBP algorithm were derived in the previous sections. A flow chart of this algorithm is shown in Fig 3.5. Each step of the chart is briefly described below.

#### Step 1. Initialization of weights and biases :

The choice of initial weights will influence whether the net reaches a global ( or only a local ) minimum of error and, if so, how quickly it reaches the minimum. The update of the weight between two units depends on both the derivative of the upper unit's activation function and the output of the lower unit. For this reason, it is important to avoid choices of initial weights that would make it likely that either activation's or derivations of activations are zero. The values for the initial weights must not be too large, or the initial input signal to each hidden or output unit will likely to fall in the region where the derivative of the sigmoid function has a very small value. On the other hand, if the initial weights are too small, the net input to a hidden or output unit will be near zero, which also causes extremely slow learning. Thus all the weights and biases are initialized by random numbers between - 0.5 and 0.5.

# <u>Step 2.</u> Choice of number of iteration, hidden layer, learning rate, momentum <u>factor</u>:

Number of iterations depends on error and output response. It can be chosen at any range. Both the learning rate and momentum factor are to be chosen between 0 to 1.

#### Step 3. Calculation of the actual output of each training pattern:

The outputs will be calculate as the Eq. (3.1) to (3.4). The sigmoid function is used as an activation function of the neurons.

#### Step 4. Adjustment of the weights :

In this step the error of the output layer will be calculated using Eq. (3.5). Then the weights of the output layer will be changed as using as Eq.(3.14), (3.15) and (3.22). The weight of the hidden layer will be changed according to Eq.(3.19),(3.20),(3.21), and (3.23).

#### Step 5. Change of the training pattern :

Repeat step 3 and step 4 until the end of the training data.

### Step 6. Change the iteration number :

Training will be continued until the maximum number of iterations.

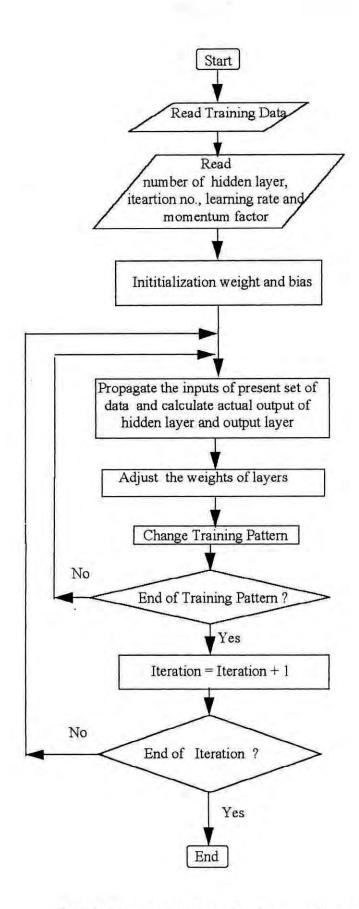


Fig3.5. Flow chart of general back propagation algorithm.

# 3.3 DYNAMIC BACK PROPAGATION ALGORITHM FOR DIAGONAL RECURRENT NETWORK

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A three layered diagonal recurrent network is shown in Fig.3.6. Each hidden neurons output is fed back to its input .

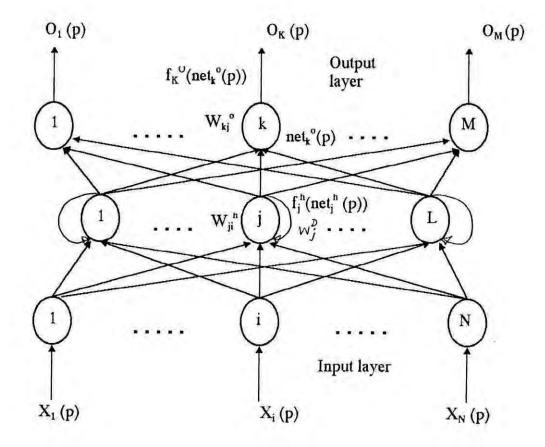


Fig. 3.6 Three -layer diagonal recurrent network.

Let us consider an input vector,  $\mathbf{X}(\mathbf{p}) = (x_{1p}, x_{2p}, \dots, x_{Np})$ , which is applied to the input layer of the network. The subscript "p" refers to p-th time. The input units distribute the values to the hidden layer units.

The net input and output of the j-th hidden unit at the pth time is [36]

$$net_{j}^{h}(p) = \sum_{i=1}^{L} w_{j}^{h} x_{i}(p) + w_{j}^{D} \cdot i_{j}(p-1)$$
(3.24)

$$i_j(p) = f_j^h(net_j^h(p))$$
 (3.25)

where the superscript

- h refers to quantities on the hidden layer;
- $w_{ji}^{h}$  is the weight on the connection from the i-th input unit;
- $w_j^{D}$  is the diagonal feedback weight;
- net<sub>j</sub><sup>h</sup>(p) is the net input of the hidden unit;
- $i_j(p)$  is the output of the hidden unit;
- $f_j^h(net_j^h(p))$  is refered to as an activation function;

The output nodes equations are

$$net_{k}^{o}(p) = \sum_{j=1}^{L} w_{kj}^{o} \cdot i_{j}(p)$$
(3.26)

$$O_k(p) = f_k^{\circ}(net_k^{\circ}(p))$$
(3.27)

where subscript "O" refers to quantities on the output layer.

In diagonal feedback network it is assumed that the activation function of output neuron is linear. Thus the R.H.S. of the Eq.(3.27) will be  $f_k^{\circ}(net_k^{\circ}(p)) = net_k^{\circ}(p)$ .

The Eq.(3.27) then becomes

$$O_k(p) = net_k^{o}(p) = \sum_{j=1}^{L} w_{kj}^{o} \cdot i_j(p)$$
 (3.28)

The error value at a single output unit "k" is defined as  $\delta_k(p) = (y_k(p) - O_k(p))$ , where the  $y_k(p)$  is the desired output value and  $O_k(p)$  is the actual output from the kth unit at pth time. The error to be minimized by the sum of the squares of the errors of all the output units, given as.

$$E(p) = \frac{1}{2} \sum_{k=1}^{M} \delta_k^2(p)$$
 (3.29)

Negative of the gradient of E(p), ( $\nabla E(p)$ ) with respect to the weights determine the direction in which to change the weights. The weight at the (p+1)th time will be

$$W(p+1) = W(p) + \eta. \left(-\frac{\partial E_{p}}{\partial W}\right)$$
(3.30)

where  $\eta$  is a learning rate.

The values of the weights can be adjusted in such a way so that the total error is reduced.

# 3.3.1 Updates of Output Layer Weights

From Eq. (3.27) and the definition of  $\delta_k(p)$ 

$$E(p) = \frac{1}{2} \sum_{k} (y_{k}(p) - O_{k}(p))^{2}$$
(3.31)

$$\frac{\partial E(\mathbf{p})}{\partial \mathbf{w}_{kj}^{\circ}} = -(\mathbf{y}_{k}(\mathbf{p}) - \mathbf{O}_{k}(\mathbf{p})) \cdot \frac{\partial \mathbf{O}_{k}(\mathbf{p})}{\partial \mathbf{w}_{kj}^{\circ}}$$
(3.32)

For linear activation function of output neuron, the derivative part of Eq.(3.32) can be

written as 
$$\frac{\partial O_k(\mathbf{p})}{\partial w_{kj}^{\circ}} = i_j(\mathbf{p})$$
. Then the Eq.(3.32) becomes  
 $\frac{\partial E(\mathbf{p})}{\partial w_{kj}^{\circ}} = -(\mathbf{y}_k(\mathbf{p}) - O_k(\mathbf{p})).i_j(\mathbf{p})$  (3.33)

Thus the weights of the output layer are updated as

$$w_{kj}^{\circ}(p+1) = w_{kj}^{\circ}(p) + \eta. (y_{k}(p) - O_{k}(p)). i_{j}(p)$$
(3.34)

The output layer error signal term is  $\delta_k^0(p)$ , defined as

$$\delta_k^{0}(p) = (y_k(p) - O_k(p))$$
(3.35)

By combining the Eq. (3.34) and (3.35) the weight update equation becomes

$$w_{kj}^{\circ}(p+1) = w_{kj}^{\circ}(p) + \eta \delta_{k}^{\circ}(p). \ i_{j}(p)$$
(3.36)

#### 3.3.2 Updates of Hidden Layer Weights

The gradient of E(p) with respect to the hidden layer weights:

$$\frac{\partial E(\mathbf{p})}{\partial \mathbf{w}_{ji}^{h}} = \frac{1}{2} \sum_{k} \frac{\partial}{\partial \mathbf{w}_{ji}^{h}} (\mathbf{y}_{k}(\mathbf{p}) - \mathbf{O}_{k}(\mathbf{p}))^{2}$$
(3.37)

$$= -\sum_{k} (y_{k}(p) - O_{k}(p)) \cdot \frac{\partial O_{k}(p)}{\partial w_{ji}^{h}}$$
(3.38)

$$= -\sum_{k} (y_{k}(p) - O_{k}(p)) \cdot w_{kj} \cdot \frac{\partial i_{j}(p)}{\partial w_{ji}^{h}}$$
(3.39)

The derivative part of the Eq.(3.39) considered as,

$$Q_{ji}(p) = \frac{\partial i_{j}(p)}{\partial w_{ji}^{h}}$$

$$= \frac{\partial i_{j}(p)}{\partial (\operatorname{net}_{j}^{h}(p))} \cdot \frac{\partial (\operatorname{net}_{j}^{h}(p))}{\partial w_{ji}^{h}}$$

$$= f'(\operatorname{net}_{j}^{h}(p)) \cdot \frac{\partial}{\partial w_{ji}^{h}} (\sum w_{ji}^{h} \cdot x_{i}(p) + w_{j}^{D} \cdot i_{j}(p-1))$$

$$= f'(\operatorname{net}_{j}^{h}(p)) \cdot (x_{i}(p) + w_{j}^{D} \cdot Q_{ji}(p-1))$$

$$Q_{ji}(p) = f'(\operatorname{net}_{j}^{h}(p)) \cdot (x_{i}(p) + w_{j}^{D} \cdot Q_{ji}(p-1)) \qquad (3.40)$$
where  $Q_{ji}(0) = 0$ 

The hidden layer weights is updated in proportion to the negative of the Eq. (3.39), thus

$$\Delta_{\mathbf{P}} \cdot \mathbf{w}_{ji}^{\ h} = \eta. \ Q_{ji}(\mathbf{p}) \cdot \sum_{\mathbf{k}} (\mathbf{y}_{\mathbf{Pk}} - \mathbf{O}_{\mathbf{Pk}}) \cdot \mathbf{w}_{\mathbf{k}j}^{\circ}$$
(3.41)

Substituting Eq.(3.35) in Eq.(3.41) rewrites as

$$\Delta_{\mathbf{P}} \cdot \mathbf{w}_{ji}^{h} = \eta Q_{ji}(\mathbf{p}) \cdot \sum_{k} \delta_{k}^{\circ}(\mathbf{p}) \cdot \mathbf{w}_{kj}^{\circ}$$
(3.42)

Every weight updated on the hidden layer depends on all the error terms,  $\delta_k^{\circ}(p)$ , on the output layer. Hidden layer error signal term  $\delta_j^{h}(p)$  can be defined as

$$\delta_j^{h}(p) = \sum_k \delta_k^{o}(p) \cdot w_{kj}^{o}$$
(3.43)

Finally, weight update equation for the hidden layer becomes

$$w_{ji}^{h}(p+1) = w_{ji}^{h}(p) + \eta \cdot \delta_{j}^{h}(p) \cdot Q_{ji}(p)$$
(3.44)

## 3.3.2 Updates of Diagonal Recurrent Weights

The gradient of E(p) with respect to the feedback layer weights is calculate as follows,

$$\frac{\partial E(\mathbf{p})}{\partial \mathbf{w}_{j}^{\mathrm{D}}} = \frac{1}{2} \sum_{\mathbf{k}} \frac{\partial}{\partial \mathbf{w}_{j}^{\mathrm{D}}} (\mathbf{y}_{\mathbf{k}}(\mathbf{p}) - \mathbf{O}_{\mathbf{k}}(\mathbf{p}))^{2}$$

$$= -\sum_{\mathbf{k}} (\mathbf{y}_{\mathbf{k}}(\mathbf{p}) - \mathbf{O}_{\mathbf{k}}(\mathbf{p})) \cdot \frac{\partial \mathbf{O}_{\mathbf{k}}(\mathbf{p})}{\partial \mathbf{w}_{j}^{\mathrm{D}}}$$

$$= -\sum_{\mathbf{k}} (\mathbf{y}_{\mathbf{k}}(\mathbf{p}) - \mathbf{O}_{\mathbf{k}}(\mathbf{p})) \cdot \mathbf{w}_{\mathbf{k}j} \cdot \frac{\partial \mathbf{i}_{j}(\mathbf{p})}{\partial \mathbf{w}_{j}^{\mathrm{D}}}$$
(3.45)

The derivative term of the R.H.S of Eq. (3.45) is calculated as

$$\begin{split} R_{j}(p) &= \frac{\partial i_{j}(p)}{\partial w_{j}^{D}} \\ &= \frac{\partial i_{j}(p)}{\partial (net_{j}^{h}(p))} \cdot \frac{\partial (net_{j}^{h}(p)}{\partial w_{j}^{D}} \\ &= f'(net_{j}^{h}(p)) \cdot \frac{\partial}{\partial w_{j}^{D}} \left( \sum w_{ji}^{h} \cdot x_{i}(p) + w_{j}^{D} \cdot i_{j}(p-1) \right) \\ &= f'(net_{j}^{h}(p)) \cdot (i_{j}(p-1) + w_{j}^{D} \cdot \frac{\partial i_{j}(p-1)}{\partial w_{j}^{D}}) \\ R_{j}(p) &= f'(net_{j}^{h}(p)) \cdot (i_{i}(p-1) + w_{j}^{D} \cdot R_{j}(p-1)) \end{split}$$
(3.46)

Then

where  $R_j(0) = 0$ 

The diagonal recurrent weights is updated in proportion to the negative of the Eq. (3.45), Thus

$$\Delta_{\mathbf{P}}.\mathbf{w}_{ji}^{h} = \eta. \ R_{i}(p). \sum_{k} (y_{\mathbf{P}k} - O_{\mathbf{P}k}).\mathbf{w}_{kj}^{o}$$
(3.47)

With the help of  $\delta_{Pk}^{o}$  from Eq. (3.35) the Eq.(3.47) can be rewritten as.

$$\Delta_{\mathbf{P}}.\mathbf{w}_{ji}^{h} = \eta.\mathbf{R}_{i}(\mathbf{p}).\sum_{k} \delta_{k}^{\circ}(\mathbf{p}).\mathbf{w}_{kj}^{\circ}$$
(3.48)

Every weight updated on the feedback, depends on all the error terms,  $\delta_k^{\circ}(p)$ , on the output layer. By defining hidden layer error term  $\delta_j^{h}(p)$  as follows

$$\delta_j^{h}(p) = \sum_k \delta_k^{\circ}(p) \cdot w_{kj}^{\circ}$$
(3.49)

and using Eq. (3.49) in Eq. (3.48) the weight update equation for diagonal recurrent is reduced as

$$w_{j}^{D}(p+1) = w_{j}^{D}(p) + \eta . \delta_{j}^{h}(p) . R_{i}(p)$$
(3.50)

#### 3.3.4. Adaptive Learning Rate

The convergence of a recurrent neural network is not easy to be guaranteed. It should be noted here that when a plant of unknown dynamics is combined with feedback neural network, it makes the convergence of NN based system more difficult. However it is well accepted that a small learning rate makes a network, though slow, more likely to converge, while large learning rate makes the system unstable. Thus to guarantee convergence and for faster training process an approach suggested in [36] is employed here to find the learning rate. In this approach adaptive learning rate was developed by introducing a Lyapunov function.

A discrete-type Lyapunov function can be defined as

$$L(p) = \frac{1}{2}e^{2}(p)$$
 (3.51)

where, e (p) represents the error in the learning process and can be written as

$$e(p) = y_k(p) - O_k(p)$$

Thus the change of Lyapunov function due to the training process is obtained by

$$\Delta L(p) = L(p+1) - L(p) = \frac{1}{2} \left[ e^2(p+1) - e^2(p) \right]$$
(3.52)

The error difference due to the learning can be represented as

$$e(p+1) = e(p) + \Delta e(p) = e(p) + \left[\frac{\partial e(p)}{\partial w}\right]^{T} \nabla W$$
(3.53)

where  $\Delta W$  represents a change in an arbitrary weight vector (normalized real vector)

The  $\nabla W$  is given as

$$\nabla W = \eta \cdot -\frac{\partial E(\mathbf{p})}{\partial W} = \eta \cdot (\mathbf{y}_{\mathbf{k}}(\mathbf{p}) - O_{\mathbf{k}}(\mathbf{p})) \cdot \frac{\partial O(\mathbf{p})}{\partial W}$$
$$= \eta \cdot e(\mathbf{p}) \cdot \frac{\partial O(\mathbf{p})}{\partial W}$$
(3.54)

From Eq. (3.52 - 3.54),  $\Delta L(p)$  can be represented as

$$\Delta L(\mathbf{p}) = \nabla \mathbf{e}(\mathbf{p}) \cdot \left[ \mathbf{e}(\mathbf{k}) + \frac{1}{2} \nabla \mathbf{e}(\mathbf{p}) \right]$$
$$= \left[ \frac{\partial \mathbf{e}(\mathbf{p})}{\partial \mathbf{w}} \right]^{\mathrm{T}} \cdot \eta \cdot \mathbf{e}(\mathbf{p}) \frac{\partial \mathcal{O}(\mathbf{p})}{\partial W} \cdot \left\{ \mathbf{e}(\mathbf{p}) + \frac{1}{2} \left[ \frac{\partial \mathbf{e}(\mathbf{p})}{\partial W} \right]^{\mathrm{T}} \cdot \eta \cdot \mathbf{e}(\mathbf{p}) \frac{\partial \mathcal{O}(\mathbf{p})}{\partial W} \right\}$$
(3.55)

For linear activation function of output neuron,  $\frac{\partial e(p)}{\partial W} = -\frac{\partial O(p)}{\partial W}$ , so that

$$\Delta L(\mathbf{p}) = -\eta \cdot e^{2}(\mathbf{p}) \left\| \frac{\partial O(\mathbf{p})}{\partial W} \right\|^{2} + \frac{1}{2} \eta^{2} \cdot e^{2}(\mathbf{p}) \cdot \left\| \frac{\partial O(\mathbf{p})}{\partial W} \right\|^{4}$$
(3.56)

$$= -\lambda e^2(\mathbf{p}) \tag{3.57}$$

where, 
$$\lambda = \eta \cdot \left\| \frac{\partial O(p)}{\partial W} \right\|^2 - \frac{1}{2} \eta^2 \cdot \left\| \frac{\partial O(p)}{\partial W} \right\|^4$$

For simplicity, it is assumed that [36]

$$g(p) = \frac{\partial O(p)}{\partial W}$$
$$g_{max} := \max_{p} ||g(p)|| \text{ and}$$
$$\eta_{1} = \eta \cdot g_{max}^{2} \quad \text{where} \qquad || \cdot || \text{ is}$$

||. || is the usual Euclidean norm

The expression for  $\lambda$  becomes

$$\lambda = \frac{1}{2} \cdot \|\mathbf{g}(\mathbf{p})\|^{2} \eta \cdot \left(2 - \eta \cdot \|\mathbf{g}(\mathbf{p})\|^{2}\right)$$
  
$$= \frac{1}{2} \cdot \|\mathbf{g}(\mathbf{p})\|^{2} \cdot \eta \cdot \left(2 - \frac{\eta_{1} \|\mathbf{g}(\mathbf{p})\|^{2}}{\mathbf{g}_{\max}^{2}}\right)$$
  
$$\lambda \geq \frac{1}{2} \cdot \|\mathbf{g}(\mathbf{p})\|^{2} \cdot \eta \cdot (2 - \eta_{1}) > 0$$
 (3.58)

The convergence is guaranteed if the following condition is satisfied.

$$\eta(2-\eta_1) > 0$$
  
or,  $\frac{\eta_1(2-\eta_1)}{g_{max}^2} > 0$ 

The above condition will be valid for  $0 < \eta_1 < 2$ . However the maximum learning rate which guarantees the most rapid or optimal convergence is corresponding to  $\eta_1 = 1$ , i.e.,

$$\eta = \frac{1}{g_{\max}^2} \tag{3.59}$$

For  $0 < |w_j^p| < 1$ , the value of  $g_{max}^2$  for output, hidden and diagonal feedback weight were given as [36]

For output layer weight,

$$g_{max}^2 = H = No \text{ of hidden layer}$$
 (3.60)

For diagonal feedback weight,

$$g_{\max}^2 = \frac{1}{h} \left[ \frac{1}{W_{\max}^0} \right]^2$$
(3.61)

where 
$$W_{max}^{O} := max_{P} \cdot \|W_{kj}\|$$

For hidden layer weight,

$$g_{\max}^{2} = \frac{1}{(N+H)} \left[ \frac{1}{W_{\max}^{0} \cdot X_{\max}} \right]^{2}$$
(3.62)  
where,  $X_{\max} = \max_{p} \| x_{i}(p) \|$ 

#### 3.3.5 Implementation of DBP for multi layer DRN

A series of equations to implement the DBP algorithm were derived in the previous sections. A flow chart of this algorithm is shown in Fig. 3.7. Each step of the chart is briefly described below.

#### Step 1. Initialization of weights :

The weights between output layer and hidden layer is initialized randomly. These values lies between - 0.5 and 0.5. The diagonal recurrent weights are initialized by 0.5.

#### Step 2. Choice of iteration no, hidden layer :

Number of number iteration depended on error and output response. It can be choice at any range.

#### Step 3. Calculation of the actual output of each training pattern:

The outputs will be calculate as the Eq. (3.24) to (3.28).

#### Step 4 : Calculation the optimum learning rate

The optimum learning rate will be calculate as the Eq.(3.60) to (3.62).

#### Step 5. Adjustment of the weights :

In this step the error of the output layer will be calculated using Eq. (3.31). Then the weights of the output layer will be changed by using Eq.(3.35) and (3.36). The weight of the hidden layer will be changed according to Eq.(3.40) to (3.45). The diagonal recurrent weights will be change by the Eq.(3.45) to(3.50).

#### Step 6. Change of the training pattern :

Repeat step 4 and step 5 until the end of the training data.

#### Step 7. Change the iteration number :

Training will be continued until the maximum number of iterations.

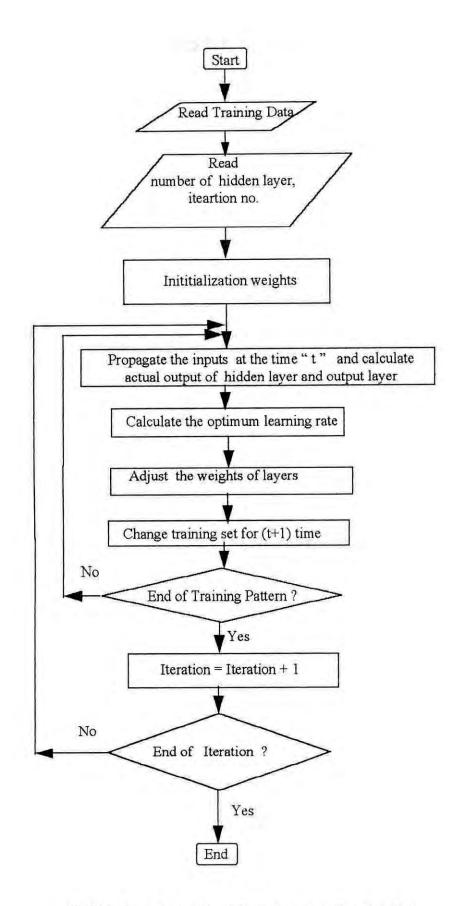


Fig3.7. Flow chart of dynamic back propagation algorithm.

# **CHAPTER - FOUR**

# PROPOSED NEURAL NET CONTROLLER

□ INTRODUCTION

- □ ANN BASED INVERSE CONTROLLER
- □ BOILER CONTROL LOOPS FOR INTEGRATION
- □ NETWORKS INPUT- OUTPUT VECTORS
- □ TRAINING OF THE PROPOSED CONTROLLER
- □ TEST RESULT AND SELECTION OF NETWORK
- □ PERFORMANCE OF THE DEVELOPED CONTROLLER
- □ RUNNING MODE OF THE PROPOSED CONTROLLER
- □ NEURAL NET CONTROLLER WITH BOTH MODE.

#### 4.0 INTRODUCTION

An adaptive gain controller has the ability to dynamically change its overall gain in response to a specific variable. Thus any change in the process gain causes a change in controller gain reciprocally to maintain the overall unity loop gain [37],[38]. The change in controller gain with change in process gain is shown in Fig 4.1. Such an adaptive controller can be designed by the inverse process dynamic technique. The inverse model of a process having an unknown transfer function is itself a process having a transfer function which is in some senses a best fit to the reciprocal of the unknown transfer function[37]. This technique can be easily implemented by neural network. A neural network can be applied as a adaptive controller of a plant after learning its inverse dynamics(input/output). Here the inverse dynamics means the boiler output quantities (controlled variables) such as steam header pressure, drum level and steam flow rate will be used as input quantities of the neural network while the three inputs of the boiler such as flow rate of gas, air and water will be used as output quantities of the neural network. In this work, this technique is implemented for developing a neural network based an integrated control system of an industrial boiler of ZFCL.

In this chapter the inverse dynamics modelling controller design methodology is presented. The training operation of the feedforward and diagonal recurrent network is briefly described. The output responses of both networks are investigated to select the best network for developing a software controller.

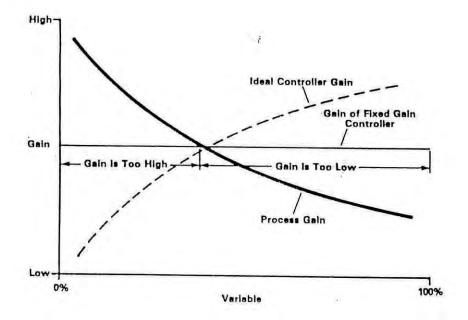


Fig. 4.1 Relationship between Process gain and Controller gain.

## 4.1 ANN BASED INVERSE CONTROLLER

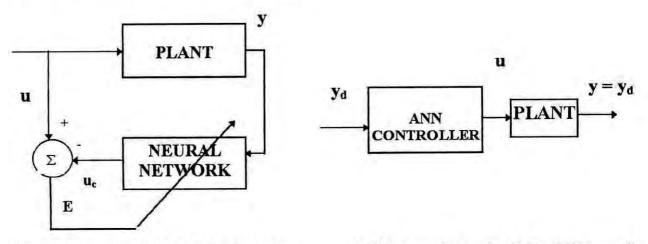
Two modes of neural net controller are: the training mode and the running mode. A general block diagram of the training mode of an ANN based controller is shown in Fig.4.2(a). The plant output (y) for the known input (u) is used as network input to obtain an output  $u_c$ . The learning process of neural network is carried out to minimize the overall squared error ( $E^2$ ) which is the difference between u and  $u_c$ . After the learning process is carried out, the weights between units (i.e., input to hidden and hidden to output) of the neural network are obtained. The trained neural network can then be used as a controller of the plant. The plant output signals of the controlled plant (y) is expected to match the desired responses (y<sub>d</sub>) which is given as the neural network input shown in fig.4.2(b). The computational function of the neural network in the training and operation phase are as follows:

Training phase: 
$$u = f(y, d)$$
 (4.1)

where d is the plant load disturbance.

Operation phase:  $u = f(y_d, d)$  (4.2)

where  $y_d$  is the desired set point of the plant.



(a) The training mode of the ANN Controller

(b) The operation mode of the ANN controller

Fig.4.2. The training and running mode of the ANN Controller.

## **4.2 BOILER CONTROL LOOPS FOR INTEGRATION**

There are three control loops (such as combustion, drum level and temperature control loops) for controlling the 120 ton/hr capacity boiler of the ZFCL as described in the chapter 2. Temperature is being controlled manually whereas combustion and drum level are being controlled automatically. Thus in this work these two automatic control loops have been considered for integration towards developing a single neural net controller. A schematic diagram of the present combustion and drum level control loops of the ZFCL boiler is shown in Fig. 4.3.

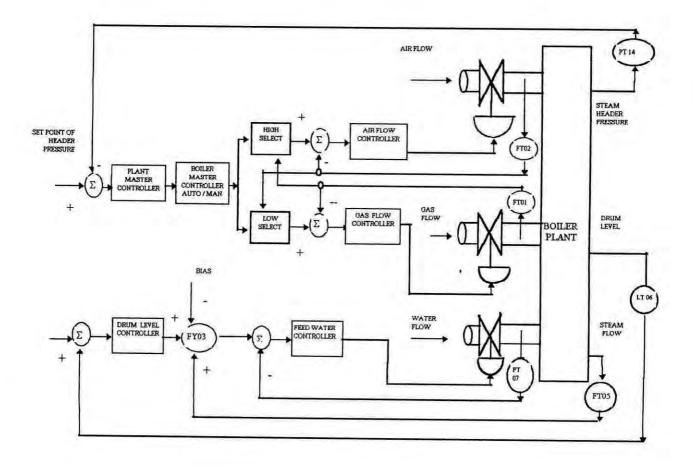


Fig. 4.3 Present PID controller controlled boiler plant of ZFCL.

### **4.3 NETWORKS INPUT - OUTPUT VECTORS**

Two networks architecture (such as feedforward and diagonal recurrent network) has been chosen to develop the proposed controller. Since the inverse dynamic modelling technique is employed for developing the controller, the input vectors of both networks are: (i) steam header pressure  $(y_1)$  (ii) drum water level  $(y_2)$  and (iii) steam flow  $(y_3)$ . The output vectors of the both networks include : (i) gas flow rate  $(u_1)$  (ii) air flow rate  $(u_2)$  and (iii) water flow rate  $(u_3)$ . Both networks structure with input-output vectors are shown in Fig. 4.4. The architecture providing the fastest convergence with minimum error and desired response is to be selected.

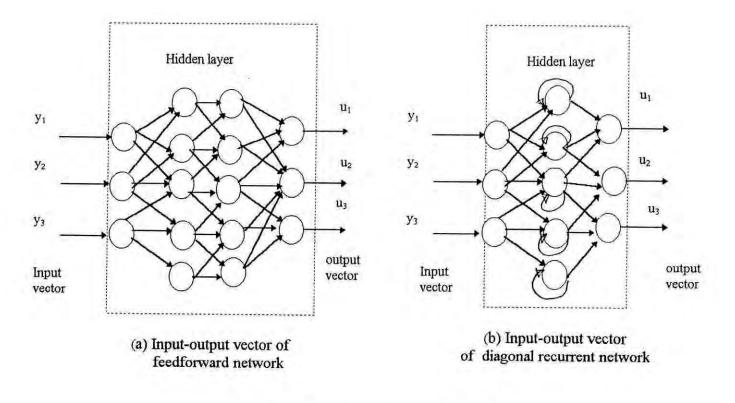
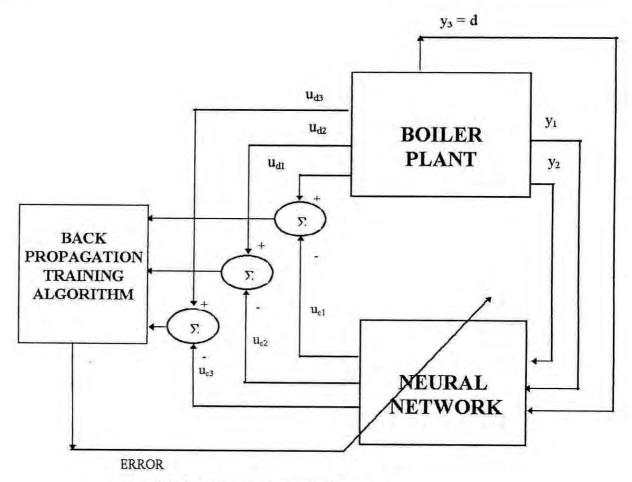
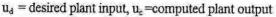


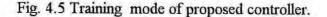
Fig. 4.4 Input-output vector of networks.

#### 4.4 TRAINING OF THE PROPOSED CONTROLLER

Feedforward network is trained using the general backpropagation algorithm while diagonal recurrent network is trained using dynamic backpropagation algorithm. Both training algorithms are described in the previous chapter. The training mode of the proposed controller is shown in Fig. 4.5. Input-output data of the present PID controller based 120 ton/hr capacity boiler of ZFCL are used as the training data of both the networks. The training data are collected from the data bank of process control computer of ZFCL. Data are given in appendix A. Faster convergence with minimum error and desired response depends on many training parameters. The following subsections discuss the selection of the training parameter in the case of both architectures.







#### 4.4.1 Feedforward Network Training

Parameters to be selected for getting the desired response from the training of a feedforward network include: (i) learning rate, (ii) momentum factor, (iii) number of hidden layer and (iv) number of neurons in each hidden layer. In selecting the learning rate and momentum factor, nine neuron with single hidden layer is chosen for network architecture.

#### 4.4.1.1 Learning Rate:

The learning rate ( $\eta$ ) is used to control the amount of weight adjustment at each step of training. Generally the  $\eta$  has an non-negative value which is less than 1.0. For the present work the different values of learning rate such as 0.01, 0.1, 0.2, and 0.3 are chosen to train the network. The training history at different values of learning rate is shown in Fig.4.6. From the figure it is found that though at the learning rate of 0.2 and 0.3 error converges fast but initially the system becomes unstable. On the other hand at the learning rate of 0.01, convergence is very slow. However convergence with stable minimum error is achieved at the learning rate of 0.1. Thus the value of the learning rate is chosen as 0.1.

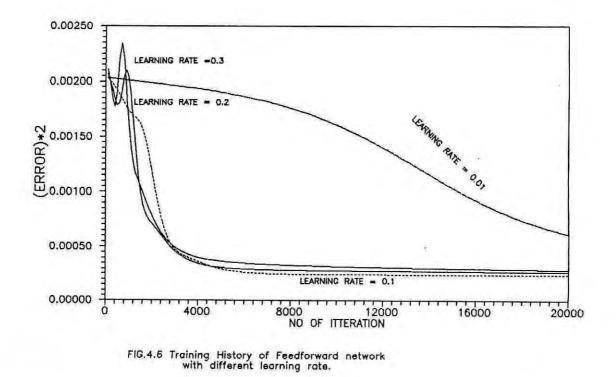
#### 4.4.1.2 Momentum Factor

Momentum allows the net to make reasonable large weight adjustment as long as the corrections are in the same general direction for several pattern, while using a small value of learning rate to prevent a large response to the error from any one training pattern. It also reduces the likelihood that the net will find weights that a local, but not a global minimum. With momentum factor the net proceeds only in the direction of the gradient, but also in the direction of a combination of current gradient and the previous direction of weight correction[33]. Thus the use of momentum factor along with the

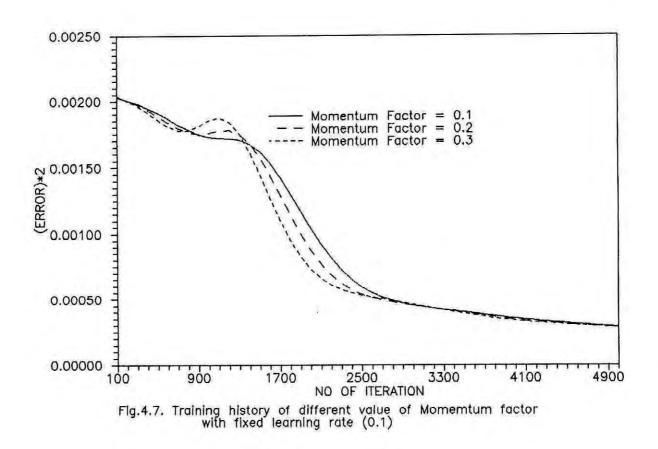
learning rate, accelerates the training speed to achieve the convergence. Generally momentum factor lies between 0.1 to 1.0. However there is no guidelines to determine the optimum momentum factor for the learning process. Thus initially during the training process various values of momentum factor such as 0.1, 0.2, and 0.3 are taken to choose the best one. The training history at different values of momentum factor with a fixed learning rate of 0.1 is shown in Fig.4.7. From the figure it is evident that the system becomes unstable for large value of momentum factor. In this problem the faster and stable errors convergence is achieved at the momentum factor of 0.1. Thus this value is taken as the momentum factor for training the network.

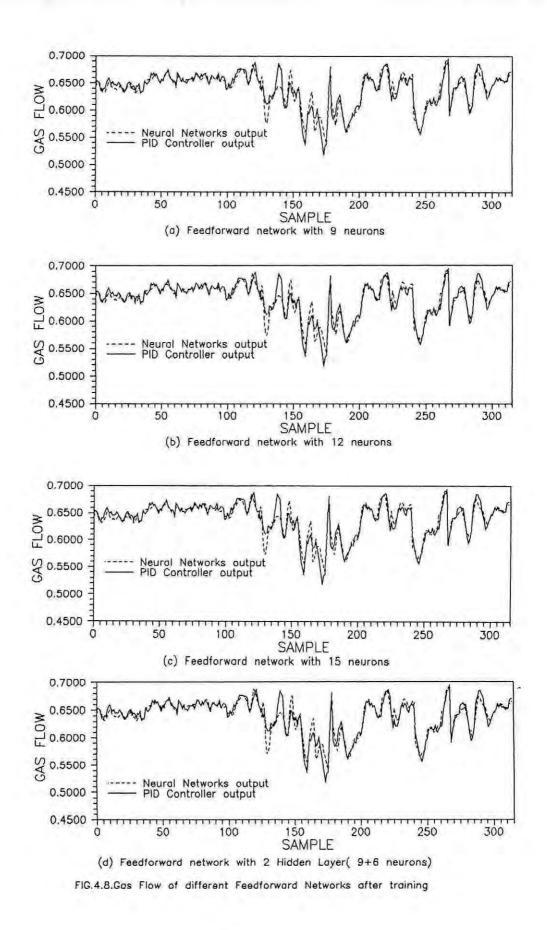
#### 4.4.1.3 Hidden layer and Neuron selection:

In this work a neural network having a single hidden layer with a various number of neurons such as 9, 12, and 15 is trained individually. A network having double hidden layer with nine neurons in the first hidden layer and six neurons in the second hidden layer is also trained. The training history of the various network is shown in fig 4.8. After 300,000 iterations for each network, the weight of the network are saved for designing the controller. Comparison between the output response of all the networks and those of the PID controller are shown in Fig.4.8 to Fig.4.10. From the figures it is evident that the output response of all the cases are close to those of the PID controller. The network with single hidden layer with nine neurons is chosen to develop the controller, because this network takes less computation time as compared to other networks. The weights obtained from the training of the selected network is given in appendix-B.









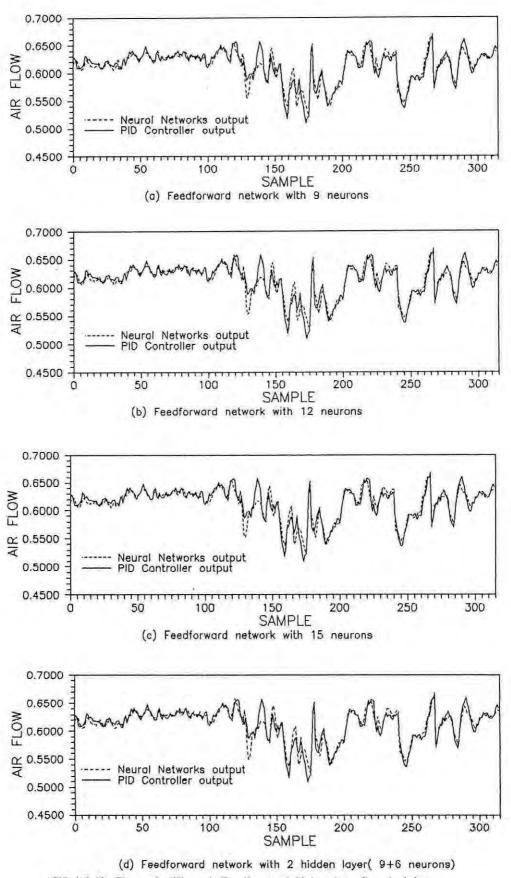


FIG.4.9.Air Flow of different Feedforward Networks after training

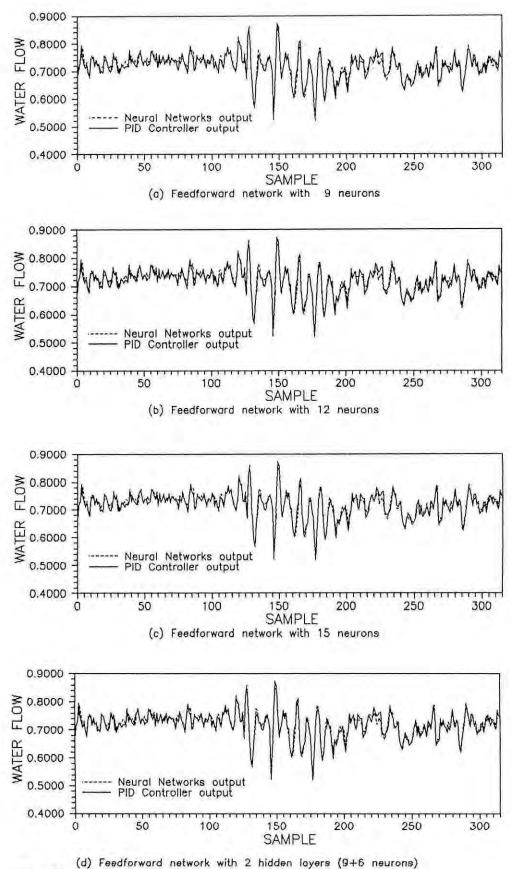


FIG.4.10. Water Flow of different Feedforward Networks after training

#### 4.4.2 Training for Diagonal Recurrent Network

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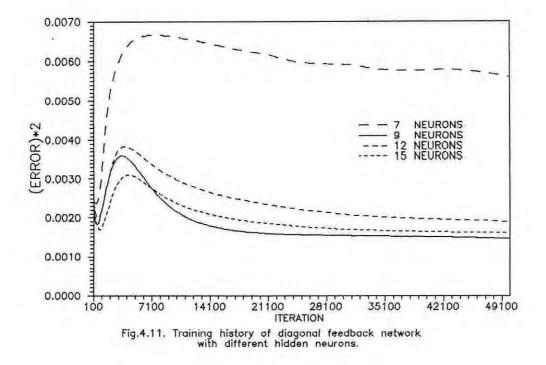
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A diagonal recurrent network with single hidden layer is trained by dynamic backpropagation training algorithm with adaptive learning rate. This learning scheme is described in the previous chapter. Various networks are trained with different number of neurons such as 7, 9, 12, and 15. After 50,000 iterations the training history for each case is depicted in Fig 4.11. From the figure it is evident that in the case of 7, 12, and 15 neurons, the training process becomes unstable and convergence becomes very slow, whereas in the case of 9 neurons, fast convergence and stable minimum error is found. Thus the network with nine neuron in hidden layer is selected for further training. After 300,000 iteration the error convergence rate is very low and the error square is 0.00023. Thus weights of the network are then saved to design the controller. The weights are given in appendix- C.

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## 4.5 TEST RESULTS AND SELECTION OF NETWORK

Initially two neural net controller are developed to choose the better one. The first N controller is designed using the weights of the feedforward network. While the sec NN controller is designed using the weights of the recurrent network. To test these controllers, four sets of test data are taken from the history file of the ZFCL while not used during the training. These sets of test data are given in Appendix D. Both developed NN controllers are tested individually by using each set of test data



developed NN controller predicts the plant inputs such as air flow, gas flow and water flow for a particular plant output. Predicted plant inputs of both NN controller are then compared with the actual plant inputs which are controlled by the conventional PID controller. These comparisons for each set of test data are shown in Figs. 4.12 to 4.15. Results in the figures show that the actual plant inputs and the predicted inputs from the NN controllers are in well agreement except for a few cases. This may be due to the use of short range of the training data. Both the NN controllers predicted gas flow rate, air flow rate and water flow rate in an hour and those predicted by conventional PID controller are also given in Table-4.1 to 4.4. From the tables it is evident that the total flow rate of gas, air, and water of the developed NN controller based plant are very close to those of the existing PID controller based plant. The comparison tables also shows that in most cases the percentage of error in the case of first NN controller based plant less than that of the second NN controller based plant. Thus the output response of the feedforward network based controller is more better than that of the recurrent network based controller. Moreover, in the case of the first NN controller based plant, the variation in flow ( i.e., the difference between the maximum and minimum flow of gas, air and water ) is smaller than that of the second NN controller based plant (refer to Figs 4.12 to 4.15. So the first NN controller based plant is more stable than the second NN controller based plant. From Figs. 4.12 to 4.15, it can also be noted here that in the case of the first NN controller ( i.e., feedforward network based controller ) based plant the variation in flow is smaller than that of the PID controller based plant. Thus the three layered feedforward network architecture with nine neurons in the hidden layer is chosen to design the proposed software controller.

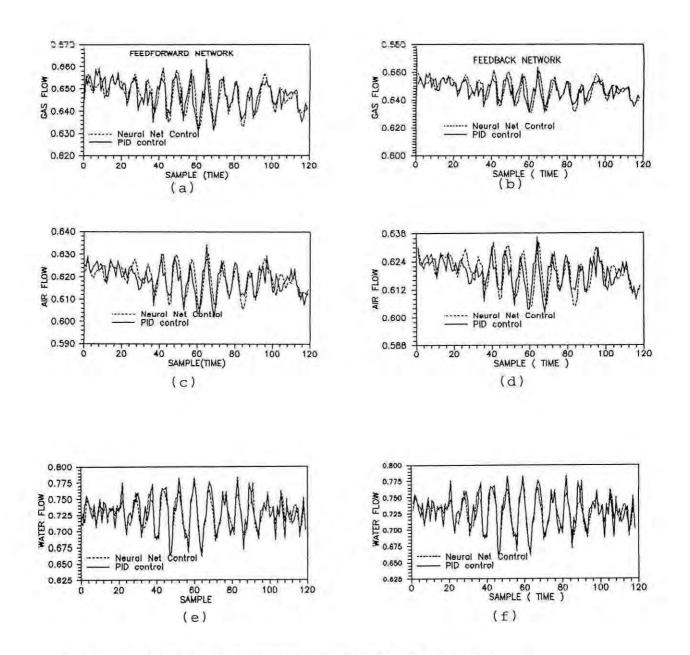


Fig.4.12 : Gas, Air, and Water Flow variation with time for 1st set of test data.

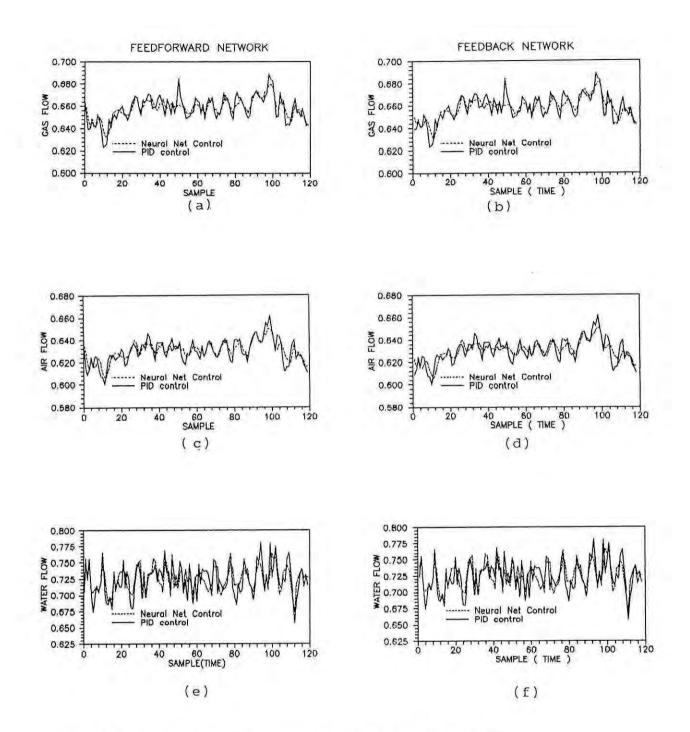


Fig.4.13 : Gas. Air, and Water Flow variation with time for 2nd set of test. data

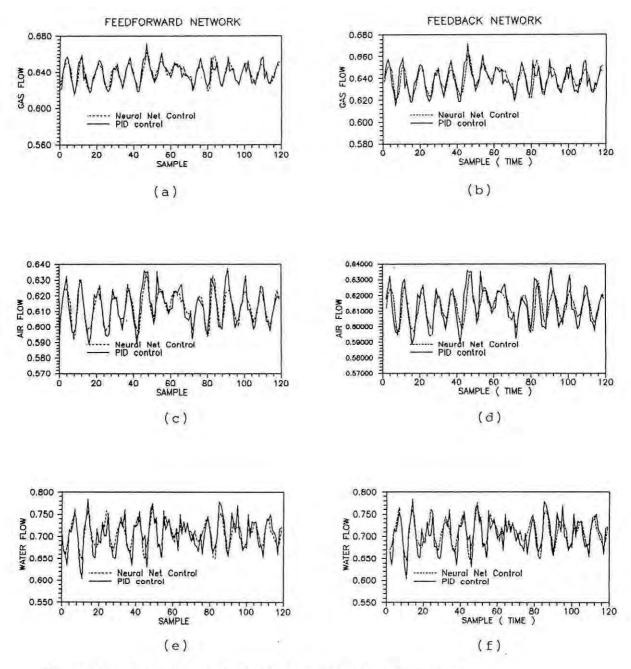


Fig.4.14 : Gas, Air, and Water Flow variation with time for 3rd set of test. data

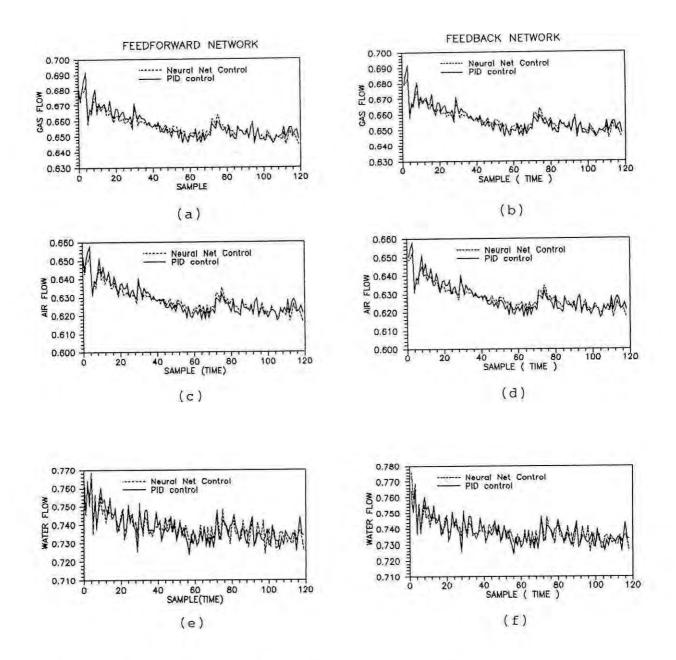


Fig.4.15 : Gas, Air. and Water Flow variation with time for 4th set of test. data

## Table-4.1

		PID controller based plant	Feedforward network based plant	Diagonal Recurrent network based plant
GAS	Total flow (NM <sup>3</sup> /HR)	8682.99	8682.73	8688.82
	Percentage of Error		0.003	0.067
AIR	Total Flow (NM <sup>3</sup> /HR	105540.6	105566.1	105625.5
	Percentage of Error		0.024	0.080
WATER	Total Flow (TON/HR)	120.92	120.72	120.60
	Percentage of Error	<u> </u>	0.165	0.266

Flow rate variation of different controller based plant for 1st set of test data.

## Table-4.2

Flow rate variation of different controller based plant for 2nd set of test data.

		PID controller based plant	Feedforward network based plant	Diagonal Recurrent network based plant
GAS	Total flow (NM <sup>3</sup> /HR)	8827.08	8829.00	8827.89
	Percentage of Error		0.022	0.009
AIR	Total Flow (NM <sup>3</sup> /HR	107419.1	107439.5	07427.8
	Percentage of Error		0.019	0.008
WATER	Total Flow (TON/HR)	120.21	120.34	120.38
	Percentage of Error		0.110	0.141

## Table-4.3

		PID controller based plant	Feedforward network based plant	Diagonal Recurrent network based plant
GAS	Total flow (NM <sup>3</sup> /HR)	8572.73	8572.12	8574.11
U.L.	Percentage of Error		0.007	0.0161
AIR	Total Flow (NM <sup>3</sup> /HR	104561.1	104523.0	104524.4
	Percentage of Error	· · · · · ·	0.0365	0.0352
WATER	Total Flow (TON/HR)	117.02	117.42	117.69
	Percentage of Error	-	0.3344	0.5725

Flow rate variation of different controller based plant for 3rd set of test data.

## Table-4.4

## Flow rate variation of different controller based plant for 4th set of test data.

		PID controller based plant	Feedforward network based plant	Diagonal Recurrent network based plant
GAS	Total flow (NM <sup>3</sup> /HR)	8809.59	8808.00	8810.66
Grid	Percentage of Error	-	0.018	0.012
AIR	Total Flow (NM <sup>3</sup> /HR	107123.6	107113.5	107137.3
	Percentage of Error	-	0.009	0.013
WATER	Total Flow (TON/HR)	122.53	122.54	122.58
	Percentage of Error	-	0.007	0.041

## 4.5 PERFORMANCE OF THE DEVELOPED CONTROLLER

The performance of the developed controller can be determined from the characteristics of the boiler such as average air/gas ratio, steam/gas ratio as well as gas and air flow due to change in steam load. Average air/gas ratio and steam/gas ratio are computed from the developed controller predicted inputs ( such as gas, air and water flow). These ratios are given in Table-4.5. From the table it can be found that the predicted ratios of of developed controller are very close to the ratios obtained from the history file of the PID controller based boiler plant. The air flow and gas flow due to steam load change are shown in Figs.4.16 and 4.17, respectively. From the figures it is evident that the characteristics of air and gas flow due to steam load change are similar for both PID and NN controller. Thus it can be concluded here that the developed NN controller has the ability to control the reference boiler (i.e. 120 ton/hour capacity boiler of ZFCL) having the non-linear process dynamics.

Average Ratio	Proposed NN controller based plant	Actual PID controller based plant			
Air / Gas	12.168	12.167			
Steam / Gas	13.556	13.553			

 Table - 4.5

 Comparison of air/gas and steam/gas ratios

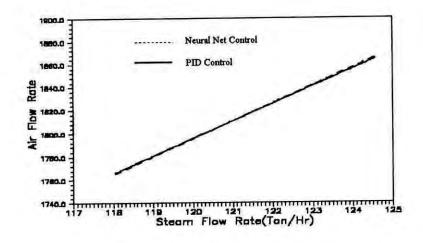


Fig. 4.16. Variation of air flow with load (steam flow).

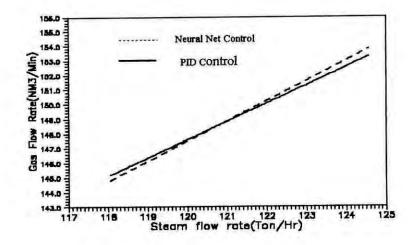
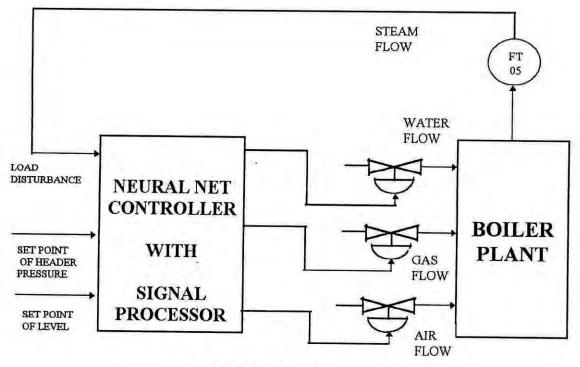


Fig. 4.17. Variation of gas flow with load (steam flow).

## 4.6 RUNNING MODE OF THE PROPOSED CONTROLLER

The running mode of the developed controller is shown in Fig. 4.18. During the normal operation of the proposed controller, the desired set points of the steam header pressure and the drum level can be changed by the operator through the keyboard. The load disturbance is sensed continuously by steam flow transmitter. Thus if any change in steam flow is occurred then the control inputs of the plant such as gas, air and water will be changed automatically by the proposed controller.

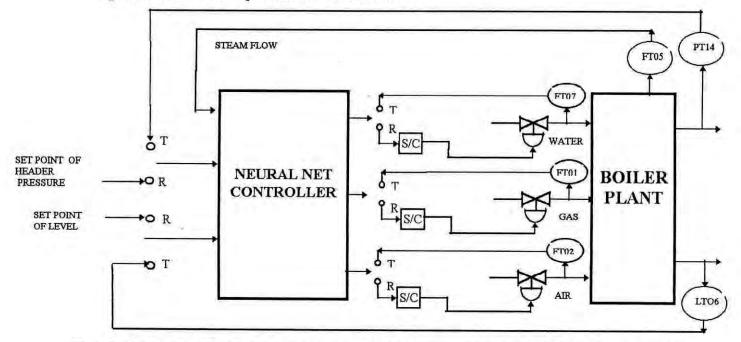


FT 05 = Steam flow transmitter

Fig. 4.18 Running mode of the proposed Neural Net Controller.

#### 4.7 NEURAL NET CONTROLLER WITH BOTH MODE

Training and running mode of the proposed neural net controller is shown in Fig. 4.19. The user can select either the training mode or the running mode through keyboard by pressing "T" for training and "R" for running. During the training mode the boiler plant output-input such as steam header pressure, drum level, steam flow, gas flow, air flow and water flow are used as training data of the NN controller as mentioned in section 4.4. The input output data can be obtained from the output of the transmitters such as PT14 for steam header pressure, LT06 for drum level, FT05 for steam flow, FT01 for gas flow, FT02 for air flow and FT07 for water flow. The training operation must be done during the plant shut down(i.e., off-line training). At running mode ( i.e. at the normal operation of the plant) the desired set points such as steam header pressure and drum level is changed by operators through computer keyboard as mentioned in the previous section. The NN controller output will change due to steam load disturbance which is used to postion the control valves.



FT01 = Gas flow transmitter, FT02 = Air flow transmitter, FT07=Water flow transmitter, FT05 = Steam flow transmitter, LT06=Drum level transmitter, PT14= Header pressure transmitter, T = Training mode, R=Running mode, S/C= Signal converter,

Fig. 4.6 Proposed Neural Net controller for 120 ton/hour capacity boiler of ZFCL.

## **CHAPTER - FIVE**

REAL TIME OPERATION OF THE PROPOSED CONTROLLER

□ INTRODUCTION

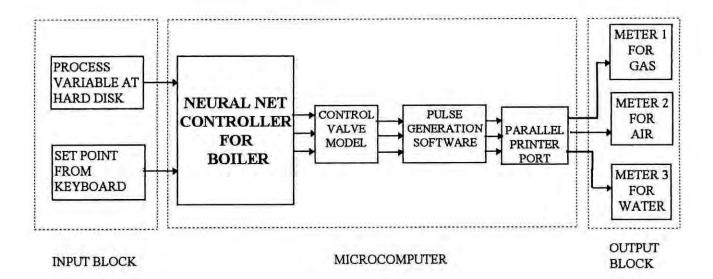
□ CONTROL VALVE MODEL

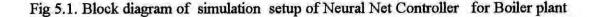
□ ON-LINE REAL TIME PULSE GENERATION

□ RESULTS

## **5.0 INTRODUCTION**

A schematic diagram for real time operation of the developed controller for boiler is shown in Fig.5.1. Each block of the diagram except the controller is described in the following sections. The operation of the control valves is investigated for different sets of test data as mentioned in the previous chapter. For the simulation the valves characteristics (e.g., flow vs. percentage of valve opening) model is developed by the best fit analysis of the data obtained from the history file of the boiler plant of ZFCL. Control valve model gets inputs (such as gas flow, air flow, and water flow) from the neural net controller for a desired plant output. The control valve model calculates the percentage valve opening for each input. A computer software is developed to generate pulse signals for the operation of control valves according to the desired percentage valve opening. The generated pulse signal is then sent to an external circuit through the parallel port of the computer. The average voltage of the pulse is measured by a voltmeter which is calibrated in terms of percentage of valve opening. The measured valve opening is then compared with actual valves opening.





## 5.1 CONTROL VALVE MODEL

The neural network controller predicts the value of plants control inputs such as gas, air, and water flow according to the desired set point of steam header pressure and drum level. To determine the control valves opening from the predicted control inputs an equation is developed by the best fit analysis of the normalized training data. It is assumed that the relationship between the control input flow and valve opening is linear. The equations for different control inputs are as follows :

For Gas	y = 0.4275x + 0.279	(5.1)
For Air	y = 2.1x - 0.582	(5.2)
For Water	y=0.2545x+0.072	(5.3)

where, x = NN controller output y = Control value opening.

From the above equation the control valve opening is determined. A corresponding electronic pulse signal is then generated whose average value of the voltage is used to position the control valve.

## 5.2 ON-LINE REAL-TIME PULSE GENERATION

The average voltage of the generated pulse is proportional to the control valve opening. This voltage can be controlled by the Pulse Width Control (PWC) technique. In this technique average voltage of the pulse is controlled by changing the pulse width. The waveform of the pulse is shown in Fig.5.2 where pulse period T represents the maximum valve opening (100%). The generated signal becomes available at the parallel port of the computer and it sustains until the next data is available.

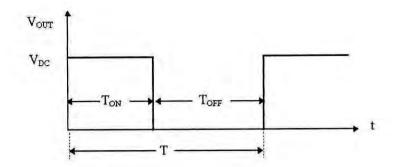


Fig.5.2. Waveform of the generated pulse.

The average voltage of the pulse is given as [39],

$$V_{a} = \frac{1}{T} \int_{0}^{T_{ON}} V_{OUT}.dt$$

$$V_{a} = \frac{T_{ON}}{T}.V_{DC}$$

$$V_{a} = D.V_{DC}$$
(5.4)

where D = Duty cycle =  $\frac{T_{ON}}{T}$ 

The period T and  $V_{DC}$  are constant. So the average voltage varies with the time  $T_{ON}$  which represents the actual valve opening.

An algorithm of PWC technique is described in the following paragraphs. This algorithm is implemented by a computer program[40][41]. A flow chart of the program shown in Fig.5.3. Brief description of each step of the flow chart is given below.

#### STEP-1:

Get the values of gas, air, and water values opening as the variables tg, ta, and tw respectively from the output of value model. Also set the total number of time segments to be scanned for generation of the pulse pattern as *num* seg = 100.

#### **STEP-2**:

This step creates an array deci[r] of decimal numbers and initializes it with binary values '0'. Here r is the segment number, r=0, 1, 2, .......... num\_seg.

#### STEP-3 TO 5 :

These steps create three arrays g[r], a[r], and w[r] for the value of gas, air and water value respectively. Binary values '1' (high) will be stored in the array positions ranging from [0] to [tg\*num\_seg], [ta\*num\_seg], and [tw\*num\_seg] for gas, air, and water value respectively. While binary values '0' (low) will be stored in the array positions starting from [tg\*num\_seg] or [ta\*num\_seg] or [tw\*num\_seg] to [num\_seg] respectively.

#### **STEP - 6 :**

This step creates an array deci[r] of decimal numbers, which incorporates each of the above three arrays (i.e., g[r], a[r], and w[r]) as deci[r]= g[r]\* $2^0$  + a[r] \* $2^1$  + w[r] \* $2^2$ . This expression represents the respective time segment of three pulses to be generated.

#### **STEP-7**:

In this step pulses are generated as a composite byte. This byte will sent at the data pin ( pin 2 for gas valve, pin 3 for air valve and pin 4 for water valve) of the parallel port which is addressed as 0x378. Each and every decimal numbers of the array deci[r] will be sustained for a time of 1 ms sequentially.

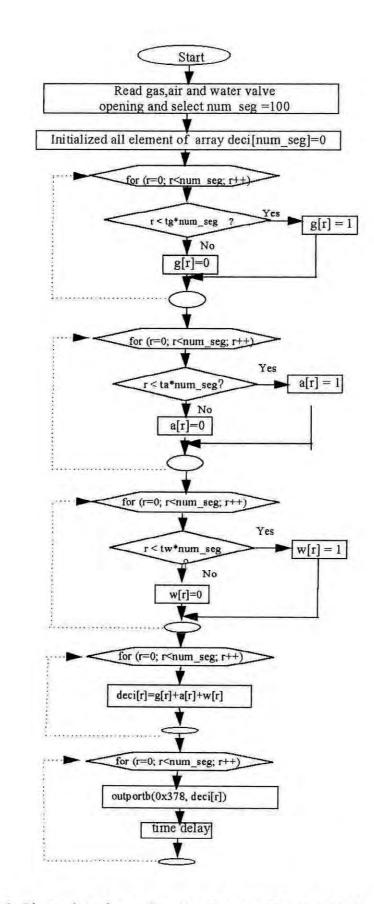


Fig. 5.3 Flow chart for on-line signal generation by PWC technique.

## 5.3 RESULT

The average voltages of the pulses at pin number 2, 3, and 4 of the parallel port of the computer are measured by voltmeters for investigating the operation of control valves for the gas, air, and water flow respectively. In all cases it is found that the percentage of valve opening corresponding to the measured voltage follows the valve characteristics. It is also found that the pulses at the port are sustained until the next set of data is available. The simulation result (i.e. the measured average voltage of the pulse corresponding to percentage of valve opening) is given in table-5.1.

## Table-5.1 : Simulation result

## Measured average voltage vs. percentage of valve opening

Average voltage of pulse (Volt)	Percentage of valve opening in
From simulation	(%)
0.0	0
1.25	25
2.50	50
3.75	75
5.00	100

# **CHAPTER - SIX**

CONCLUSION

 $\Box$  CONCLUSION

□ RECOMMENDATION FOR FUTURE WORKS

#### **6.1 CONCLUSION**

In this thesis, a multi-layered neural network based an integrated controller has been developed to control a nonlinear MIMO boiler plant. Drum level control and combustion control of the boiler is performed by the integrated controller. The process inverse dynamic methodology has been applied to design the integrated NN controller. The real time input output data of 120 ton/hour capacity boiler of ZFCL, Ashuganj, Bangladesh has been used for training of the networks. Nonlinear activation function has been considered because of nonlinear process of boiler plant.

Two neural networks such as feedforward and diagonal recurrent networks have been trained over the full working range of the boiler to memorize the reverse input/output mapping of the boiler plant. General backpropagation and dynamic backpropagation training algorithm is implemented for feedforward and diagonal recurrent network respectively to obtain the network weights which produce minimum difference between networks predicted output and desired input. The proposed software controller is then developed using the weights of the feedforward networks. Because feedforward network based controller has been shown better output response and performance than those of the feedback network based controller.

The developed controller has been tested by using different sets of boiler plant inputoutput data which were not used during the training. The output response and performance of the developed controller has also been compared with that of the existing six single input single output PID controller. Comparison shows that the developed controller has the learning capability and ability to control a boiler plant having the nonlinear process dynamics. It can be noted that the integrated controller has also the ability to solve the loop interaction problem in MIMO plant by its parallel operation. A real time operation of the developed controller has been implemented. The valves characteristics model has been developed by the best fit analysis. The control valve model calculates the percentage valve opening for each input. A computer software has been developed to generate pulse signals for the operation of control valves. The generated pulse signal is then sent to an external circuit through the parallel port of the computer is sustained until any disturbance is occurred.

The main drawback of the neuro control approach is it prior training. The success of the NN based controller depends on the proper choice of training data and the learning parameters. Once the neural networks is trained, the NN controller is self-tuned and does not consist any requirement for tuning. Whereas the conventional controller requires tuning which is very difficult task especially in the case of nonlinear plant.

The advantage of the developed controller over the traditional adaptive and conventional controller is that the developed controller can be used to highly nonlinear plants. The non-linear sigmoid functions in the hidden neurons allow the network to learn and solve nonlinear control problems where to this end traditional controllers have no solution yet. Moreover, the parallel operation of the proposed controller are more robust even some of the synaptic connections failed. The benefits of the use of the proposed NN based integrated controller include faster response, adaptive control, simplicity and reliability. This technique can also be implemented in real time control of other process industries such as refinery plant and distillation plant.

## **6.2 RECOMMENDATION FOR FUTURE WORKS**

The following recommendations have been made to extend the proposed controller.

- 1. The temperature control loop has not been considered for integration because of the nonavailability of loop input data ( i.e., the quantity of spray water). If this data is available, the present work can be extended by considering the temperature control loop in addition to the drum level control loop and combustion control loop for integration.
- 2. The on-line operation of the developed NN controller performance has been investigated by observing the operation of the control valves which are simulated by voltmeters. If the mathematical model of the boiler process is known, further investigation of the performance of the NN controller can be carried out by observing the plant output.
- 3. The developed NN based controller is a direct inverse controller. It does not have the error correction capabilities. This can be introduced by using errors (which is the difference between desired plant output and actual measured output) as NN inputs instead of direct plant outputs.
- 4. The developed controller is based on the feedforward network which is trained by GBP algorithm. Further work can be carried out by training the feedforward network by backpropagation through time training algorithm to improve the controller performance.

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## **APPENDIX - A**

## TRAINING DATA

	STEAM HEADER PRESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN		WATER VALVE OPEN
Unit	BAR	MMH2C	TONES PER HOUR	NM3 PER MIN	NM3 PER MIN	TONES PER HOUR		%	%
Min Max	0.0 140.0	-250.0 250.0		0.0 225.50	0.0 2866.0	0.0 166.0	0.0 100.0		0.0 100.0
IVIAA	140.0	250.0	100.0	223.30	2000.0	100.0	100.0	100,0	100.0
TIME									
16:00:3	0 90.008	53.344	116.587	135.765	1657.920	120.184	52.163	47.850	5 27.577
16:01:0	0 89.906	54.990	116.698	134.097	1650.630	115.78	5 52.819	49.200	27.096
16:01:3			and the second sec		1657.800			50.22	7 26.231
16:02:0	0 89.965	56.219	116.573	135.610	1647.290	114.374	\$ 52.981	50.11	7 27.465
16:03:0	0 90.008	58.042	116.515	133.792	1669.740	113.468	3 53.540	48.162	2 28.067
16:03:3	0 90.037	58.938	116.501	133.040	1642.630	123.193	3 53.137	48.952	2 26.204
16:04:0	0 90.037	57.500	116.871	134.919	1625.140	109.31	52.006	49.519	27.594
16:05:0	0 90.037	56.969	117.632	134.187	1665.560	123.082	2 52.917	48.46	5 26.442
16:06:0	0 89.862				1650.930				
16:06:3	0 89.731	59.240	119.565	136.705	1703.710	) 111.116			
16:07:0	0 89.775	57.802	119.191	138.302	1703.890	115.432	2 54.369	50.340	27.125
16:07:3	0 89.965	61.969	118.669	136.940	1639.590	) 111.715			
16:08:0	0 89.965	52.813	118.974	136.897	1648.010	115.861	53.142	51.102	2 28.619
16:08:3	0 89.994	55.531	118.316	135.991	1647.530	113.011	53.171	51.029	28.010
16:09:0	0 89.950				1684.610			49.92	5 28.581
16:09:3	0 89.979				1664.430			50.123	3 27.029
16:10:0	0 90.023				1684.430				
16:10:3	0 89.877				1640.720				
16:11:0	0 89.965				1684.670				
16:11:3					1645.980				
16:12:0					1618.870				
16:12:3					1636.360				
16:13:0	0 89.892				1702.460				
16:14:0					1638.690				1
16:14:3					1676.310				
16:15:0					1700.430				
	0 89.935								and the second se
	0 90.081			C. B. C. Contraction of the	1645.140				
	0 89.862								
	0 90.183								
	0 90.213								
	0 89.994								
16:20:0	0 89.979	52.646	118.614	136.597	1662.870	116.450	5 53.267	50.485	5 28.631

	STEAM HEADER PRESSUR	LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN		WATER VALVE OPEN
Unit	BAR	MMH2C	TONES	NM3	NM3	TONES	%	%	%
			PER	PER	PER	PER			
			HOUR	MIN	MIN	HOUR	5		
TIME								- 58-5 AA	
16:20:3	0 90.14	48.104	116.567	134.652	1629.970	) 126.12	2 52.385	50.152	28.058
16:21:3	0 90.00	8 62.042	115.750	132.326	1619.940	106.43	4 52.967	50.823	3 27.246
16:22:0	0 89.83	65.979	117.054	136.846	6 1672.250	97.318	52.885	50.987	27.496
16:23:3	0 90.14	40 59.167	116.712	129.296	5 1636.780	) 111.88	4 53.006		3 26.879
16:24:0	0 90.00	8 56.813	116.708	131.894	1648.600	) 118.31	3 53.013	48.125	5 27.425
16:25:0	0 89.8	9 62.646	117.601	132.571	1642.030	) 107.17	4 53.025	50.325	
16:26:0	0 90.2	46.073	113.551	133.820	1594.450	116.07	52.240	48.967	
16:26:3	30 90.12	5 54.917	114.509	131.240	5 1600.960	) 113.30	2 52.225	48.388	
16:28:0		73 64.625	121.069	138.960	1700.970	) 109.99	2 54.254		27.042
16:28:3		50 53.708	120.599	136.530	5 1659.410	0 117.87	4 53.540	50.273	3 29.915
16:29:0		55 48.406							
16:30:0		50 57.427	119.354	141.07	4 1709.98	0 115.56	7 53.925	5 52.700	
	30 89.9		119.918					51.354	
16:31:	30 89.9	65 60.375						50.979	
16:32:0	0 89.7	90 62.802	121.315	137.25	1689.26	0 112.79	7 53.671	52.150	
16:32:	30 89.4	69 63.396	124.749	140.97	5 1761.39	0 114.18	0 55.38	5 53.55	
16:38:	00 90.4	90 64.844	110.860	123.80	4 1541.60	0 100.87	3 51.26		
16:39:		33 47.354	109.197	123.77	1 1555.04	0 121.36	3 51.68	3 42.91	5 26.644
16:40:		27 56.063	111.241	122.46	1 1499.87	0 107.45	7 50.50	5 46.41	
16:41:		92 55.156	110.947	130.17	0 1571.22	0 115.59	8 51.27	3 46.42	3 26.604
	30 90.2	erer charcerere	108.595					5 46.55	
	00 89.9		113.375						
16:43:	30 90.1	54 46.656	110.068	126.61	4 1533.72	0 115.99	9 50.91		3 27.704
16:44:	00 89.9	21 57.510	112.026	125.82	0 1573.79	0 106.23	0 51.63		
16:45:	00 89.8	04 59.010	113.409	131.94	1 1590.74	0 106.74	8 51.93		
16:45:	30 89.8	48 56.594	114.312	130.24	0 1576.30	0 104.80	8 52.38		
16:46:	00 89.9	21 55.156	114.519	129.69	1 1593.07	0 116.72	6 52.43	3 47.49	
16.47	30 89.8	77 58.417	115.211	131.38	7 1593.13	0 114.06	53 51.79	8 48.67	
16:48:	00 89.8	63 58.938	8 114.779	130.69	6 1634.75	0 114.78	36 53.05	4 47.32	1 26.040
16:51:	00 89.9	79 54.615	5 113.568	127.63	3 1572.95	0 113.83	38 51.74	2 47.23	3 27.223
16:52:	00 89.9	79 57.271	114.094	131.47	1 1587.82	0 109.87	78 51.70	4 46.79	2 28.844
16:52:	30 89.9	50 52.125	5 113.527	129.34	8 1593.73	0 117.0	1 52.49	6 47.28	7 27.335
16:53:	00 89.9	79 59.250	113.316	129.11	8 1595.52	0 112.21	9 52.05	6 47.55	6 27.173
16:54:	00 89.6	73 61.146	115.785	135.19	7 1625.55	0 107.9	55 53.26	0 50.85	6 27.863
16:54:	30 89.8	77 60.229	116.148	134.74	6 1632.12	0 110.93	33 52.96	9 49.58	7 27.425
16:55:	00 90.2	27 53.865	5 113.918	129.63	9 1596.18	0 107.5	33 52.90	6 47.35	4 28.915
16:56:	00 90.3	29 50.979	111.877	127.85	4 1550.26	0 116.40	56 51.94	0 47.10	4 27.092
16:56:	30 90.2	56 58.56	3 111.638	125.40	1 1553.19	0 103.69	98 51.91	5 46.07	1 26.685
16:57	00 90.1	54 57.58	3 110.943	127.63	8 1548.71	0 107.80	59 50.65	8 46.70	0 25.992
16:57	30 90.3	344 52.42	7 107.876	124.15	7 1541.96	50 110.20	56 51.62	3 45.03	1 27.160
16:58	:00 90.1	83 60.82	3 110.376	123.13	7 1538.44	10 103.7	92 51.45	2 45.42	1 26.256
16.58	30 89 8	319 71.06	3 112.790	126.63	7 1608.12	100.7	97 53.06	0 46.32	5 24.865

	HE.	FEAM ADER ESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW		GAS VALVE OPEN		WATER VALVE OPEN
Unit	В	AR	MMH2O	TONES	NM3	NM3	TONES	%	%	%
				PER	PER	PER	PER			
				HOUR	MIN	MIN	HOUR			
TIME										
22:00:	30	90.227				1674.400				
22:01:	00	90.300	50.844	118.050	134.844	1650.930	115.287			1 29.754
22:02:	30	90.213	57.188	118.064	135.619	1654.930	118.648	3 53.671	49.415	5 28.375
22:03:	00	89.892	64.094	120.087	135.676	1674.690	111.611	53.444	51.123	3 28.058
22:03:	30	89.877	60.719	120.689	139.345	1686.760	104.148	3 54.017	52.448	3 29.212
22:04:	00	90.169	51.375	119.420	136.747	1671.950	122.653	3 53.454	50.092	2 28.571
22:04:	30	90.008	55.385	119.717	135.385	1650.100	120.008	3 53.098	51.525	5 28.369
22:05:	00	90.154	49.448	117.255	136.972	1672.130	124.877	53.388	50.215	5 28.552
22:05:		89.994				1660.130				27.042
22:06:		90.096				1642.510				5 26.860
22:06:	30	90.198	55.677	115.782	134.266	1636.720	113.236	5 52.056	49.63	28.917
22:07:	30	90.344				1613.370			48.242	2 28.117
22:09:	00	89.906				1674.690				27.765
22:09:	30	90.037				1660.250				5 28.475
22:10:		90.110				1653.140				5 28.885
22:11:		89.921				1666.100				27.383
22:12:		90.140				1641.080				27.942
22:12:		89.935				1644.780				4 27.550
22:13:	00					1727.600				27.329
22:13:		90.008				1696.070			50.17	5 28.515
22:14:		90.067				1675.710				5 27.454
22:15:		89.717				1723.180				27.573
22:15:		89.833				1708.730				27.788
22:16:		89.585				1720.190				26.629
22:16:						1790.170				5 26.954
22:17:		90.183				1711.530				2 28.265
22:17:		90.023				1625.730				3 29.917
22:18:		89.352				1611.220				
22:19:						1643.170				
22:19:						1632.120				
						1628.180				
						1737.150				
						1694.580				
						1680.790				
						1700.430				5 25.781
						1717.680				5 26.044
						1711.360				7 26.100
						1660.780				
						1618.690				
						1662.510				25.788
						1632.420				
						1683.350				

	STEAM HEADER PRESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN	AIR VALVE OPEN	WATER VALVE OPEN
Unit	BAR	MMH20	O TONES	S NM3	NM3	TONES	%	%	%
			PER	PER	PER	PER			
and have			HOUR	MIN	MIN	HOUR			
TIME	ia y alt stafe								
22:31:3	84.904	58.708	117.884	137.997	1704.130	106.814	\$ 53.775	49.160	26.754
	84.933							51.290	25.363
	0 84.700							51.623	25.473
22:33:3	0 84.729	60.281	120.336	141.722	1765.210	107.748	55.121	50.913	26.385
	0 84.919							50.619	26.623
22:35:0					1768.020			52.342	25.377
	0 84.744	and a state of			1757.330			53.479	26.721
	0 85.065							52.298	27.252
	0 85.167							50.050	27.417
22:37:0	0 85.006							51.538	26.577
	0 84.977				1681.920			52.827	26.381
	0 84.919							52.306	26.077
22:38:3	0 85.137	60.667	118.206	139.054	1687.230	107.094	54.181	51.727	26.165
	0 85.590							48.065	26.017
	0 84.817							51.554	24.994
22:41:3	0 85.210	54.281	116.968	136.169	1662.450	119.243	53.779	48.462	26.415
	0 85.400							47.777	26.325
	0 84.773							51.052	
22:47:3	0 84.919	66.594	116.791	137.113	1711.000	105.330	54.804	49.550	24.246
	0 85.138							49.429	25,410
22:48:3	0 85.210	57.802	118.050	132.420	1625.260	117.262	52.773	49.048	25.350
22:49:0	0 84.875	55.479	118.731	135.065	1675.350	110.414	53.190	49.060	26.698
22:49:3	0 84.846	52.708	118.645	136.752	1716.550	107.444	54.277	49.165	
22:50:00	0 84.904	55.250	119.254	138.805	1687.770	103.785	54.094	50.446	29.031
	84.846							51.237	
	84.919							50.008	
22:52:00	84.831	56.302	118.538	142.788	1731.840	112.966	54.856	52.694	28.200
22:53:00	85.852	43.771	112.852	130.973	1615.880	104.379	52.798	47.146	30.017
22:53:30	85.998	48.354	110.193	124.481	1527.330	125.340	51.085	45.808	25.521
22:54:00	85.269	62.990	112.845	124.406	1533.660	105.977	51.765	47.796	23.313
22:54:30	84.744	74.635	115.235	131.969	1613.490	83.387	51.806	50.335	26.098
22:55:00	84.700	69.823	118.068	134.910	1668.370	115.954	53.885	50.869	23,608
2:58:00	87.252	53.000	111.351	138.711	1697.860	110.594	54.158	50.813	27.627
2:58:30	87.617	64.708	111.434	136.103	681.380	101.471	54.117	52.477	25.773
2:59:00	88.054	77.583	112.717	138.358	1709.270	84.529	54.415	51.085	24.079
2:59:30	88.944	66.740	111.773	137.982 1	657.740	96.128	52.535	50.333	26.931
3:00:00	90.081	45.760	108.640	130.922 1	578.030	117.289	51.575	49.965	26.727
3:00:30	90.840	41.531	104.860	128.267 1	613.430	113.976	52.502	46.560	26.627
3:01:30	91.510	73.854	108.685	137.442 1	701.500	81.254	54.735	51.402	23.627
3:03:00	93.115	37.354	106.818	121.089 1	474.910	122.449	49.733	44.996	26.940
3:04:00	92.750	38.073	99.275 1	16.226 1	423.200	111.746	48.315	42.700	26.794
3:18:30	92.138	46.104	118.787	149.431 1	825,700	115 470	56 073	53 685	31 310

	HI	STEAM EADER ESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN	AIR VALVE OPEN	WATER VALVE OPEN
Unit	10	BAR	MMH2C	TONES	NM3	NM3	TONES	%	%	%
				PER	PER	PER	PER			
				HOUR	MIN	MIN	HOUR			
TIME										
23:19:	00	92.867	44.063	113.132	140.491	1692.970	109.059	53.694	52.094	29.8
23:19:	30	92.998	45.479	107.751	133.463	1624.960	126.250	51.679	48.702	27.6
23:20:	00	93.188	41.281	102.692	125.552	1587.460	109.996	52.069	43.752	28.7
23:21:	00	92.852	63.073	99.451	120.821	1473.300	103.536	49.442	43.702	25.30
23:21:	30	92.823	63.917	98.438	120.234	1471.270	93.461	49,498	42.769	25.30
23:22:	30	92.196	69.573	104.134	122.193	1520.710	113.053	50.490	45.242	21.9
						1525.070				
						1503.210				
						1552.110			46.583	
23:25:						1645.740				
Inclusion in the second second	- C - C - C - C - C - C - C - C - C - C	a provide and an				1691.230				
						1679.230				
						1713.680				
23:30:						1680.010				
		1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1			(1999) K (1997) B (19	1611.940				
20010020			C CAR MC	Carry Color Marcal Col	2 C 20 3 2 5	1687.050				
						1683.470				
						1718.700		Contraction and the second		
		94.821				1744.250				
		and the second second				1714.820				
						1633.560				
23:37:						1670.520				
23:38:						1667.950			49.598	
23:40:						1644.540				
23:41:						1582.680				
23:42:						1632.120				
		99.750				1580.770				
						1537.900				
						1607.880	<ol> <li>State of the state of the state</li> </ol>			
						1526.500				
						1534.980				
						1455.510				
						1461.240				
						1471.870				
						1480.700				
						1507.750				
						1514.970				
						1518.980				
						1529.070				
						1503.990			Contraction of the second second	
						1512.350				
23-54-	00	99 940	59.583	100 310	122 447	1527 220	08 262	52 152	15 811	26 75

	HE	STEAM EADER ESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW			GAS VALVE OPEN	VALVE V	WATER VALVE OPEN
Unit	I	BAR	MMH2C	TONES	NM3 PER	NM3 PER	TONES PER	%	%	%
				HOUR	MIN	MIN	HOUR			
TIME										
23:54:3	30	99.983	57.167	100.433	123.696	1554.320	101.571	50.954	44.131	27.240
23:55:0	00	99.969	57.240	100.644	122.902	1535.460	108.094	51.002	45.202	26.771
23:55:3	30	99.925	59.750	100.914	124.734	1516.950	101.032	51.167	46.119	26.056
23:56:0	00	99.910	58.344	100.883	125.603	1528.410	96.889	50.669	46.287	26.827
23:56:3	30	99.969	54.240	100.468	125.514	1558.980	107.374	51.931	44.615	26.731
						1566.380				
						1579.340				
						1585.010				
						1577.490				
		10000				1588.060				
						2 1735.000				
						1720.070				
						1689.560				
						8 1768.500				
						1787.840				
						3 1775.000				
						2 1769.090				
						3 1766.170				
						5 1757.930				
						1767.120				
						1794.110				
						5 1838.120				
						8 1642.930				
						6 1675.470				
						1699.060				
						1744.910				27.729
						1728.730				
						5 1771.780				
						1763.540				
						1760.850		C. I. M. Martin		
						1708.730				
						1731.420				
						1747.120				
						1715.770				
						1709.680				
						5 1749.570				
						1725.270				
								and a star of the start of	and the second s	
						5 1712.910				
						1732.910				
						1703.890		1		
13:28:3						1716.490				

	STEAM HEADER PRESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN	AIR VALVE OPEN	WATER VALVE OPEN
Unit	BAR	MMH2C	TONES	NM3	NM3	TONES	5 %	%	%
			PER	PER	PER	PER			
			HOUR	MIN	MIN	HOUR			
TIME									
	30 104.956	57 604	112 859	140 91	0 1770 15	0 118 51	1 55.06	53 63	5 27.550
	00 105.058								
15:30:	30 105.146	59.135	113.388	130 89	0 1720 49	0 11735	2 54 846	5 51.95	
	00 105.088								
	30 105.073								
	00 104.985								
	30 104.971				1716.67				20 10 10 10 10 10 10 10 10 10 10 10 10 10
	00 104.956								
	30 105.000				1696.43				
	00 104.985				5 1724.19				
	30 104.971				5 1730.04				
	00 104.942				3 1730.70				
	00 105.000				3 1766.41				
	30 105.073				3 1742.52				
	00 105.160				5 1705.27		a - to s carendaria	52.97	
	30 105.175						· · · · · · · · · · · · · · · · · · ·		
	0 105.073				1694.70			52.42	
	30 104.971	C. C. C. Level and			1703.89			52.77 53.490	
	0 104.942				1724.43				
	0 105.015							53.827	
	0 105.102				1707.24			53.098	
	0 105.088				1697.09			52.975	
the state of the	0 104.985				1717.92			52.900	
	0 104.983				1725.390				
	0 105.073	2010112-004						53.425	
	0 105.088				1695.890				
	0 105.117							141.96.102.91.4	
	0 105.131								Constraint Sec.
5.15.2	0 105.102	57 100	111.515	120 110	1701 000	118.//	54.040	52.142	28.462
5.45.0	0 104.942	50 147	111.036	138.119	1705.010	106.242	54.163	52.967	27.894
5.40.0	0 104.796	63 922	111.033	142.18/	1715 200	106.243	54.300	54.015	28.200
5.40.5	0 104.869	60 844	112.327	141.30/	1713.300	106.181	54.404	54.327	27.819
5.17.2	0 105.015	56 072	112.402	142.417	1728.010	1109./19	54.948	53.757	28.585
5.10.0	0 105.131	51 125	113.492	141./2/	1/09.2/0	110.988	54.642	53.008	28.967
5.40.0	0 105.233	51.135	113.030	137.884	1692.310	121.374	54.492	52.208	28.248
5-10-0	0 105.190	53.100	112.707	137.123	1690.580	114.042	54.471	51.992	29.638
5.51.0	0 105.073	51.222	111.2/2	138.338	10/3.080	119.849			
5.52.0	0 105.044	01.335	112.313	138.814	1/05.150	112,731	54.494	53.090	27.879
5.52.0	0 105.131	53.719	112.123	138.565	1086.880	121.564	54.331	51.527	28.525
5.52.0	0 105.029	33.396	112.195	137.043	1671.350	116.155	53.792	52.106	29.035
5.52.2	0 104.942	49.115	110.494	136.263	1664.010	114.557	54.179	53.342	28.885
5.54.0	0 104.942	57.208	110.099	140.642	1686.520	115.899	53.875	53.321	27.879
5:54:00	0 104.956	61.073	110.936	140.698	1699.710	108.951	53.969	53.131	28.102
5:54:30	0 105.073	60.438	111.061	138.607	1687.110	113.606	54.313	52.652	27.350

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	STEAM HEADER PRESSURI	DRUM LEVEL	STEAM FLOW	GAS FLOW		FLOW '		VALVE V	VATER VALVE OPEN
Unit	BAR	MMH2C	TONES		NM3	TONES	%	%	%
			PER	PER	PER	PER			
TIM			HOUR	MIN	MIN	HOUR			
TIME		0 50 1 67	111 112	174 704	1.000 000	111000			
		8 58.167							
	00 105.32				5 1645.980				
		3 53.083							
		0 56.156							
		0 57.844							
		8 61.500							
	00 104.91	3 63.760							
					1674.400				
	30 104.92				1676.960				
	30 105.99				1750.410				
		6 59.063							
	30 106.02 00 106.02				1760.560				28.658
	30 106.02				1769.270				
		5 57.531			1778.350				
	30 105.91								
	00 105.86				1754.640				
		8 58.333							
	30 105.90				1803.780				
		6 57.521							
		5 58.000							29.604 28.669
	30 106.00				1794.290				
	0 106.09				1799.540			54.644	
	0 106.06	201 (201 (00) (00) (20 (20)			1792.200				
	0 105.97				1779.360				
	0 105.83				1796.620			56.013	
		4 57.365							
		7 52.344							
		5 62.063							
		56.958							
	0 106.02				1785.690				
		3 53.000							
		7 58.010							
		7 55.500							
		56.802							
		4 60.833							
		5 62.792							
		56.469							
		5 58.323							
		61.000							
		5 57.688							
		54.135							30.308
		3 50.167							
		49.104							
	0 105.933								

STEAM HEADER PRESSURE	DRUM STEAM LEVEL FLOW	GAS FLOW	AIR FLOW			VALVE V	WATER VALVE OPEN
Unit BAR M	IMH2O TONES PER HOUR	PER	NM3 PER MIN	TONES PER HOUR	%	%	%
TIME							
	59.635 116.280	144.663	3 1801.340	115.920	56.704	55.802	29.479
	59.063 117.459						
	64.073 118.233						
08:24:00 106.050	60.677 119.261	149.770	1820.260	117.331			
	52.177 118.728						to be a second of
08:25:00 106.108	53.479 118.534	147.261	1781.690	127.142			
08:25:30 106.021	52.354 117.459	146.711	1794.950	120.464			
	56.469 117.320						
08:26:30 105,700	58.094 117.231	147.782	1802.530	118.514	56.556		
08:27:00 105.729	61.729 118.078	149.934	1841.280	114.858	56.996		
08:27:30 105.933	60.844 118.361	151.855	1846.770	120.381	56.619		
08:28:00 106.021	61.083 119.762	152.029	1827.070	115.214	56.602	55.960	28.337
08:28:30 106.050	54.458 119.434	151.484	1815.130	121.910	56.335	55.167	30.206
08:29:30 106.065	54.042 117.345	147.585	1790.650	126.354	56.010	54.810	29.565
08:30:00 106.006	53.313 116.784	145.955	1809.280	124.503	57.098	54.752	29.644
08:31:00 105.963	61.250 117.545	148.182	1804.800	117.525	56.046	56.179	28.692
	61.573 118.531					54.981	28.658
08:32:00 106.225						54.444	29.469
	52.427 117.497					53.821	29.660
	54.125 116.677						29.983
	63.510 118.092					56.260	29.423
	58.417 119.205					56.923	29.979
	57.760 119.703				56.977	57.142	29.079
	56.469 120.149				56.660	55.915	29.400
	53.240 119.046					57.002	31.046
	59.781 118.977				56.477	57.217	28.652
	60.031 119.357				56.969	56.271	29.946
	57.521 119.752					55.417	28.852
08:39:30 106.108	55.188 119.274	152.316	1817.100	120.495	55.652	54.960	29.663
08:40:30 105.890	60.760 118.994	149.149	1815.130	120.077	56.267	56.854	30.231
08:41:00 105.758	57.281 118.939	153.091	1855.130	119.375	56.471		
08:41:30 105.890 (	50.521 119.568	155.501	1854.660	121.754	56.469	57.015	29.694
08:42:00 105.992	59.302 119.420	152.602	1863.310	122.581			
08:42:30 106.167	50.208 119.472	152.612	1828.500	115.536	56.273		29.165
08:43:00 106.283	54.531 118.527	148.379	1793.450	128.612		55.267	29.371
08:43:30 106.298					55.810	54.258	
08:44:00 106.210	49.104 117.487	146.096	1784.860	124.248			30.779
08:44:30 106.094 5	04.448 116.781	146.998	1775.660	121.152		54.173	
08:45:00 105.860 (					55.421	56.042	29.329
	50.760 119.008					56.606	
08:46:00 105.802 6	51.083 119.703	151.231	1829.100	117.663	56.546		
08:46:30 105.846 5	9.865 119.911	152.344	1835.070	122.667	56.487	57.763	
08:48:00 105.919 5	07.125 120.613	151.855	1867.730	123.307	57.165	56.998	29.742
08:48:30 106.123 5	4.938 118.974	152.344	1841.700	125.856	56.508	56.140	29.194
08:49:00 106.152 5	06.635 118.853	149.817	1817.700	122.747	56.373	55.958	29.185

	STEAM HEADER PRESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN	AIR VALVE OPEN	WATER VALVE OPEN
Unit	BAR	MMH2O	TONES	NM3	NM3	TONES	%	%	%
			PER	PER	PER	PER			
			HOUR	MIN	MIN	HOUR			
TIME									
08:50:3	0 106.094	4 54.854	118.002	146.47	5 1787.600	118.02	3 56.477	55.29	0 30.146
					9 1793.280				5 30.050
					7 1803.370				7 29.069
08:52:0	0 106.065	5 64.323	117.525	149.94	3 1820.560	116.17	6 56.160	55.49	4 28.419
08:52:3	0 106.298	\$ 55.656	116.698	148.440	0 1812.020	119.15	0 56.596	5 53.790	5 29.688
08:53:0	0 106.327	54.698	116.753	146.48	1769.870	121.49	5 55.560	52.958	8 29.340
08:53:3	0 106.298	55.490	115.612	144.048	3 1750.940	122.43	5 55.385	52.54	4 29.333
08:54:0	0 106.269	52.188	113.437	143.249	1742.820	115.03	1 55.060	52.279	
08:54:3	0 106.167	54.781	113.292	141.534	1719.060	118.11	5 54.623	53.460	29.319
08:55:3	0 106.050	59.781	113.807	143.986	5 1757.690	120.02:	5 55.192	54.38	28.410
08:56:0	0 106.035	64.406	114.789	145.321	1775.660	114.54	7 55.610	54.033	3 28.248
08:56:3	0 106.094	62.135	115.740	145.119	1779.300	108.98	5 55.792	53.331	29.417
08:57:0	0 106.196	53.635	115.104	143.601	1750.290	117.739	55.483	52.883	
08:57:3	0 106.196	58.010	114.761	144.423	8 1739.540	120.55	4 54.898	52.475	5 29.204
08:58:0	0 106.065				1723.360				
08:58:3	0 105.919				3 1747.120				
08:59:0	0 105.817	52.354	113.485	144.339	1764.020	118.72		55.250	
08:59:3	0 105.758				8 1791.480				
09:00:00	0 105.787				1801.520				
05:00:2	0 105.992				1739.960			a standard	
05:00:5	0 105.787				1792.980				
05:01:20	0 105.831				1780.560				
05:01:5	0 105.963				1813.160			55.508	
05:02:20	0 105.963				1780.260			55.819	
05:02:50	105.919				1772.080			56.356	and the second second
05:03:20	105.904				1774.290			57.042	
05:03:50	105.890				1807.840				
	105.904				1799.430				
05:04:50	106.021				1817.580				
05:05:20	106.035	60.354	117.611	150.517	1803.960	115.660	56 202	56 706	29175
05:05:50	106.138	55.104	117.729	149.088	1805.580	121 592	56 454	55 344	28 083
05:06:20	106.225	57.688	118.213	145.142	1775.540	117.657	56.529	54.371	28 438
05:06:50	106.196	48.781	116.795	143.766	1733.690	124 348	55 619	54 440	29 752
					1740.910				
					1742.700				
05:08:20	105.831	60.271	115.439	145 983	1791.130	111 715	56 631	56 085	28.004
05:08:50	105.773	61,969	117.448	146.636	1794.770	114 108	56 469	57 465	27 060
05:09:20	105.802	62.865	117.822	148 670	1827.550	111 002	57 710	57 104	27.909
05:09:50	105.992	65.771	118 707	148 971	1830.590	113 062	57 321	56 152	20.213
05:10:20	106.108	54.698	118,455	148 007	1796.920	126 055	56 632	55 760	27.031
05:10:50	106 283	47 979	117 576	145 009	1765.330	126.333	56 160	51 100	20.927
05:11:20	106 225	48 063	115 906	143 300	1735.960	122.547	55 515	51 185	20.238
05:11:50	106 004	52 354	115 166	143 211	1748.080	122.391	55 003	54.403	29.000
	105.875								

			STEAM EADER RESSURE	LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW		AIR VALVE OPEN	WATER VALVE OPEN
	Unit		BAR	MMH2	O TONE		NM3	TONES	%	%	%
					PER	PER	PER	PER			
					HOUR	MIN	MIN	HOUR			
	TIME										
	05:12:	50	105.729	65.042	2 116.812	2 147.186	1804.920	109.20	7 56.675	56.869	27.823
	05:13:2	20	105.744	62.302	2 117.628	3 148.994	1817.160	112.932	2 56.754	57.533	28.246
	05:13:5	50	105.948	60.604	4 118.109	9 148.609	1806.830	116.024	\$ 56.760	57.181	27.825
	05:14:2	20	106.152	57.688	3 117.888	3 148.877	1804.620	119.79	56.921	56.031	28.598
	05:14:5	50	106.342	54.448	3 117.784	4 145.565	1772.440	121.879	56.169	54.554	28.196
	05:15:2	20	106.429	47.979	116.491	143.681	1721.450	125.645	5 55.675	53.548	29,742
	05:15:5	50	106.327	47.740	) 114.288	3 140.665	1717.450	122.214	55.223	52.723	29.069
	05:16:2	20	106.108	51.781	112.769	139.439	1698.160	121.114	54.758	54.046	29.073
	05:16:5	50	105.773	62.375	5 113.707	142.164	1766.110	110.549	55.798	55.265	27.231
	05:17:2	20	105.583	67.479	115.401	145.617	1799.600	113.938	56.752	56.998	27.758
	05:17:5	50	105.758	61.010	116.964	149.211	1811.730	117.639	56.875	57.035	28.175
	05:18:2	20	105.963	62.448	118.147	148.863	1807.780	116.176	56.892	56.065	27.775
	05:18:5	50	106.167	55.010	117.729	146.406	1773.270	116.473	56.133	55.071	29.573
	05:19:2	0	106.269	48.865	116.594	145.480	1750.170	123.020	55.837	53.913	30,142
	05:19:5	0	106.269	48.792	115.270	143.268	1733.390	122.712	55.617	52.819	29.304
	05:20:2	0	106.138	54.042	114.198	142.497	1727.540	116.065	55.204	52.860	29.231
	05:20:5	0	105.919	57.281	113.841	141.797	1722.580	120.523	55.183	54.346	28.527
	05:21:2	0	105.685	61.646	114.488	144.696	1765.510	108.270	56.210	55.981	28.575
	05:21:5	0	105.613	65.292	116.252	145.866	1781.570	118.444	56.477	57.531	27.173
	05:22:2	0	105.773	64.313	117.320	153.434	1816.680	109.155	55.465	57.221	28.000
	05:22:5	0	105.977	59.708	118.382	149.535	1807.490	112.219	56.646	56.296	28.462
	05:23:2	0	106.240	53.240	117.355	146.946	1772.560	122.453	56.256	54.748	29.440
	05:23:5	0	106.313	50.000	115.723	146.256	1737.810	124.030	54.933	54.304	28.958
	05:24:20	0	106.240	50.646	114.180	142.854	1736,790	126.592	55.754	53.004	28.596
	05:24:50	0	105.992	52.177	114.253	143.061	1723.830	117.625	55.246	53.946	29.998
	05:25:20	0	105.685	58.729	114.775	143.874	1771.300	116.200	56.508	55.525	28.150
	05:25:50	0	105.656	62.219	115.118	147.890	1794.050	112.133	56.210	57.208	27.700
	05:26:20		105.758	64.969	117.238	148.543	1815.370	106.952	57.200	57.517	28.204
	05:26:50		105.875	63.510	118.669	150.958	1821.520	116.660	56.515	57.002	28.242
	05:27:20		106.138	59.302	119.164	148.388	1808.080	115.889	56.798	55.610	29.060
	05:27:30		106.313	48.698	117.659	142.878	1763.000	128.273	57.004	54.813	30.006
	05:28:20		06.298	46.198	115.660	145.184	742.400	125.641	55.298	54.596	29.760
	05:28:50		06.181	52.917	114.699	144.090	1760.380	118.811	55.648	53.175	29.017
	05:29:20		05.963	59.302	114.948	144.235	761.870	116.494	56.035	53.608	28.379
	05:29:30		05.860	60.281	115.380	143.860 1	733.570	115.740	55.515	55.594	27.837
	05:30:20		05.802	01.323	115.290	144.733 1	796.080	120.537	56.685	56.325	
	05:30:50		05.875	02.698	116.930	150.028 1	800.260	110.300	56.162	56.529	28.560
	05.31:20		06.120	01.107	117.241	148.933 1	800.740	115.844	56.175	55.602	28.252
	05.20.00		06.070	54.448	116.961	146.495 1	776.860	123.262	56.244	54.496	29.327
1	05.32.20		06.100	51.625	115.581	144.057 1	767.660	124.009	56.354	54.602	28.733
	05.32.30		801.00	52.990	115.398	145.391 1	752.440	122.162	55.698	54.319	
	05:33:20		06.035	57.115	115.318	143.301 1	739.480	115.100	55.867	54.629	28.760
	05.24.00		05.021	00.271	114.744	144.005 1	745.390	111.611	55.706	54.879	28.167
	05.34:20	1	03.903	00.198	115.360	144.320 1	758.410	114.810	56.288	55.129	28.837

	STEAM HEADER PRESSURE	DRUM LEVEL	STEAM FLOW	GAS FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN	AIR VALVE OPEN	WATER VALVE OPEN
Unit	BAR	MMH2O	TONES	NM3	NM3	TONES	5 %	%	%
			PER	PER	PER	PER			
			HOUR	MIN	MIN	HOUR			
TIME									
05:34:5	0 105.93	3 58.083	116.044	143.723	1743.300	114.61	6 55.873	56.09	4 28.700
05:35:2	0 105.933	3 57.281	116.266	144.141	1752.080	117.97	4 56.023	56.65	4 28.931
05:35:5	0 105.890	56.469	116.079	144.696	1762.350	112.32	7 56.015	57.319	29.063
05:36:2	0 105.875	5 55.823	116.183	149.065	1777.870	119.89	4 55.460	57.825	5 28.033
05:36:5	0 106.006	61.250	116.625	146.683	1799.250	118.44	4 56.721	56.335	5 28.760
05:37:2	0 106.108	3 56.958	116.186	148.515	1785.210	114.72	0 56.167	55.319	28.892
05:37:5	0 106.167	57.438	116.325	143.390	1776.200	119.69	3 56.667	54.169	29.267
05:38:2	0 106.108	55.344	115.785	144.409	1738.700	121.27	0 55.419	54.073	3 28.517
05:38:5	0 105.992	56.063	114.343	143.413	1740.550	120.04	2 56.083	54.731	28.390
05:39:2	0 105.948	60.677	115.021	143.329	1740.250	115.13	8 55.906	55.406	5 27.519
05:39:5	0 105.773	57.125	115.768	145.607	1786.950	115.46	56.069	55.971	29.085
05:40:2	0 105.787	62.938	117.158	147.322	1795.780	113.81	4 56.640	56.783	28.456
05:40:5	0 105.860	58.260	117.988	149.535	1808.680	119.73	4 56.344		
05:41:2	0 105.963	55.906	117.974	146.772	1806.890	122.18	3 56.952	56.060	29.133
05:41:5	0 106.050	56.625	117.009	145.894	1788.140	115.899	56.548	55.587	
05:42:2	0 106.079	55.917	116.650	147.101	1774.350	121.67	55.788	55.417	28,798

### APPENDIX-B Weights of the Feedforward Network

#### Weights between Hidden units to Input units:

#### Biases of Hidden Units:

-2.547429 -2.248640 0.799262 -1.286236 -2.043156 1.648581 1.843474 4.057236 -0.535920

Weights between Output Units to Hidden units:

1.7948702.649074-1.4039502.651125-0.542122-1.430088-1.838513-3.6680920.3882561.5071062.709671-1.5619273.3101311.344991-0.940774-1.925971-3.3107760.6268470.4797730.1283360.6860395.840600-2.6624553.8831222.181360-0.1859833.877370

**Biases of Output Units** 

-0.511899 -0.970527 -0.973443

7

### APPENDIX-C

### Weights of the Diagonal Recurrent Networks

#### Weights Between hidden units and Input units

#### Diagonal Recurrent Weights of Hidden units

0.682956 0.259470 0.260337 0.259677 0.260824 0.260224 0.269923 0.262091 0.261537

Weights Between Output units and hidden units

-1.2848558.325061-5.0227101.7519323.2152891.387959-12.7673491.925872-0.693107-1.1391077.381287-4.6017211.2859973.5082751.681475-12.237741.891842-0.799903-3.6385924.312669-0.6772781.550705-6.3072887.7916660.7866240.720946-1.104216

# APPENDIX-D 1ST SET OF TEST DATA

STEAM HEADER PRESSURE		EL FLOW		LOW VAL	LVE VALVE OPEN OPE		
BAR	TONES M			TONES	% %	o %	
		20 PER		PER			
	HOUR	MIN	MIN	HOUR			
TIME							
05:00:30 105.8	390 118.780	60.760 1	44.517 179	1.840 118.		72.708	25.569
05:01:00 105.8	390 119.589		47.895 179			73.737	26.067
05:01:30 105.9	992 120.371		46.927 180			72.706	27.102
05:02:00 105.9	992 119.734		47.956 178			72.471	27.290
05:02:30 106.0	006 119.236		47.195 178			72.742	27.506
05:03:00 105.9	992 118.880		46.251 179			73.069	26.765
05:03:30 105.9	948 119.406		48.586 179			73.329	26.869
05:04:00 105.9	919 119.340		47.909 179			73.498	27.298
05:04:30 105.9	963 119.596		48.623 178			74.010	26.252
05:05:00 106.0	035 120.039		46.312 178			73.806	26.200
05:05:30 106.	108 119.416		47.364 179			71.977	27.458
05:06:00 105.9	977 118.448		47.764 179			71.596	26.198
05:06:30 105.	992 118.801		45.875 176			73.279	26.531
05:07:00 105.	948 119.337		45.833 178			74.277	27.425
05:07:30 105.	977 119.700		47.449 179			73.787	26.260
05:08:00 106.	021 120.004		48.017 179				26.452
05:08:30 106.	035 119.810		47.049 178				27.065
05:09:00 106.	006 119.731		47.007 177				26.933
05:09:30 105.	992 120.142		148.215 179				
05:10:00 106.	006 119.980		146.786 178				27.085
05:10:30 106.	006 119.762		146.561 177				26.498
05:11:00 106.	050 119.070		147.148 177				27.119
05:11:30 106.	035 118.766		146.937 178			72.129	
05:12:00 105.	977 118.213		144.856 177				26.375
05:12:30 105.	963 118.759		145.631 178				26.525
05:13:00 105.	963 119.347		147.176 179			73.752	26.300
05:13:30 106.	006 119.876		147.219 178				
05:14:00 106.	035 120.423		147.688 178				
05:14:30 106.	108 119.911	56.313	146.833 17	4.710 124	.237 55.563		26.856
05:15:00 106.	123 119.140	50.729	144.409 170	60.620 123	.756 56.079	71.727	27.752
05:15:30 106.	094 118.662	53.802	145.260 176	51.330 125	.963 55.658	70.902	26.852
05:16:00 105.	977 118.088	59.458	145.654 17	4.650 123	.767 55.548	71.540	26.663
05:16:30 105.	948 117.870	59.615	144.982 17	2.500 114	.689 55.552	72.906	26.769
05:17:00 106.			147.261 178	34.380 117	.929 55.608	71.427	26.008
05:17:30 106	.021 119.731	62.063	144.879 170	58.800 122	.487 55.987	71.856	26.248
05:18:00 106	.094 119.274	56.969	146.350 17	71.480 118	.683 55.608	70.721	27.427
05:18:30 106	108 119.285	5 51.219	145.786 17	76.860 121	.806 55.573	69.060	27.887
05:19:00 106	.035 117.739	51.865	143.221 17.	39.780 126	.368 55.110	71.200	27.558
05:19:30 105	.948 117.34	5 52.427	144.959 17	54.970 128	.280 55.563	71.698	27.006
05:20:00 105 05:20:30 105	.802 117.570	62.781	146.833 17	73.450 114	.502 55.427	73.715	25,535
						I have an exception of	10000

STEAM	STEAM	DRUM	GAS	AIR	WATER	GAS	AIR	WATER	
HEADER	FLOW	LEVEL	FLOW	FLOW	FLOW	VALVE	VALVE	VALVE	
PRESSURE						OPEN	OPEN	V OPEN	
BAR	TONES	MM	NM3	NM3	TONES	S %	%	%	
	PER	H2O	PER	PER	PER				
	HOUR		MIN	MIN	HOUI	R			

05:21:00	105.992	119.956	64.156	147.702 1805.750	114.253	56.115	73.640	25.360	
05:21:30	106.108	120.945	58.333	147.313 1778.410	124.497	55.458	72.833	27.356	
05:22:00	106.210	119.748	49.760	147.120 1780.680	126.883	55.419	69.748	27.904	
05:22:30	106.152	118.130	49.115	143.503 1757.270	126.938	55.677	68.912	27.913	
05:23:00	106.050	116.553	50.000	144.428 1753.990	127.453	55.348	69.329	27.415	
05:23:30	105.904	116.632	53.396	143.841 1753.450	122.539	55.490	71.667	26.865	
05:24:00	105.744	117.798	67.563	147.294 1791.250	110.034	55.983	72.998	24.525	
05:24:30	105.802	119.686	68.438	147.543 1801.870	110.974	56.015		25.215	
05:25:00	105.977	120.689	61.813	147.933 1793.690	122.214	55.815	73.052	26.981	
05:25:30	106.094	120.661	53.885	146.608 1771.360	121.443	55.329	72.688	27.815	
05:26:00	106.196	119.651	52.427	144.987 1781.100	125.043	55.688	70.140	27.363	
05:26:30	106.167	117.528	48.708	146.664 1757.810	129.854	54.992	68.998	26.844	
05:27:00	106.021	116.812	53.146	143.319 1734.640	125.257	55.069	70.848	27.348	
05:27:30	105.948	116.591	58.740	145.199 1765.150	119.309	55.617	71.158	26.050	
05:28:00	105.890	117.189	60.917	145.969 1771.180	114.460	55.458	72.077	25.971	
05:28:30	105.860	118.555	64.646	147.294 1793.280	115.138	55.833	72.563	25.525	
05:29:00	105.977	119.880	65.135	148.464 1784.980	110.795	55.358	72.454	26.333	
05:29:30	106.138	120.281	56.229	145.081 1766.290	124.071	55.890	70.542	26.827	
05:30:00	106.240	119.012	51.375	144.334 1754.760	125.306	55.450	69.046	27.069	
05:30:30	106.225	117.345	46.438	143.127 1729.570	129.968	55.002	68.069	27.775	
05:31:00	106.079	115.896	47.573	142.258 1729.510	124.884	54.777	68.229	27.833	
05:31:30	105.875	115.795	59.063	143.977 1751.780	119.714	55.040	71.298	25.679	
05:32:00	105.817	116.847	65.615	146.270 1784.320	112.956	55.621	72.058	25.608	
05:32:30	105.817	118.648	68.688	145.152 1786.530	109.709	56.029	74.771	24.940	
05:33:00	105.875	120.281	62.542	149.553 1817.580	117.974	56.104	72.760	25.900	
05:33:30	106.079	120.810	61.167	146.617 1782.890	119.613	56.027	71.746	26.981	
				145.241 1761.390				27.365	
				144.052 1738.400				27.475	
05:35:00	106.123	116.473	52.021	142.347 1725.450	127,498	54.985	69.075	26.917	
		116.010	- E	143.761 1751.120			70.192	26.858	
				144.804 1781.930	115.605	56.006	71.590	25.065	
05:36:30	105.787	118.123	62.385	147.303 1781.450	114.419	55.598	73.463	25.848	
05:37:00				147.463 1797.400		55.854	72.969	26.081	
				147.284 1778.110		55.421	71.606	26.900	
				145.795 1775.540		55.798	70.344	27.013	
				145.809 1756.440		55.350	69.448	27.067	
				144.550 1751.900			70.623	26.925	
05:39:30	105.904	117.767	56.073	144.978 1757.630	118.984	55.250	72.402	26.208	

STEAM	STEAM	DRUM	GAS	AIR	WATER	GAS	AIR	WATER
HEADER	FLOW	LEVEL	FLOW	FLOW	FLOW	VALVE	VALVE	VALVE
PRESSUR	E					OPEN	OPEN	J OPEN
BAR	TONES	MM	NM3	NM3	TONES	5 %	%	%
	PER	H2O	PER	PER	PER			
	HOUR		MIN	MIN	HOUF	2		

05:40:00	105.846	118.361	59.063	145.227 1781.810	115.176	56.165	73.565	26.471	
05:40:30	105.948	119.143	61.490	147.195 1795.190	117.310	56.060	72.623	25.992	
05:41:00	106.035	119.478	62.615	147.252 1792.020	115.429	55.606	70.856	25.938	
05:41:30	106.152	119.281	52.917	145.354 1769.990	124.375	55.865	69.308	27.358	
05:42:00	106.152	117.189	49.917	144.461 1753.510	130.023	55.304	68.440	27.271	
05:42:30	106.094	116.065	51.375	143.446 1756.080	122.764	55.194	67.975	26.819	
05:43:00	106.006	115.868	56.875	143.799 1752.550	120.070	55.017	68.546	26.483	
05:43:30	105.890	116.470	61.896	144.287 1766.410	111.580	55.433	70.227	25.733	
05:44:00	105.860	118.289	63.510	146.091 1783.180	119.205	55.913	70.794	25.919	
05:44:30	105.977	119.223	60.271	145.335 1775.720	116.909	55.606	71.487	26.408	
05:45:00	106.079	118.904	54.542	146.598 1781.570	128.418	55.625	69.633	26.938	
05:45:30	106.108	117.414	52.760	143.582 1751.180	126.302	55.310	69.983	27.254	
05:46:00	106.065	117.310	45.948	144.240 1750.170	121.823	55.277	70.665	27.860	
05:46:30	105.904	117.065	58.906	145.570 1767.780	119.627	55.367	71.113	26.231	
05:47:00	105.846	117.670	62.385	146.119 1791.190	117.455	55.946	71.867	26.387	
05:47:30	105.817	118.974	63.115	147.040 1781.570	114.336	55.802	73.033	26.375	
05:48:00				147.031 1791.130		55.854	73.575	25.973	
05:48:30				146.956 1768.850			74.525	26.535	
05:49:00				147.411 1803.840				26.875	
05:49:30				146.796 1786.290			72.160	26.492	
05:50:00				146.711 1784.920		55.819		27.771	
		118.607		145.255 1757.990		55.333	70.273	26.452	
05:51:00				145.203 1757.270					
05:51:30				144.865 1780.920		56.094	70.933	26.171	
05:52:00	and the second second	Contraction of the second second	Charles and a second second	145.621 1771.480			71.552	25.983	
05:52:30				146.650 1758.530		55.192	71.963	26.708	
				144.480 1759.720				25.975	
				145.264 1767.960				27.119	
				146.490 1771.840			70.438	27.125	
		118.036	and the second second	145.823 1778.590			71.583	26.869	
05:55:00				145.950 1772.740			72.127	26.650	
05:55:30				146.213 1787.300		55.498	71.577	27.085	
05:56:00				146.002 1774.410		55.294	71.612	26.358	
		118.797		146.246 1787.300		55.715		26.715	
		118.427		146.415 1765.990		55.279	69.383	26.929	
05:57:30				144.442 1763.300		55.571	68.721	27.800	
05:58:00				144.066 1748.080		55.100	68.960	26.758	
05:58:30				143.254 1756.850				26.196	
				143.695 1741.090				26.015	
05:59:30				145.034 1751.720				27.458	
06:00:00	105.948	117.511	57.844	144.569 1754.940	116.411	55.271	70.827	25.633	

## 2ND SET OF TEST DATA

	DER FI SSURE		VEL FLO			VALVE OPI	EN OP	E VALVE EN OP	EN
BA		ONES N		M3 NM		NES %	0	% %	
					ER PE				
		HOUR	M	IN M	IIN HO	DUR			
Min	0.0	0.0	-250.0	0.0	0.0	0.0	0.0	0.0	0.0
	140.0	166.0	250.0	225.50	2866.0	166.0	100.0	100.0	100.0
TIME									
17:00:30	89.513	115.256	63.479	132.589	1615.880	105.500	52.831	50.506	26.029
17:01:00	89.658	116.324	60.531	135.765	1602.990	102.377	52.025	50.790	27.754
17:01:30	89.950	114.360	46.365	133.195	1581.790	119.233	51.908	49.427	28.379
17:02:00	89.877	113.471	50.073	131.471	1606.330	114.201	52,473	48.471	27.265
17:02:30	89.775	114.436			1626.210		52.123	48.994	27.485
17:03:00	And the second second	113.689			1635.350			48.727	26.454
17:03:30		112.638			1550.200			49.502	26.642
17:04:00		109.671			1528.650			45.894	26.733
17:04:30		106.160			1495.930			43.165	26.913
17:05:00	a survey a	105.759			1453.890			43.827	25.794
17:05:30		105.998		THE PART OF THE	1457.120	To 67 (17 2 Au) 1 - 1 - 2		44.998	24.510
17:06:00		107.153 107.416			1511.630		49.450		24.242
17:06:30 17:07:00		107.410	a subset of Cal		1448.940 1494.610	104.884		45.831	26.379
17:07:30		107.702			1514.200	108.371		43.881 44.802	25.804 26.673
17:08:00		110.400			1536.770	97.259	50.165	46.123	25.877
17:08:30		110.214			1526.380			45.969	25.240
17:09:00					1546.680		51.371	44.792	25.844
17:09:30		111.531			1565.970		51.881	45.669	24.954
17:10:00	89.731	112.147			1558.620		51.873	47.675	25.500
17:10:30		111.759			1575.820		52.471	45.952	27.419
17:11:00		111.704			1572.950		51.996	46.077	26.290
17:11:30	89.760	112.399	55.448	129.587	1567.640	111.403	52.015	47.823	26.033
17:12:00	89.615	114.243	62.802	130.771	1616.000	103.612	52.765	47.796	26.829
17:12:30	89.498	116.020	62.573	134.614	1619.110	105.030	52.100	50.840	26.404
17:13:00				the strength where the	1619.820		Contraction of Contraction	and the second second	26.950
					1576.240				
					1618.090				
					1559.040				
					1542.140				
					1536.950				
					1516.470				
					1522.200				
					1510.970				
					1522.740				
					1504.230				
17:18:30	90.183	108.232	55.229	121.751	1477.000	112.652	50.473	45.633	25.890

STEAM	STEAM	menterie.	100 000	AIR	WATER	GAS	AIR	WATER
HEADER	FLOW	LEVEL	FLOW	FLOW	FLOW	VALVE	VALVE	Carlo manage of the
PRESSURI	5					OPEN	OPE	A OPEN
BAR	TONES	MM	NM3	NM3	TONES	5 %	%	%
	PER	H2O	PER	PER	PER			
	HOUR		MIN	MIN	HOUF	2		

TIME									
17:19:00	89.965	110.376	66.750	121.789 1471	.390	97.487	50.212	47.596	24.808
17:19:30	89.863	111.441	62.958	126.280 1589	.370	107.748	51.919	44.340	25.756
17:20:00	90.037	110.791	50.375	125.401 1518	.800	111.960	50.362	46.619	26.862
17:20:30	90.096	109.733	50.688	123.673 1509	.960	122.214	50.421	45.640	25.560
17:21:00	90.008	109.439	49.396	124.828 1531	.570	120.893	50.823	45.200	26.063
17:21:30	89.819	109.397	57.427	125.275 1581	.910	105.794	52.233	45.021	24.967
17:22:00	89.804	110.456	63.552	127.177 1574	.150	98.037	51.496	46.465	26.796
17:22:30	90.096	109.723	55.531	125.120 1544	.410	111.839	51.496	45.338	25.673
17:23:00	90.169	108.944	59.167	122.991 1504	.290	103.923	49.962	45.431	25.969
17:23:30	90.154	108.758	58.792	125.312 1499	.150	107.890	49.108	45.004	26.733
17:24:00	90.140	108.308	54.083	121.840 1539	.750	114.516	51.398	42.775	25.565
17:24:30	90.067	108.543	59.708	120.990 1499	.630	103.269	50.502	45.081	25.981
17:25:00	90.008	108.332	54.542	123.828 1538	.680	106.887	50.894	44.148	26.756
17:25:30	89.965	109.128	59.688	122.602 1505	.000	104.044	50.565	46.042	25.325
17:26:00	90.008	109.557	59.396	124.142 1484	.290	106.738	50.148	46.808	26.310
17:26:30	89.877	110.176	60.240	123.889 1517	.180	100.188	50.896	46.894	26.429
17:27:00	89.935	110.182	57.729	124.739 1584	.830	113.703	52.410	43.458	25.181
17:27:30	89.950	110.231	56.896	125.317 1504	.290	107.668	50.837	46.931	26.329
17:28:00	90.008	109.487	54.625	124.283 1539	.870	109.218	50.425	44.942	26.240
17:28:30	89.950	109.788	55.000	123.884 1540	.170	107.959	51.294	45.027	25.656
17:29:00	89.892	110.082	56.135	124.565 1555	.220	106.731	51.465	45.354	26.050
17:29:30	90.037	109.934	61.438	125.876 1528	.890	108.941	50.898	45.642	25.212
17:30:00	89.921	109.875	55.375	126.219 1555	.100	108.906	50.367	45.067	26.423
17:30:30	90.008	110.328	54.917	124.232 1527	.750	112.534	50.998	45.479	25.683
17:31:00	89.950	110.549	54.396	125.124 1545	.370	114.782	51.023	45.394	25.660
17:31:30	89,935	110.003	57.958	125.453 1540	.950	109.411	51.165	46.290	25.879
17:32:00	89.979	110.940	57.115	125.261 1549	.490	108.934	51.754	45.679	26.398
17:32:30	89.833	111.815	58.042	127.069 1571	.220	97.359	52.408	45.871	26.915
17:33:00	89.790	112.583	57.500	126.971 1559	.040	105.908	52.123	47.313	27.348
17:33:30	89.760	113.119	57.052	129.587 1589	.310	103.522	51.523	47.246	26.352
17:34:00	89.819	114.087	56.365	132.946 1565	.670	115.031	51.085	48.027	26.092
17:34:30	89.688	115.031	58.781	130.062 1616	.540	110.698	52.790	47.667	25.823
17:35:00	89.702	114.741	59.094	133.891 1614	.450	113.520	51.890	48.260	26.792
17:35:30	89.848	114.578	50,604	132.754 1609	.970	115.757	52.442	47.902	27.006
17:36:00	89.848	114.170	52.427	131.269 1579	.640	110.466	51.938	49.158	26.283
17:36:30	89.804	114.637	59.083	131.885 1599	.760	108.405	52.631	48.771	26.406
				131.645 1639					
				134.468 1601					
				130.391 1551					
				131.133 1585					
				129.244 1612					
17:30:30	80 807	115 140	60 760	131.448 1600	040	110 000	50 000	40 162	76 740

STEAM	STEAM	DRUM	GAS	AIR	WATER	GAS	AIR	WATER
HEADER	FLOW	LEVEL	FLOW	FLOW	FLOW	VALVE	VALVE	VALVE
PRESSUR	E					OPEN	OPE	N OPEN
BAR	TONES	MM	NM3	NM3	TONE	S %	%	%
	PER	H2O	PER	PER	PER			
	HOUR		MIN	MIN	HOU	R		

	17:40:00 17:40:30 17:41:00 17:41:30 17:42:00 17:42:30 17:42:30 17:43:00	89.979 89.892 89.892 89.892	115.405 115.342 115.142	55.906 58.177	134.130 1607.100 127.971 1598.390 133.463 1615.050	117.725	51.823 52.927 52.377	48.650 48.013 47.996	26.750 25.704 26.779	
	17:41:00 17:41:30 17:42:00 17:42:30	89.892 89.892 89.892	115.342 115.142	58.177						
	17:41:30 17:42:00 17:42:30	89.892 89.892	115.142		133.463 1615.050	110.736	52.377	17 006	000 000	
	17:42:00 17:42:30	89.892		55 118			50.011	47.990	20.119	
and the second	17:42:30		110 000	33.440	133.844 1584.060	115.813	51.540	49.890	26.177	
			115.356	57.417	130.832 1621.430	117.231	53.065	48.350	26.163	
3	17:43:00	89.790	116.584	58.417	132.989 1618.810	115.304	52.796	49.894	26.169	
		89.804	116.286	58.865	134.727 1628.360	105.666	53.323	50.112	27.467	
13	17:43:30	90.198	113.624	54.167	133.360 1616.240	114.976	52.344	47.206	27.121	
	17:44:00	90.256	112.565	50.760	129.019 1620.780	113.824	52.692	45.265	26.706	
	17:44:30	90.154	112.610	57.198	128.028 1574.090	103.584	52.554	46.696	26.740	
	17:45:00	90.140	112.901	60.229	128.328 1550.620	112.766	51.975	47.931	25.688	
1	17:45:30	90.125	113.478	61.281	128.258 1572.590	110.428	52.137	46.596	25.219	
	17:46:00	90.154	112.213		127.295 1567.760		51.942	46.865	27.315	
13	17:46:30	90.081	112.413		127.736 1589.910		52.660	46.263	26.402	
1	17:47:00	89.760	114,938		132.044 1610.330		52.435	47.985	26.421	
	17:47:30		114.692	53.792	131.758 1563.940	115.681	51.410	50.356	26.440	
	17:48:00		115.384		129.846 1588.600		52.271	48.048	27.733	
	17:48:30		116.304	57.729	134.173 1620.840	114.377	52.677	47.865	25.494	
	17:49:00		115.930		133.313 1615.520		52.625	49.483	27.679	
	17:49:30		116.231	56.510	133.693 1650.810	115.595	53.017	48.733	26.671	
	17:50:00		117.262		134.891 1688.370		53.710	48.423	25.650	
	17:50:30		117.711		136.113 1660.720		53.383	50.325	27.715	
	17:51:00		118.590		136.301 1633.730		52.473	50.665	26.294	
	17:51:30		119.005		134.962 1621.550		53.217	51.779	27.815	
	17:52:00		116.093		132.148 1655.110		53.375	47.606	27.719	
	17:52:30		115.380		131.016 1604.060		52.671	48.648	26.771	
	17:53:00		116.193		134.628 1633.200		52.602	48.929	27.058	
	17:53:30		116.477		134.229 1625.910		52.698	49.973	26.915	
	17:54:00		116.055		134.093 1614.570		52.288	49.269	27.990	
	17:54:30		116.387		133.712 1602.690		51.767	48.962	26.363	
	7:55:00		116.750		133.595 1644.180		53.706	48.258	27.677	
	7:55:30		116.909		136.075 1665.920		52.460	48.677	25.485	
	7:56:00		116.691		133.510 1650.570		53.217	48.487	27.427	
	7:56:30		116.024		134.478 1633.020		52.260	48.813	27.569	
	7:57:00		116.369		132.524 1631.760		52.742	48.810	26.494	
	7:57:30		116.788		134.548 1619.640		52.302	50.619	26.383	
	7:58:00				133.383 1617.490			49.408	27.492	
	7:58:30		115.813		133.519 1620.240		52.104	48.896	27.319	
	7:59:00		117.697		131.946 1602.450		52.688	52.002	25.375	
	7:59:30				137.099 1684.190		53.558	51.767	25.369	
1	8:00:00	89.921	117.497	53.333	137.499 1673.260	114.381	53.544	50.573	28.487	

## 3RD SET OF TEST DATA

	STEAM HEADER PRESSUE	FLOW	DRUM LEVEL	gas Flow	AIR FLOW	WATE FLOW	R GAS VALVE OPEN	AIR VALVE OPEN	OPEN	ε
	BAR	TONES		PE	R PE	R PER		%	%	
		HO	UR	ΜП	N MI	IN HOL	JR			
10.	0.0	0.0	-250.0	0.0	0.0	0.	0	0.0	0.0 0.	0
Min Max	140.0	166.0	250.0	225.5					0.0 100	0
TIM	E 0:20 105.9		070 51 0	10 12	0 905 16	90 740	17874	54 394	53 623	28.271
08:0	0:20 105.	903 112.	6/0 51.9	40 13	0 100 17	18 320	110 563	56 273	55.529	28.044
08:0	0:50 105.	542 113.	048 03.8	50 14	4 400 17	70 530	110.305	56.194	S. C. 100	26.794
08:0	1:20 105.	554 115.	038 07.5	38 14	7 202 17	0.000	en entretter statistication	56.563	100 Berlin (1997) 11	28.704
	1:50 105.			17 14	8.219 18	12 380			e de la competencia de la comp	28.023
	2:20 106.				6.298 17				e de la construction	28.696
	2:50 106.			00 14	2.807 17	32 710		55.475		29.927
	3:20 106.			04 14	1.412 17	00 740		54.996		30.033
	3:50 106.				8.650 17			55.181	52.631	28.446
	)4:20 106.			142 15	1.144 17	10 000	113 513	54.775	55.531	27.723
	04:50 105.				1.144 17 16.537 17	19.000	102 608	55.590	57.240	
	05:20 105			1/1 14	10.03/1/	200.140	100.036	56.673	57.590	
	05:50 105			188 14	1/.4// 10	00.140	100.236	56.671	56.054	
	06:20 105			S96 14	18.515 18	500.110	118.922	56.627	54.631	
	06:50 106			938 14	42.314 1	707.040	122.079	55.138	53.525	
	07:20 106				43.907 17			54.833	52.410	
	07:50 106						120.118	54.648	52.777	
	08:20 106		the second second				117.442	54.523	54.706	28.913
	08:50 105		Classifi and all				109.038	54.925		27.333
	09:20 105						108.011	56.212		27.517
	09:50 105						118.974		57.746	
	10:20 105						114.668	56.298		28.185
	10:50 105			833 1	47.209 1	785.160	113.772	56.142		27.644
	11:20 106						121.294	56.560		29.219
08:	11:50 106	.269 116					116.363	55.737		29.083
08:	12:20 106	.385 114	.343 45	719 1	42.502 1	731,660	110.518	55.742		29.085
08:	12:50 106	.269 113	582 46	917 1	40.468 1	704.070	124.548	54.592	53.446	
08:	13:20 106	.079 112	2.714 57	521 1	39.495 1	702.700	112.382			
08	13:50 105	5.773 112	2.707 60	198 1	40.092 1	707.120	112.199	54.950	55.540	27.940
08	14:20 10:	5.656 114	1.955 65	.125 1	41.534 1	756.200	108.280	56.015	56.648	27.004
08	:14:50 105	5.729 115	5.927 60	.688 1	45.377 1	788.620	107.959	56.331		27.440
08	:15:20 10:	5.890 110	5.826 57	.115 1	44.865 1	771.840	114.851		56.885	
08	:15:50 100	5.079 110	5.529 55	.094 1	46.490 1	774.050	120.758		55.250	
08	:16:20 10	5.225 11:	5.273 49	.604 1	43.911 1	741.630	121.550		54.163	
08	16:50 10	5.225 11	4.357 52				119.804		53.054	
08	17.20 10	5 077 11.	4 284 55	.021 1	40.346 1	1714.160	126.053		54.404	
08	17.50 10	5 729 11	3 717 59	708 1	42.948 1	1739.120	113.205	55.548	56.346	28.919
08	18:20 10	5,700 11	5.235 64	.156 1	45.137 1	1761.210	111.013	55.932	51.392	21.598
00	19.50 10	5 802 11	6 733 67	885 1	46 561 1	1783.960	111.071	56.550	) 57.419	20.708
08	3:19:20 10	6.035 11	6 708 61	.240	147.980	1788.320	105.528	\$ 56.275	56.021	29.052
08	3:19:50 10	6.313 11	6.511 5	5.990	144.780	1762.290	120.320	56.104	4 54.450	28.281
						100	)			

STEAM	STEAM	DRUM	GAS	AIR	WATER	GAS	AIR	WATER
HEADER PRESSURI		LEVEL	FLOW	FLOW	FLOW	VALVE	VALVE	
BAR	TONES	MM	NM3	NM3	TONE	S %	%	%
	PER	H2O	PER	PER	PER			
	HOUR		MIN	MIN	HOUI	R		

		HOUR		MIN	MIN	HOUR				
TIME										
	106.444	115.481	54.125	143.592	1735.900	119.821	55.725	53.223	28.385	
					1714.520					
					1689.800					
					1725.980					
					1778.770					
					1795.720	and the second se				
					1822.650					
The second second					1818.770					
					1820.680					
					1766.290					
					1759.600					
					1725.570					
					1739.420					
					1820.800					
					1782.890					
					1784.500					
					1785.510					
					1762.530					
08:29:20	106.065	115.543	53.156	144.879	1764.680	122,792	55.667	54.300	28.456	
					1743.180					
08:30:20	105.919	115.481	57.688	143.037	1753.150	115.142	55.875	55.362	27.615	
08:30:50	105.890	116.203	62.302	144.517	1753.750	116.515	55.552	56.523	27.679	
08:31:20	105.875	116.964	55.823	146.688	1784.320	118.154	56.263	56.642	28.258	
08:31:50	105.890	117.158	60.104	146.227	1783.960	111.026	56,508	56.660	28.210	
08:32:20	105.904	117.151	55.104	145.518	1782.350	124.476	56.856	57.119	28.194	
08:32:50	106.021	116.854	58,740	146.091	1792.020	117.760	57.054	56.569	28.929	
08:33:20	106.079	116.529	52.427	143.094	1798.230	121.602	57.144	55.406	29.096	
08:33:50	106.225	116.574	56.802	144.062	1771.240	117.701	56.410	54.235	28.681	
08:34:20	106.196	115.560	53.792	143.366	1737.690	121.235	55.663	54.290	28.821	
08:34:50	106.181	114.855	55.260	143.521	1735.120	117.082	55.602	53.456	28.748	
08:35:20	106.167	114.540	56.073	142.723	1731.780	114.481	55.500	52.996	28.954	
					1745.270					
					1696.970					
					1730.880					
					1759.120					
					1773.270					
08:38:20	106.006	116.670	58.177	147.712	1766.770	109.646	55.431	55.108	29.050	
					1760.440					
					1754.580					
					1712.610					
					1709.210					
					1744.550					
and the second	and strength	a shart the t	Crysteral.	Sec. Sum		and a second second	0.25	COLORISE		

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STEAM HEADER	STEAM FLOW	DRUM LEVEL	( - o and )	AIR FLOW	WATER FLOW	GAS VALVE	AIR VALVE	WATER VALVE
PRESSUR	E					OPEN	OPEN	OPEN
BAR	TONES	MM	NM3	NM3	TONES	5 %	%	%
	PER	H2O	PER	PER	PER			
	HOUR		MIN	MIN	HOUL	2		

08:41:20	105.656	114.308	67.719	147.853 1807.780	110.487	56.179	56.046	26.900	
08:41:50	105.787	117,400	70.948	144.874 1804.080	112.538	57.625	56.208	25.862	
08:42:20	105.948	118.406	60.917	144.748 1790.530	115.315	56.481	55.681	28.275	
08:42:50	106.225	117.269	50.333	146.866 1762.230	129.321	55.475	54.346	28.721	
08:43:20	106.298	115.671	47.813	143.597 1719.180	128.159	55.429	53.513	29.363	
08:43:50	106.210	113.931	48.948	141.172 1719.540	124.908	54.971	52.883	28.142	
08:44:20	105.919	113.122	56.396	140.825 1715.300	121.384	55.083	54.494	28.000	
08:44:50	105.773	114.336	58.344	143.470 1774.590	111.358	55.983	55.092	27.646	
08:45:20	105.715	115.622	68.198	144.311 1809.640	109.083	57.202	56.071	27.150	
08:45:50	105.758	116.501	63.844	148.060 1826.530	115.934	57.323	55.742	26.977	
08:46:20	106.021	117.255	59.146	144.480 1792.560	125.050	57.242	55.337	27.633	
08:46:50	106.152	116.864	52.990	144.959 1774.590	120.973	56.023	54.529	28.602	
08:47:20	106.210	115.927	53.979	145.227 1746.110	117.881	55.617	53.692	29.094	
08:47:50	106.210	114.561	54.125	142.352 1718.160	127.616	55.010	53.098	28.017	
08:48:20	106.108	114.118	52.510	142.004 1729.690	116.093	55.179	52.590	29.042	
08:48:50	105.875	113.392	55.094	141.257 1731.300	115.342	55.421	54.252	28.517	
08:49:20	105.773	114.557	63.823	143.150 1755.660	110.902	55.777	55.631	27.000	
08:49:50	105.758	115.135		144.682 1763.420		55.990	57.123	27.867	
08:50:20	105.831	116.646		146.575 1796.380		56.519	56.985	28.102	
08:50:50	106.065	117.303	57.042	144.174 1813.460	124.372	57.258	55.450	28.185	
08:51:20	106.210	116.255	55.750	147.059 1751.420	115.965	54.938	55.444	29.167	
08:51:50	and the second second	Colore Coloresto		143.766 1750.760		55.888	the second second	27.919	
				141.468 1736.430					
08:52:50		1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		141.872 1715.120		54.833	53.348	28.506	
08:53:20	105.860	114.512	55.104	141.201 1721.210	116.031		54.396	28.760	
08:53:50				143.902 1751.060		55.542	56.071	28.467	
				144.475 1764.260			57.229	27.346	
				147.571 1794.650		56.150		28.533	
08:55:20				148.008 1792.440		56.406		28.621	
08:55:50				142.685 1768.970		56.827		28.521	
08:56:20				144.466 1731.180		54.754	54.442	28.796	
08:56:50				141.501 1728.070		54.935	54.273	27.933	
08:57:20				141.356 1711.770		55.071	55.123	27.767	
08:57:50				143.329 1737.510		55.008	55.190	28.379	
08:58:20				142.798 1751.720		55.742	56.219		
08:58:50				144.672 1765.570		56.150		27.315	
				146.580 1777.270		55.879	56.510	27.610	
08:59:50	106.050	116.663	56.396	146.993 1771.600	119.693	55.767	55.708	28.215	

## 4TH SET OF TEST DATA

HEA	EAM IDER H SSURE	STEAM D LOW LE	RUM GA VEL FLO					VALVE		
B	AR '	TONES N	AM N.	M3 NM	13 TO	NES %	9	6 %		
		PER H	120 P.	ER PI	ER PE	R				
		HOUR	M	IN M	IN HO	DUR				
22:04:00	106 04	8 124 537	56 753	154 106	5 1877.160	127 332	57.171	82.728	27.524	
		1 123.129			1847.000		56.614		27.195	
		5 124.038			1863.160		57.013			
		0 124.397			1877.070		56.866		27.406	
		3 124.870			1885.460		56.898	85.216		
		1 121.083			1808.800		56.045	75.800		
		3 121.995			1831.890		56.484	77.159		
22:32:00	105.91	7 121.805			1827.250		56.273	77.729	27.033	
22:36:00	105.90	0 123.028			1843.240		56.398	80.676	27.183	
		9 123.582			1865.380		56.824	81.839	27.435	
22:44:00	106.07	5 122.487			1838.770		56.738	78.151	27.109	
22:48:00	105.96	8 122.826			1853.280		56.781	81.019	27.348	
22:52:00	106.01	5 122.146			1835.770		56.433	77.971	27.166	
22:56:00	106.06	3 122.436			1832.140		56.384	77.574	27.295	
23:00:00	105.95	7 122.552			1846.260		56.660	78.699	27.120	
23:04:00	106.06	121.682			1824.580		56.209	76.434	27.302	
23:08:00	105.97	7 121.658			1826.130		56.299	77.762	27,230	
23:12:00	106.033	2 122.193			1837.470		56.333	78.552	26.989	
23:16:00	105.990	121.488			1825.340		56.314	77.121	27.096	
23:20:00	105.993	5 120.881	57.746	149.240	1811.840	122.692	56.056	75.820	26.865	
23:24:00	105.99	7 121.595	56.503	150.575	1825.390	123.169	56.136	77.121	27.224	
23:28:00	106.000	5 121.524	56.050	150.568	1827.430	124.255	56.337	77.290	27.122	
23:32:00	105.973	3 121.023	57.864	149.209	1818.930	121.537	56.294	76.698	26.987	
23:36:00	106.017	121.120	57.663	149.836	1819.850	122.289	56.114	76.187	26.912	
23:40:00	106.004	121.270	56.560	150.160	1827.740	124.635	56.259	76.470	26.967	
23:44:00	106.015	5 120.773	56.037	149.106	1806.300	122.982	55.861	75.845	27.177	
		120.917		149.167	1814.040	123.829	56.066	75.984	26.603	
		121.026			1816.630		56.191	75.751	26.957	
		120.790			1806.590		55.891	76.321	27.018	
00:00:00	105.946	120.159			1803.470			74.739	26.818	
		122.148		151.266	1834.780	124,789	56.469	77.863	27.312	
					1819.800			80.450	27.025	
00:12:00					1806.240			75.206	26.827	
00:16:00					1819.940			76.025	27.082	
		120.920		149.114	1812.550	124.158	56.118	76.249	27.008	
00:24:00	105.992	120.855	58.020	149.158	1813.040	122.370	56.062	76.472	26.813	
00:28:00	105.990	120.936	57.900	148.867	1810.330	122.360	56.191	76.823	26.633	
00:32:00	106.026	120.515	57.991	148.279	1801.100	122.385	55.885	75.582	26.779	
00:36:00	105.937	120.663	57.313	148.658	1807.150	122.238	56.032	75.997	26.762	
00:40:00	106.085	120.463	56.999	148.062	1801.880	123.958	55.996	75.112	26.961	
00:44:00	106.003	120.359	56.897	147.934	1799.320	122.711	56.033	75.077,	26.925	

STEAM HEADER	STEAM FLOW	the server of the cost	00000	AIR FLOW	WATER FLOW	GAS VALVE	AIR VALVE	WATER VALVE
PRESSURE	4					OPEN	OPE	N OPEN
BAR	TONE	S MM	NM3	NM3	TON	ES %	%	%
	PER	H2O	PER	PER	PER			
	HOU	R	MIN	MIN	HOU	R		

00:48:00	105.990	120.547	57.253	148.301 1803.300	123.198	55.907	75.740	26.680	
00:52:00	106.025	120.111	56.755	148.083 1799.500	121.372	55.924	74.453	26.797	
00:56:00	105.968	120.685	57.542	148.595 1802.580	122.108	55.928	76.512	26.697	
01:00:00	106.012	120.412	55.960	147.151 1794.170	122.573	56.010	75.030	26.921	
01:04:00	105.997	119.936	56.581	147.296 1789.610	122.204	55.807	74.711	26.733	
01:08:00	106.035	120.195	55.885	147.096 1789.430	122.509	55.949	74.451	26.815	
01:12:00	105.982	120.606	56.917	147.781 1794.900	123.628	55.906	75.178	26.932	
01:16:00	106.019	119.962	57.159	147.028 1786.070	122.359	55.810	74.345	26.913	
01:20:00	106.003	120.159	56.465	147.332 1791.870	123.291	55.895	74.646	26.802	
01:24:00	106.037	119.730	57.514	146.429 1782.980	121.416	55.823	72.966	26.583	
01:28:00	105.957	120.498	57.193	147.543 1795.350	122.054	56.031	75.481	26.884	
01:32:00	105.973	120.374	56.432	147.159 1794.700	123.166	56.005	75.393	26.752	
01:36:00	105.994	120.310	57.029	147.332 1790.970	121.803	55.919	76.124	26.757	
01:40:00	106.043	119.758	57.449	146.255 1781.600	122.613	55.779	73.510	26.929	
01:44:00	106.013	119.994	56.371	147.558 1786.690	121.712	55,685	74.587	26.807	
01:48:00	106.013	119.643	56.928	145.650 1772.690	121.054	55.661	73.697	27.014	
01:52:00	106.006	119.892	57.958	146.864 1790.640	120.186	55,941	74.499	26.826	
01:56:00	105.950	119.139	57.521	146.367 1775.400	121.927	55.530	73.913	26.557	
02:00:00	106.030	119.125	56.089	145.716 1773.900	121.101	55.615	72.723	26.764	
02:04:00	105.981	119.620	57.382	146.695 1781.320	121.931	55.771	73.729	26.793	
02:08:00	105.966	119.755	57.717	146.631 1785.380	120.907	55.884	74.260	26.868	
02:12:00	106.010	119.667	57.604	146.395 1777.490	121.293	55.620	73.817	26.921	
02:16:00	106.014	120.014	56.362	147,179 1786.760	122.188	55.790	74.310	26.881	
02:20:00	105.997	119.294	57.466	145.792 1770.020	121.334	55.430	73.307	26.933	
02:24:00			56.359	146.466 1783.440	122.646	55.785	74.122	26.774	
02:28:00			57.385	145.646 1770.800	120.859	55.452	72.606	26.528	
02:32:00			56.556	147.047 1785.860	121.638	55.756	74.479	26.812	
02:36:00			57.534	145.903 1772.380	120.820	55.652	72.882	26.737	
02:40:00			56.329	146.486 1783.800	121.830	55.872	73.396	26.800	
02:44:00				146.874 1786.070		55.798	74.653	26.712	
02:48:00			56.637	146.664 1779.570	122.068	55.633	74.010	26.518	
02:52:00			55.732	148.417 1803.640	124.060	56.205	75.925	26.988	
02:56:00			57.717	148.058 1802.200	121.551	56.180	76.148	26.844	
03:00:00			58.359	147.586 1796.670	121.686	55.942	75.727	26.741	
03:04:00			56.199	148.722 1810.790	123.196	56.263	76.960	26.996	
03:08:00	106.005	121.210	57.505	148.325 1801.610	123.045	55.997	75.939	26.822	
03:12:00				147.632 1794.830		55.919	74.979	26.798	
03:16:00				147.315 1795.990		55.941	75.051	26.808	
03:20:00	105.972	120.073	58.372	147.622 1791.170	122.723	55.865	74.956	26.594	
1.00 A.M.			0.212.02	10 million and 01013			9 4828	9045	

STEAM HEADER PRESSURE		UM GAS VEL FLOW	AIR FLOW	WATER FLOW	GAS VALVE OPEN		WATER VALVE N OPE	
BAR	TONES N	MM NM3	3 NM3	TON		9/1		
		120 PER		PER				
	HOUR	MIN		HOU	IR			
03:24:00 106.0	065 120.282	56.455 1	46.881 17	81.250 1	22.871	55.659	73.713	26.883
03:28:00 105.9	986 120.566	56.471 1	47.836 17	98.380 1			75.308	
03:32:00 106.0	035 119.766	57.162 1	46.370 17	81.390 1	22.812	55.881	73.330	26.598
03:36:00 105.9	986 119.887	57.169 1	46.832 17	82.300 1	22.194	55.799	73.935	26.515
03:40:00 106.0	013 119.566	57.353 1	46.194 17	80.050 1	21.344	55.817	73.224	26.695
03:44:00 106.0							72.878	26.577
03:48:00 105.9						56.145	75.029	
03:52:00 105.9						55.852	74.280	26.619
03:56:00 106.0							73.554	
04:00:00 105.9	995 119.542		46.910 17			55.857	73.874	
04:04:00 105.9	983 119.688					55.850	73.512	26.823
04:08:00 106.0			47.238 17			55.979	74.056	26.690
04:12:00 105.9							73.157	
04:16:00 105.8						56.062	75.551	26.694
04:20:00 105.9							76.086	26.724
04:24:00 106.0							72.578	26.784
04:28:00 105.9							74.255	26.791
04:32:00 105.9	a time more state where a	1911 19 19 19 19				55.851	74.599	26.825
04:36:00 106.0							72.863	26.480
04:40:00 105.9							73.310	26.661
04:44:00 106.0							72.714	26.779
04:48:00 105.9						Contraction of the local sectors of the local secto	73.304	
04:52:00 105.9							73.714	26.870
04:56:00 106.0							72.829	26.776
05:00:00 105.9							72.969	26.514
05:04:00 106.0							72.027	26.601
05:08:00 106.0						55.638		26.818
05:12:00 105.9					2000-1-8-00 - 1	55.906		26.570
05:16:00 106.0						55.780		
05:20:00 105.9								
05:24:00 106.0	12 118 945	57.214 14	16 791 179	81 080 1	21 810	55 713	72 228	26.741
05:28:00 105.9	57 119 730	57 505 1	17 839 180	0 450 1	21 644	56 108	73 599	20,493
05:32:00 106.0	61 118 308	56 797 1/	16 321 175	80 170 1	21.044	55 777	70 572	20.007
05:36:00 105.9	53 110 120	57 112 1	17 070 170	1 670 1	21.400	56 069	70.543	26.040
05:40:00 105.9	00 120 070	57 001 1	7 700 101	12 260 1	1 072	50.000	72.304	20.469
05:44:00 105.9	84 110 502	57 486 1	17 700 170	5 560 1	21.0/0 .	55.997	73.001	20.739
05:48 00 106 0	04 110 372	56 699 1	16 642 175	22 700 1	20.497	5 761	73.803	20.010
05:48.00 106.0	70 110 427	56 401 1	17 101 170	2.700 12	21.942	55.707	73.019	20.440
05:52:00 106.0	70 119.437	56 760 14	17.191 178	54.150 L	23.495	55.727	/2.462	26.453
05:56:00 105.9	00 110 424	57 (26 14	17.422 175	1.690 12	21.896	55.943	72.330	26.320
06:00:00 106.0	08 118.434	57.636 12	10.132 178	\$0.230 12	21.897	55.749	72.000	26.433



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