Addis Ababa University
Addis Ababa Institute of Technology
School of Electrical and Computer Engineering

Optimal Controller for Steam Boiler Drum Water Level Control Using Neural Network Estimator and LQR

A thesis submitted to Addis Ababa Institute of Technology, School of Graduate Studies, Addis Ababa University

In partial fulfillment of the requirement for the **Degree of Master of Science in Electrical Engineering (Electrical control Engineering)**

By: Asmamaw Amesha Adasho

Advisor: Dr. Dereje Shiferaw Negash

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APPROVED BY BOARD OF EXAMINERS

______________________________________ ____________________

Chairman, Department of Graduate Committee Signature

Dr. Dereje Shiferaw Negash ____________________

Name of Advisor Signature

______________________________________ ____________________

Name of External Examiner Signature

______________________________________ ____________________

Name of Internal Examiner Signature

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Declaration

I declare that this thesis is my work and that all source materials used for this thesis have been properly acknowledged. This thesis has been submitted in partial fulfillment of the requirements for M.Sc. degree in control engineering at Addis Ababa University. I earnestly declare that this thesis is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

Name: Asmamaw Amesha Adasho

Signature: ___________________

Place: Addis Ababa, Ethiopia

Date of Submission: ___________________

This thesis has been submitted for my approval as a university advisor.

Name: Dr. Dereje Shiferaw Negash

Signature: __________________

Abstract

The water level of boiler drum is one of the crucial control parameters for any process industries, which reflects the control of mainly boiler load and feed water indirectly. The increasing demand for rapid changes in industries leads to more uncompromising requirements on the control systems for the processes. A very common control problem elsewhere in steam generation is that of controlling the water level in a boiler drum. Effectively controlling the drum water level in an industrial boiler helps to maximize overall energy efficiency. The problem behind various approaches used to control the drum water level is lack of practical aspects such as online tuning and ease of implementation within a real plant distributed control system and also bad parameter tuning leading to poor level performance. An optimization technique can solve those problems stated by simplifying the design process and allowing easily usage with physical system while satisfying the optimality condition such as speed and accuracy of the response should be within specified limits.

In this thesis an optimal controller using a multivariable feedback technique using a neural network state estimator based linear-quadratic regulator control is introduced. The purpose of NN based LQR is to keep the level of the steam boiler drum water at the specified zero reference value which avoids damage of boiler occurs by either overflow of water on the top of drum which affects steam quality or by shortage of water in the drum causes the drum burnt. Controller is designed and simulated on MATLAB/SIMULINK environment and the designed optimal controller is compared with conventional PID controller. Simulation result indicates that PID controller reaches its steady state value of pressure of 5.45 bar and water level oscillates about the set with slightly increasing amplitude. The NN based LQR controller achieves steady state pressure and level value of 5.455 bar and 0.00322 mm respectively. Comparing the two controllers, the proposed neural network based linear quadratic regulator achieved good performance in both steady state response tracking and speed of response.

Key word: Drum level control, optimal control, linear quadratic regulator, neural network estimator

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List of Abbreviations

Symbol	Description
c	Condensation
d	Drum
d_c	Down-comer
f_w	Feed-water
r	Riser
t	Total
s	Steam
w	Water
NN	neural network
ANN	artificial neural network
LQR	linear quadratic regulator
PID	proportional integral derivative

Chapter One

1. Introduction

This thesis is concerned with modeling, analysis and control of steam boiler systems. The goal is to develop advanced control strategies capable of handling the complex dynamics of the steam boiler drum while seeking to minimize water level variations to allow improvement of steam quality and avoid damages on the boiler drum.

1.1 Background of the Study

Boiler is a closed vessel (container) that stores water for the production of steam. By applying heat, the stored water continuously evaporates into steam. In technical terms, a boiler is defined as a closed vessel where water or some other liquid is heated; steam or vapor is generated and superheated. This function is accomplished under pressure or vacuum for use external combustion of fuels, electricity or solar energy and so on.

At present, industries are increasingly shifting towards automation. As boiler operates under pressure, there is always the potential for explosion. The input for the boiler is fuel and feed-water, whereas the output of the boiler is combustion and steam. Like the product of combustion, the blow-down of water from the boiler is also a waste.

The boiler parameters should be designed with the value of pressure and level not more than the maximum allowable working point of the boiler unless all the accessories will not work correctly and fail [1].

The water level of boiler drum is one of the crucial control parameters for any process industries; this reflects the control of mainly boiler load and feed water indirectly. Boilers are the important instrument in any production plant which is used to store large amount of water for the purpose of production of steam. The steam temperature has to be kept under control in order to avoid the excess usage of feed water in the boiler. The generated steam is used to drive the prime mover (turbine) in power generation or in process industry for various applications like heating and cleaning equipment [2].

1.2 Statement of the Problem

The demand for rapid changes in industries is increasing. This leads to more uncompromising requirements on the control systems for the processes. Boiler is drawing significant attention in community of process control and instrumentation, as far as its efficiency and control is concerned. A very common control problem elsewhere in steam boiler operation is that of controlling the level in a boiler drum. Many industrial plants have boilers for generating process steam, and of course boilers are central to thermal power generation.

Effectively controlling the drum level in an industrial boiler helps to maximize overall energy efficiency. When the drum level varies it can not only impact boiler efficiency, but also overall reliability due to unplanned shutdowns.

The drum level must be controlled to the limits specified by the boiler manufacturer. If the drum level does not stay within these limits, there may be water overflow. If the level exceeds the limits, boiler water carryover into the super heater or the turbine may cause damage resulting in extensive maintenance costs or outages of either the turbine or the boiler. If the level is low, overheating of the water wall tubes may cause tube ruptures and serious accidents, resulting in expensive repairs, downtime, and injury or death to personnel. To achieve quality requirements in steam production and maintain safety of the boiler it is necessary to control the boiler drum level by searching and implementing appropriate optimizing control strategies [2].

1.3 Objectives

The main objective of this work is to design an optimizing controller for the water level and pressure control of boiler drum which is required to the water/steam interface at its optimum level to provide a continuous mass/heat balance by replacing every pound of steam leaving the boiler with a pound of feed-water to replace it.

The Specific objectives are:

- To study and implement the boiler drum dynamics in MATLAB.
- To Design state feedback estimator using artificial neural network method
- To construct a conventional PID controller and multivariable LQR controller.

- To compare the performance of the conventional controller with the proposed LQR method

1.4 Methodology

My thesis firstly undertakes study of literatures about controller designs and theoretical backgrounds about non-linear dynamic system behavior and optimal controller. After reading and getting a better understanding about non-linear drum dynamics and different control strategies from the literatures, I have compared various controller performances and then an appropriate technique is selected to solve the problems of the system.

Since appropriate model dynamic equation of a drum is important for controlling of a nonlinear system, the thesis has two modeling phases. Firstly, the dynamics of the Boiler drum model and its nonlinear state space representation developed by Astrom – Bell model is studied for a suitable realization of the system dynamics for the controller design.

During this representation, the steam flow rate and feed water flow rate are taken as input, and drum pressure, total drum water volume, steam bubble volume inside the drum and steam quality ratio which is the ratio of steam to feed-water are taken as state variables.

Then neural network state estimator and LQR controller is designed based on optimal control theory. Finally after designing the controller, the stability and accuracy of the system is investigated for both PID controller and proposed neural network based LQR controller using MATLAB.

1.5 Scope of the Thesis

The scope of the thesis can be summarized in to three categories as follows:

- First the mathematical model of drum dynamics and its state space representation is studied.
- PID controller is designed and integrated with the plant model and output level is simulated on MATLAB
- Finally artificial neural network state estimator and linear quadratic regulator are developed and integrated with the system and result analyzed using MATLAB.

1.6 Outline of Thesis

This thesis is organized into five chapters. In Chapter 1 introductions and the problems observed on drum level control are stated clearly. In addition; overall tasks, scopes and the methods used for achieving the main objective are shortly summarized.

In chapter two different types of literatures are reviewed and summarized.

Chapter 3 gives a short definitions, types and principle of operations of steam boiler. Also describes about the derivation of nonlinear equations of the boiler drum and its state space representation. Different control strategies to control the level are mentioned and described briefly. PID control and its tuning methods, LQR control design and neural network estimators are discussed in this chapter.

In Chapter 4 PID and neural network based LQR level control is designed and simulated in MATLAB and their performance is evaluated under different response specifications.

Finally, chapter 5 summarizes the work done and results obtained. Recommendations for future work are also presented.

Chapter Two

2. Literature Review

The process controllers have to be designed in a way which can simultaneously fulfill the load demand as much as possible while considering safety and life span of the plant crucial elements. One of the common challenges in boiler operation is control of steam boiler drum units handling supply of the steam continuously with steam at high pressure and temperature. Natural-circulation boilers are widely used in various chemical processing and related industries. These types of boiler operate by the density difference of cold water fed from water tank and hot water inside the boiler drum. Due to the heat applied, water circulating inside the drum tubes evaporates and taken out of the drum in the form of steam. So that if there is no water feeding to compensate the outgoing steam, level of water decreases and drum becomes dry.

The controller should maintain drum pressure and water level within acceptable ranges for all operating conditions. If the level exceeds upper limits, water would be carried over to the super-heater leading the turbine to outage in thermal power generation or the boiler itself. Falling below lower limits would cause overheating of the water wall tube resulting in serious tube rupture and severe damage [3], [4]. A boiler trip interlock is supposed to prevent these types of damage, but boiler trips can take considerable time to clear, during which the expensive production equipment is often forced to sit idle. A high-priority challenge to the control engineer is the ability to control the water level in the drum very precisely.

As indicated in various literatures, drum level control problems can cause production inefficiencies, product quality issues, and production limits, and in some cases can even create safety risks. In extreme cases, level control problems have resulted in costs of millions of currency per year. The control engineer has a responsibility to asses and to implement a simple but systematic analysis of the control system to establish the root cause of the control problem and reestablish effective drum level control [5].

Previous works have investigated the boiler drum level control and proposed various control strategies in literatures in the recent years. Robust control using H-infinity mixed-sensitivity [6] and H-infinity loop-shaping approaches [7], predictive control method [8], adaptive techniques utilizing grey predictor based algorithm (GPBA) [9] and genetic algorithm [10] and nonlinear sliding mode control [11] are among the works done. The problem behind the above approaches stated is lack of practical aspects such as online tuning and ease of implementation within a real plant distributed control system due to their use of higher order mathematics and complexity of design.

Classical control design methods using PID-controllers are well used to compensate such effect. However as the process is quite complicated, dealing with several input variables to regulate each process variable separately might end up with bad parameter tuning and poor level performance observed during load changes, eventually leading the boiler unit to trip or even worse cause emergency shutdown of the process[12]

In [13], it was described that in the control of an industrial boiler system, multi-loop (de-centralized) PI control is used because of its simplicity and the existence of simple on-line tuning rules. They had shown that such control schemes sacrifices robustness and performance of the overall system. In particular, under normal boiler operating conditions, they designed a robust multivariable controller using the H∞ loop-shaping technique but stated that it is difficult for real time implementation because of tediousness of the methods and hardness to decentralize in to multi-loop system. For reason of implementation, they reduced this controller to a multivariable PI structure and tested using complex nonlinear simulation software.

Literature in [14], was discussed the application of a genetic algorithm to control system design for boiler-turbine plant. In particular they studied the ability of the genetic algorithm to develop a proportional-integral (PI) controller and a state feedback controller for a nonlinear multi-input/multi-output (MIMO) plant model. It was found that GA/PI control strategies achieve with a good steady state tracking but oscillation due to the integral action was prevalent.

Another research conducted by [15]; describes Internal Model Control of pressure using ARM Microcontroller. The conventional PID control and the tuning of controller parameters is a time consuming process and also depends upon an extensive specific process characteristics .So the PID and IMC algorithm is embedded into the target ARM microcontroller and its performance is studied with real time experimental setup. But ARM microcontroller is a 32 bit instruction device and when the process load is high, it will not operate.

Optimization of boiler parameters using soft computing techniques [16] [17] described multi Parameter Monitoring and Controlling for a Boiler using PIC Controller. The mechanical strength, efficiency, availability and round the clock are also important aspects for any boiler. High pressure boilers which are provided with optimized heat transfer areas for its rated duty requires some of the important parameters like pressure, drum level, water flow can be monitored and controlled by PIC controller.

Control of Boiler Operation in [18]: stated Control of Boiler using PLC-SCADA. In this the input is passed into the boiler at required temperature, so as constantly maintain a particular temperature to the boiler. In order to automate a power plant and minimize human intervention, there is a need to develop a SCADA system to monitor the plant. PLC is also used for internal storage of instruction for the implementing functions. Most often SCADA system is applicable in remote control system and for the systems with local control, use of SCADA becomes costly.

A literature in [19]: dealt with the level control of steam drum using double feedback loop method along with set point filter. In double feedback loop method, the inner loop consists of a proportional controller and is tuned with the help of Ziegler Nichols (ZN) method while the outer loop consists of a proportional integral derivative (PID) controller and is tuned by internal model control (IMC). The internal loop is employed for attaining the process stability while the external loop helps in fine tracking of set point. Disadvantage of this approach is slow response to changes in system parameter due to uncertainty and to reference change.

In summary of the various literature works reviewed above, it is necessary to control the level of water inside the drum to safeguard the drum from damage. It also noted that when the water level goes above specified level, the water will pass to the saturated steam and will make the production with low quality. To avoid this problems, the listed literatures have been done but the problems is some of them are more robust and modern control approaches but becomes difficult for online tuning and implementation because of the higher dynamics they used and are difficult for decentralization.

PID-controllers can be implemented within a real plant distributed control system. However as the process dynamics become complicated with multiple inputs multiple output systems, regulation of each process variable separately might be difficult and lead to bad parameter tuning requires designing an optimal controlling approach which will improve the system performance.

Chapter Three

3. Steam Generation Process and Modeling

3.1 Introduction

In this chapter the procedures to generate steam and equipment's used for the process are discussed. First the operation principles and different types of steam boilers are discussed briefly. Secondly the process and stages in steam generations are also explained and the components used to drive the system for the production are mentioned. Next mathematical modeling of the drum is developed and finally different control strategies used to automate and regulate the process are described briefly.

3.2 Working Principle and Types of Steam Boiler

Boiler or more specifically steam boiler is an essential part of thermal power plant and is basically a closed vessel into which water is heated until the water is converted into steam at required pressure.

3.2.1 Working Principle of Boiler

The basic working principle of boiler is very simple and easy to understand. The boiler is essentially a closed vessel inside which water is stored. Fuel (generally coal) is burnt in a furnace and hot gasses are produced. These hot gasses come in contact with water vessel where the heat of these hot gases transfer to the water and consequently steam is produced in the boiler. Then this steam is piped to the turbine of thermal power plant or other plants those require the steam for operation as seen in Fig 3-1.

The design principle uses the difference in density between cooler water in the down-comer and the steam/water mixture in the riser to drive the steam/water mixture through the tubes. The boiler drum separates steam from water and contains inventory to accommodate operational changes. Water enters the riser tube, is heated, and undergoes a transition from a single-phase liquid to a mixture of saturated liquid and steam. As heat input increases, the proportion of steam vapor in the riser tube increases [20].

The water/steam interface level is subjected to several disturbances in the water/steam drum; not the least of which, are drum pressure and feed water temperature. As steam pressure rises or falls due to load demand there is a transient change in drum level due to the expansion or contraction of the steam bubbles in the drum water. When the steam pressure is lowered the water level rises as the steam bubbles expand (swell). Conversely as the steam pressure raises the water level lowers due to compression (shrinking) of the steam bubbles [21].

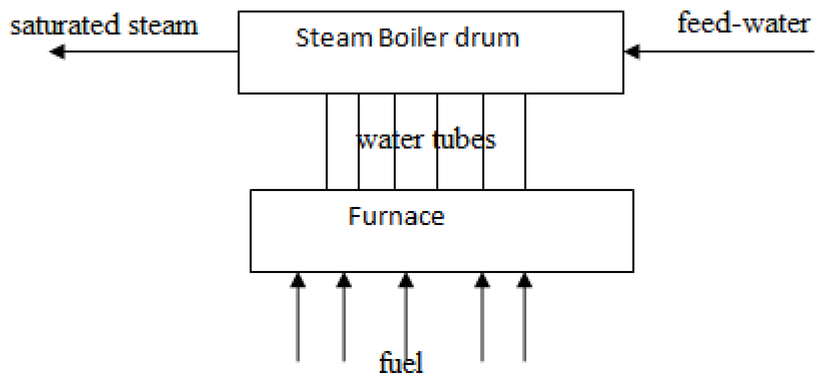

Fig 3-1: working principles of steam boiler

There are many different types of boiler utilized for different purposes like running a production unit, sanitizing some area, sterilizing equipment, to warm up the surroundings etc.

3.2.2 Types of Boiler

There are mainly two types of boiler – water tube boiler and fire tube boiler. In fire tube boiler, there are numbers of tubes through which hot gases are passed and water surrounds these tubes. Water tube boiler is reverse of the fire tube boiler. In water tube boiler the water is heated inside tubes and hot gasses surround these tubes. These are the main two types of boiler but each of the types can be sub divided into many which will be discussed later.

3.2.2.1 Fire Tube Boiler

As it indicated from the name, the fire tube boiler consists of numbers of tubes through which hot gasses are passed. These hot gas tubes are immersed into water, in a closed vessel. Actually in fire tube boiler one closed vessel or shell contains water, through which hot tubes are passed. These fire tubes or hot gas tubes heated up the water and convert the water into steam and the steam remains in same vessel. As the water and steam both are in same vessel a fire tube boiler cannot produce steam at very high pressure.

Operation of fire tube boiler is as simple as its construction. In fire tube boiler, the fuel is burnt inside a furnace. The hot gases produced in the furnace then passes through the fire tubes. The fire tubes are immersed in water inside the main vessel of the boiler. As the hot gases are passed through these tubes, the heat energy of the gasses is transferred to the water surrounds them. As a result steam is generated in the water and naturally comes up and is stored upon the water in the same vessel of fire tube boiler. This steam is then taken out from the steam outlet for utilizing for required purpose. The water is fed into the boiler through the feed water inlet.

As the steam and water is stored in the same vessel, it is quite difficult to produce very high pressure steam from. General maximum capacity of this type of boiler is 17.5 kg/cm^2 and with a capacity of 9 Metric Ton of steam per hour. In a fire tube boiler, the main boiler vessel is under pressure, so if this vessel is burst there will be a possibility of major accident due to this explosion.

Advantages of Fire Tube Boiler

1. It is quite compact in construction.
2. Fluctuation of steam demand can be met easily.
3. It is also quite cheap.

Disadvantages of Fire Tube Boiler

1. As the water required for operation of the boiler is quite large, it requires long time for rising steam at desired pressure.
2. As the water and steam are in same vessel the very high pressure of steam is not possible.
3. The steam received from fire tube boiler is not very dry.

3.2.2.2 Water Tube Boiler

A water tube boiler is such kind of boiler where the water is heated inside tubes and the hot gasses surround them. The working principle of water tube boiler is very interesting and simple. It consists of mainly two drums, one is upper drum called steam drum, other is lower drum called mud drum. These upper drum and lower drum are connected with two tubes namely down-comer and riser tubes.

Water in the lower drum and in the riser connected to it, is heated and steam is produced in them which comes to the upper drums naturally. In the upper drum the steam is separated from water naturally and stored above the water surface. The colder water is fed from feed water inlet at upper drum and as this water is heavier than the hotter water of lower drum and that in the riser, the colder water push the hotter water upwards through the riser. So there is one convectional flow of water in the boiler system. See Fig 3-2

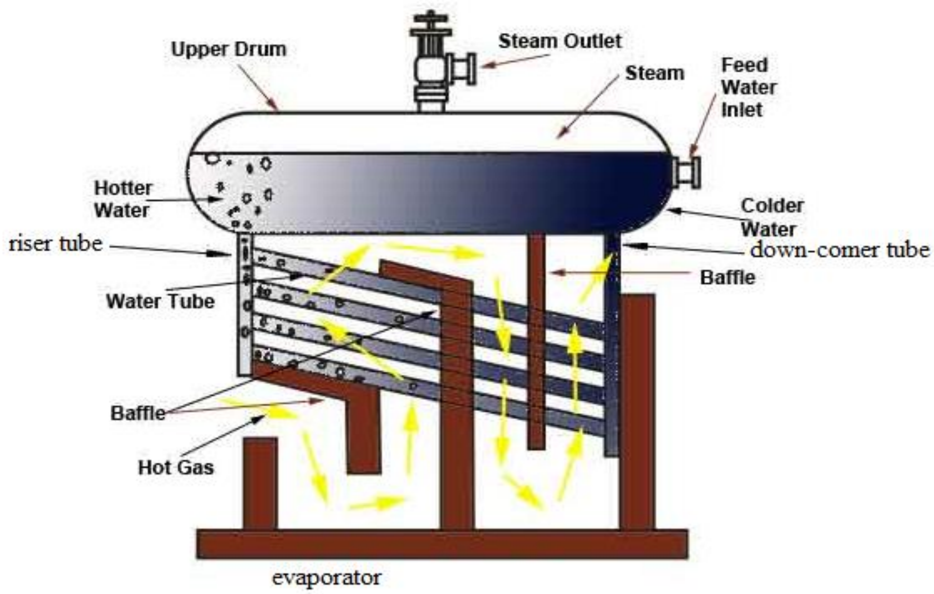

Fig 3-2: Schematic diagram of water tube boiler [21]

More and more steam is produced, the pressure of the closed system increases which obstructs this convectional flow of water and hence rate production of steam becomes slower proportionately. Again if the steam is taken through steam outlet, the pressure inside the system falls and consequently the convectional flow of water becomes faster which result in faster steam production rate. In this way the water tube boiler can control its own pressure. Hence this type of boiler is referred as self-controlled machine.

Advantages of Water Tube Boiler

There are many advantages of water tube boiler such that these types of boiler are essentially used in large thermal power plant.

1. Larger heating surface can be achieved by using more numbers of water tubes.
2. Due to convectional flow, movement of water is much faster than that of fire tube boiler; hence rate of heat transfer is high which results into higher efficiency.
3. Very high pressure in order of 140 kg/cm^2 can be obtained smoothly.

Disadvantages of Water Tube Boiler

1. The main disadvantage of water tube boiler is that it is not compact in construction.
2. Its cost is not cheap.
3. Size is a difficult for transportation and construction.

Steam boiler efficiency

The percentage of total heat exported by outlet steam in the total heat supplied by the fuel (coal) is called steam boiler efficiency.

$$\text{Steam boiler efficiency}(\%) = \frac{heat\ exported\ by\ outlet\ steam}{heat\ supplied\ by\ the\ fuel} \text{x}100 \qquad (3.1)$$

It includes with thermal efficiency, combustion efficiency & fuel to steam efficiency. Steam boiler efficiency depends upon the size of boiler used. A typical efficiency of steam boiler is 80% to 88%. Actually there are some losses occur like incomplete combustion, radiating loss occurs from steam boiler surrounding wall, defective combustion gas etc. Hence, efficiency of steam boiler gives this result.

Parts of water tube boiler

i. Steam Drum

The functions of steam drum in steam boiler are:

1. To store water and steam sufficiently to meet varying load demands.

2. To provide a head and thereby aiding the natural circulation of water through water tubes.
3. To aid in chemical treatments to remove dissolved O_2 and to maintain required pH.
4. To separate vapour or steam from water- steam mixture, discharged by the risers.

Steam must be separated from the mixture before it leaves the drum, because:

- Any moisture carried with steam contains dissolved salts. In the super heater, water evaporates and the salt remain deposited on the inside surface of the tubes to form a scale. This scale reduces the life of the super-heaters.
- Some of the impurities in the moisture (like vaporized silica) may cause turbine blade deposits.

One of the important functions of steam-drum is to separate steam from steam water mixture. At low pressure (below 20 bar; 1 bar = 1.0197 kg/cm^2) simple gravity separation is used. In the method of gravity separation the water particles disengaged from steam due to higher density. As the pressure inside the boiler drum increases, steam is compressed and the density of steam increases. Hence difference between the densities of steam and water decreases so that gravity separation fails. In the steam drum of the high pressure boilers, there are some mechanical arrangements (known as 'drum internals' or 'anti-priming arrangements') for separating steams from water. Following picture in Fig 3-3 illustrates different Anti-priming arrangements used in thermal power plants :

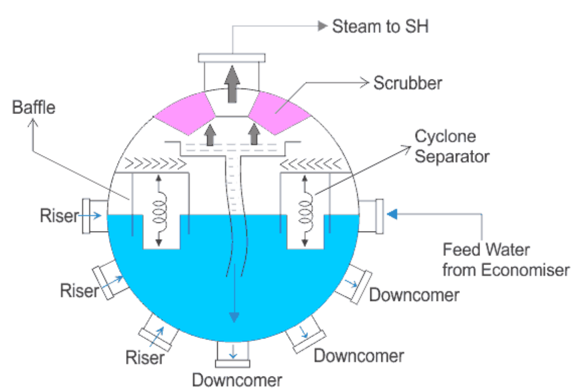

Fig 3-3: Schematic diagram of water tube boiler steam drum [21]

"Baffles" in Fig 3-3 are separators which separate the hot steam-water mixture from dry steam and provide a guided path for the dry steam. In the "cyclone separator" steam water two-phase mixture is allowed to move in a helical path and due to centrifugal forces the water particles separate out from the two-phase mixture. The small vanes inside the cyclone separator collect the deposited water particles. In the "scrubber" the two phase mixture is allowed to move in a zigzag path and it provides the ultimate stage of drying the steam. After scrubber steam is allowed to move to super-heated through a perforated screen.

ii. Water Tubes

Water tubes are bent or straight hollow tubes through which steam water mixture circulates. There are two types of water tubes, down-comer and riser. This down-comer, riser assembly is also known as "Evaporator" (or "boiler proper"). In the evaporator actual state change from water to steam occurs.

A. Down comer Water Tubes

As the name suggests down comers are the water tubes through which water comes down from steam drum to mud drum. No vapor bubble should flow along with saturated water from the drum to the down comers. This will reduce the density difference and the pressure head for natural circulation.

B. Risers Water Tubes

Risers are the water tubes through which steam water two-phase mixture at saturation temperature goes up from mud drum to steam drum. Risers are usually close to furnaces, while the down-comers are away from the furnaces.

3.3 Steam Generation Process

Steam is generated in main generation plants, and/or at various process units using heat from flue gas or other sources. Heaters (furnaces) include burners and a combustion air system, the boiler enclosure in which heat transfer takes place, a draft or pressure system to remove flue gas from the furnace, soot blowers, and compressed-air systems that seal openings to prevent the escape of flue gas. Boilers consist of a number of tubes that carry the water-steam mixture through the furnace for maximum heat transfer. Steam flows from the steam drum to the super heater before entering the steam distribution system.

3.3.1 Heater Fuel Unit

Heaters may use any one or combination of fuels including refinery gas, natural gas, fuel oil, and powdered coal. Refinery off-gas is collected from process units and combined with natural gas in a fuel-gas balance drum. The balance drum provides constant system pressure, fairly stable content fuel, and automatic separation of suspended liquids in gas vapors, and it prevents carryover of large slugs of condensate into the distribution system. Fuel oil is typically a mix of refinery crude oil with straight-run and cracked residues and other products. The fuel-oil system delivers fuel to process-unit heaters and steam generators at required temperatures and pressures.

3.3.2 Feed-Water Unit

Feed-water supply is an important part of steam generation. There must always be as many pounds of water entering the system as there are pounds of steam leaving it. Water used in steam generation must be free of contaminants including minerals and dissolved impurities that can damage the system or affect its operation. Suspended materials such as silt, sewage, and oil, which form scale and sludge, must be coagulated or filtered out of the water. Dissolved gases, particularly carbon dioxide and oxygen, cause boiler corrosion and are removed by degeneration and treatment. Dissolved minerals including metallic salts, calcium, carbonates, etc., that cause scale, corrosion, and turbine blade deposits are treated with lime or soda ash to precipitate them from the water. Re-circulated cooling water must also be treated for hydrocarbons and other contaminants.

The most potentially hazardous operation in steam generation is heater startup. A flammable mixture of gas and air can build up as a result of loss of flame at one or more burners during light-off. Each type of unit requires specific startup and emergency procedures including purging before light off and in the event of misfire or loss of burner flame. If feed-water runs low and boilers are dry, the tubes will overheat and fail. Conversely, excess water will be carried over into the steam distribution system and damage the turbines/ plants. Feed-water must be free of contaminants that could affect operations. Boilers should have continuous or intermittent blow-down systems to remove water from steam drums and limit buildup of scale on turbine blades and super-heater tubes. Care must be taken not to overheat the super heater during startup and shut-down. Alternate fuel sources should be provided in the event of loss of gas due to refinery unit shut down or emergency. Knockout pots provided at process units remove liquids from fuel gas before burning.

3.3.3 Stages in Steam Generation Process

There are different components present in feed water and steam circuit of boiler. Some of the essential components of these circuits are economizer, boiler drums, evaporator, water tubes, and super heater.

Production of high pressure steam is carried out using high and low pressure drum-boiler units according to the following process.

1. **Economizer stage:** Water fed by the pump supplied to the drum inlet is preheated in order to reduce energy consumption. Economizer is a component that consists of water pipes that are placed on the track of fuel gases after evaporator pipes. Economizer pipes are made of steel or cast iron materials that are able to withstand high heat and pressure. Economizer serves to heat feed water before it enters steam drum and evaporator. Because of the Water fed to the evaporator is at high temperature and difference in temperature is not high, evaporator pipes are not easily damaged due to thermal equilibrium.
2. **Evaporator stage:** Due to the gravity water flows down through a down comer-riser closed loop producing saturated steam which flows along the riser tubes before being collected and fed back into the drum. Evaporator is one of components which serve to convert water into saturated steam. Evaporator pipes in steam boiler are usually located on the floor (water floor) and also on the wall (water wall). In this pipes, quality of saturated steam at 0.80 to 0.98, so most are still shaped in liquid phase. Evaporator will heat water that falls from steam drum which still in liquid phase to form the saturated steam so it can be forwarded to super heater.
3. **Super heater stage:** The saturated steam flows through the water level till it exits upon reaching the drum outlet. Then it is reheated one more time producing superheated steam supplied to the turbine/plant. Super-heater is basically a heat exchanger in which heat is transferred to the saturated steam to increase its temperature. In super-heater the rate of heat absorption is more. Hence, in the modern water tube boilers there are more super heating surfaces. Super-heater tubes are

exposed to the highest steam pressure and temperature on the inside and the maximum gas temperature on the outside.

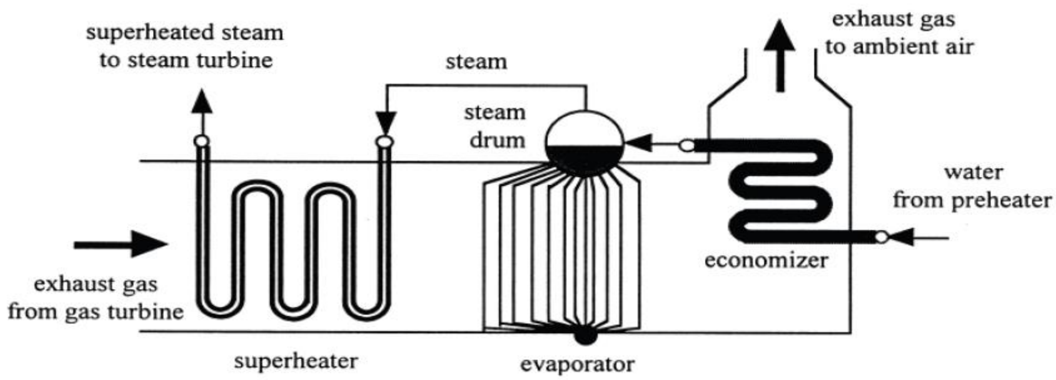

Fig 3-4: Heat Recovery Steam Generator [20]

The simplified process relevant to my analysis concerning steam generation using the drum-boiler unit is illustrated in Fig 3-5. Supplied inflow from the feed-water pump is regulated using one control valve. As for the steam flow rate leaving the drum, it can be regulated using different valves connected in parallel with distinctive construction and functionalities.

1. **Water tank control valve:** always kept opened at a predefined position
2. **Bypass valve: A** butterfly valve handling heat supply
3. **Security valve:** for safety matters when the drum pressure exceeds limits
4. **Feed water control valve**: controls inlet water

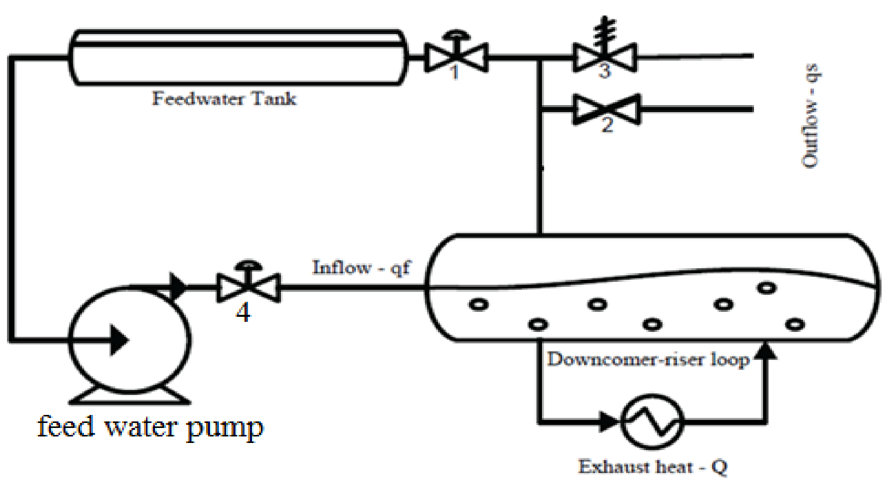

Fig 3-5: Schematic diagram of the steam generation process [20]

The water tank control valve regulates the flow of water from the source to water tank and also controls condensation water flow released from drum. The bypass valve (butterfly valve) controls the out flow of saturated steam generated in the drum to the super heater. Valve 3 is placed for security use to prevent damage due to water overflow and to relief the drum if excess steam is produced. Valve 4 is the feed water control valve which controls the water flow to the drum which is pumped by the water pump.

3.4 Mathematical Modeling of Steam Boiler

3.4.1 Drum-Boiler Mass and Energy Balance

Fig 3-6 illustrates the detailed process of steam generation within the drum. Its complex geometry, number of riser and down-comer tubes and specially the two phase flow modeling attempt is usually quite complicated requiring typically usage of partial differential equations. In literature there exist a lot of research papers that were devoted into developing relatively simple physical models [3], [6], [20], [21]

In this thesis the well-developed Astrom - Bell model is being considered [6]. The majority of the system attitude can be captured through a 4th order nonlinear model by means of defining mass flow and energy balance with the help a physical mechanism introduced under the following elementary assumptions.

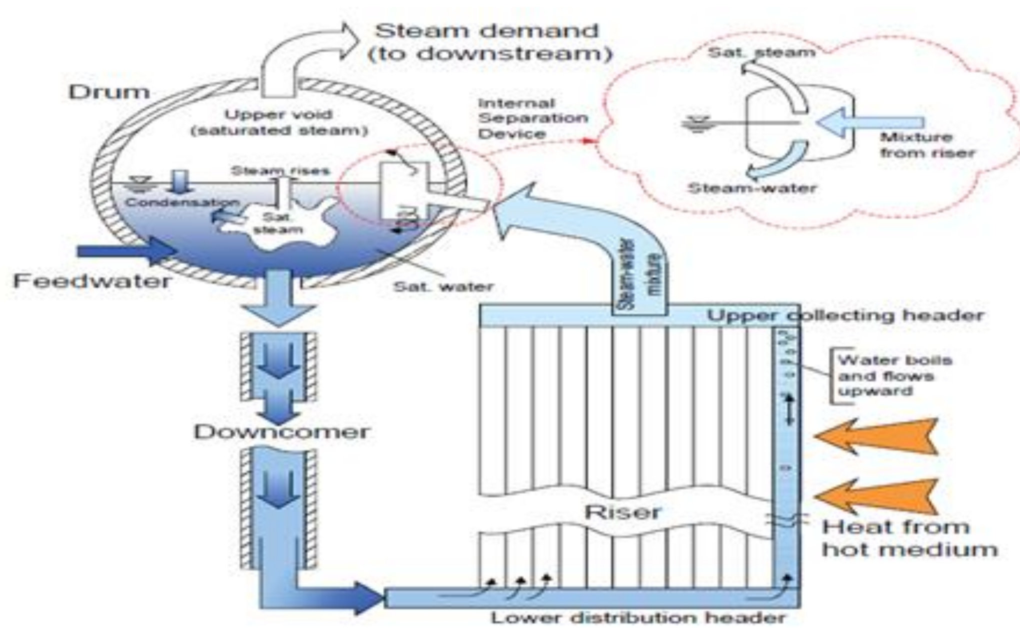

Fig 3-6**:** Schematic diagram of the down-comer-riser circulation loop [22]

Most of the system parts will be under thermal equilibrium due to their direct contact with saturated liquid/vapor mixture. The energy stored in the mixture is either absorbed or released quickly following drum pressure changes, meaning that various metal parts of the system would adapt their temperatures in the same manner.

Equation (3.2) present the mass and energy balance for the drum in terms of feed-water flow rate q_f, steam flow rate $q_s$and heat flow rate $\dot{Q}$ respectively. It describes the drum pressure dynamical behavior quite well by simply computing properties of liquid/vapor mixture using steam tables. Condensation of the steam within the drum causes the coupling between the drum pressure P and water total volumeV_{wt}.

$$\frac{d}{dt}(\rho_s V_{st} + \rho_w V_{wt}) = q_f - q_s$$

$$\frac{d}{dt}\left(\rho_s h_s V_{st} + \rho_w h_w V_{wt} - P V_{wt} + m_t c_p t_{sat}\right) = \dot{Q} + q_f h_{fw} - q_s h_s \quad (3.2)$$

Distribution of steam along the riser tubes was carried out using a lumped model which represents the energy and mass balance caused by the naturally circulated down-comer-riser closed loop as seen in equation (3.3). The steam mass fraction $\alpha_r$assumed to vary linearly from the inlet to the outlet of the riser is characterized in response to changes in the down-comer flow rateq_{dc}, riser flow rate $q_r$and heat flow rates $\dot{Q}$respectively.

$$\frac{d}{dt}[(\rho_s \bar{\alpha}_v V_r + \rho_w (1 - \bar{\alpha}_v) V_r] = q_{dc} - q_r$$

$$\frac{d}{dt}\left[\rho_s h_s \bar{\alpha}_v V_r + \rho_w h_w (1 - \bar{\alpha}_v) V_r - P V_r + m_r c_p t_{sat}\right]$$
$$= \dot{Q} + q_{dc} h_w - q_r (h_w + \alpha_r h_c) \quad (3.3)$$

The empirical equation (3.4) defines mass balance of the steam bubbles under the water level in terms of condensation flow $q_{cd}$and steam flow through the liquid surface q_{sd}driven by density difference of the mixture and momentum of the flow $q_r$entering through the riser tubes. It can capture most of the process dynamics by proper parameterizations of residence time of steam inside the drum T_d, the bubbles steam volume at hypothetical situation $V_{sd}^o$and empirical coefficient β correspondingly.

$$\frac{d}{dt}(\rho_s V_{sd}) = \alpha_r q_r - q_{cd} - q_{sd}$$

$$q_{sd} = \frac{\rho_s}{T_d}(V_{sd} - V_{sd}^o) + \alpha_r q_{dc} + \alpha_r \beta (q_{dc} - q_{r}) \quad (3.4)$$

3.4.2 Drum-Boiler Nonlinear State Equations

To derive a state model, chosen state variables should have a good physical interpretation. Drum pressure P is chosen as it describes the total energy of the system. The accumulation of water related to total water volume V_{wt}in the system is selected since it represents the storage of mass.

Steam quality $\alpha_r$in the riser tubes and steam bubbles volume under the liquid level $V_{sd}$are chosen as well to describe distribution of steam under the water, thus estimating the level. The resulting nonlinear state-space model would be a 4th order system whose states are:

$$X = \begin{bmatrix} P, \text{drum pressure} \\ V_{wt}, \text{total water volume} \\ \alpha_r, \text{steam quality} \\ V_{sd}, \text{steam bubbles volume} \end{bmatrix}$$

The model actuating variables are:

$$u = \begin{bmatrix} q_f, \text{feedwater flow rate} \\ q_s, \text{steam flow rate} \end{bmatrix}$$

$q_f$and $q_s$are manipulated to control primarily the drum water level and pressure respectively, whereas the heat flow rate $\dot{Q}$is rather considered as a model input disturbance *z* due to the fact that its amount is associated with the gas turbine exhaust heat which in return corresponds to its electrical output power as we elaborated concisely the combined cycle working principle in section (3.3). On the contrary heat flow rate becomes a control variable in thermal plants as it can be regulated directly by adjusting the boiler firing rate.

Arrangement of the mass and energy balance differential equations was carried out in order to derive the algebraic state equations. The liquid/vapor mixture properties time derivatives in terms of the drum pressure are calculated using the coefficients e_{nm}provided in appendix (B).

$$\frac{dP}{dt} = \frac{e_{12}\dot{Q} + q_f\left(e_{12}h_{fw} - e_{22}\right) - q_s(e_{22} - e_{12}h_s)}{e_{12}e_{21} - e_{11}e_{22}} \tag{3.5}$$

$$\frac{dV_{wt}}{dt} = \frac{1}{e_{12}}\left[q_f - q_s - e_{11}\frac{dP}{dt}\right] \tag{3.6}$$

$$\frac{d\alpha_r}{dt} = \frac{1}{e_{33}}\left[\dot{Q} - \alpha_r h_c q_{dc} - e_{31}\frac{dP}{dt}\right] \tag{3.7}$$

$$\frac{dV_{sd}}{dt} = \frac{1}{e_{44}}\left[\frac{\rho_s}{T_d}\left(V_{sd}^o - V_{sd}\right) - q_f\frac{h_{fw} - h_w}{h_c} - e_{41}\frac{dP}{dt} - e_{43}\frac{d\alpha_r}{dt}\right] \tag{3.8}$$

Equations (3.5), (3.6) rearrange the drum mass and energy balance, equation (3.7) combines the mass and energy balance of the down comer-riser closed loop in a single equation and equation (3.8) considers only the mass balance of steam bubbles under water level.

3.4.3 Mass flow control valve

The process concerned with regulation of feed-water flow rate supplied from the pump can be simplified and highlighted as seen in Fig 3-7. The flow is computed with the aid of the nonlinear equation (3.9) essentially used by mechanical engineers to size their valves and meet mass flow requirements.

$$q_f = x_f \cdot \frac{K_{vf} \cdot \rho_w \cdot \sqrt{\Delta P}}{3600} \tag{3.9}$$

The pressure drop ΔP across the valve would be the difference between the feed-water pump and drum pressures; x_f is its percentage opening ranging from 0% to 100% and finally k_v is the valve sizing coefficient.

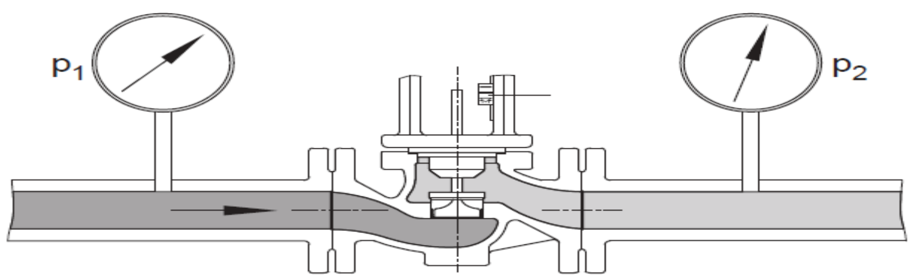

Fig 3-7: Flow through control valve for liquid service [23]

The dynamics related to regulation of steam flow rate are quite complicated where additional considerations have to be taken care of when compared to feed-water mainly due to the difference in properties between both [23]. One good approximation to describe the flow rate through a control valve meeting practical needs can be achieved using equation (3.10) where m the head loss coefficient and the compressibility factor Z are taken into account to distinguish between saturated and superheated steam.

$$q_s = x_s \cdot \frac{K_{vs} \cdot Z \cdot m}{3600} \tag{3.10}$$

Clearly the valve position value would vary according to the type of valve being used. The inherent flow characteristic depicted in Fig 3-8 highlight the comparison between the commonly used control valve demonstrating that mass flow rate for the same opening position and pressure drop across it is obviously altered according to the category it belongs.

Examining halfway opened linear, butterfly and relief valves correspondingly, undoubtedly the butterfly valve would supply approximately one-third of the total amount provided using the linear valve while the relief valve employed for safety precautions would grant roughly twice the flow afforded by the linear valve.

The actuators used to operate the control valve handle the positioning imposed by the controller using electrical motors with 3 basic states which are opening, closing or holding the same opening percentage. The rate of opening/closing is correlated to the motor maximum speed.

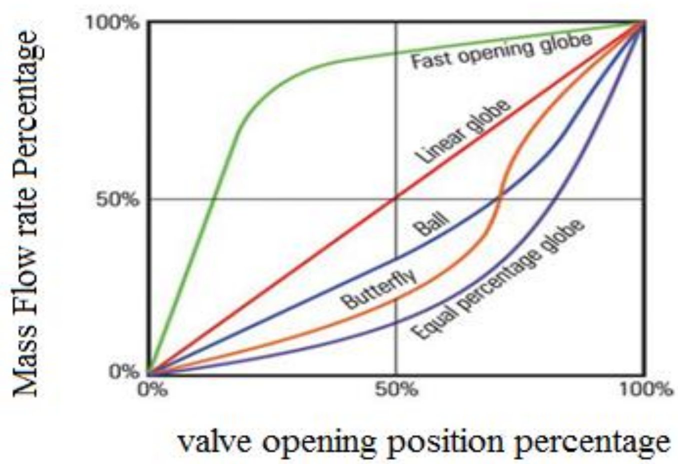

Fig 3-8**:** Inherent flow characteristics of typical control valves [23]

3.5 Controller Design

In this work two strategies of controller discussed above have been developed. The first is PID control design and the second one is the design of proposed optimal control which is the optimal controller with neural network state estimator and linear quadratic regulator.

3.5.1 PID Controllers

PID controllers are found in a wide range of applications for industrial process control. Approximately 95% of the closed loop operations of industrial automation sector use PID controllers. PID stands for Proportional-Integral-Derivative. These three controllers are combined in such a way that it produces a control signal [24].

As a feedback controller, it delivers the control output at desired levels. Before microprocessors were invented, PID control was implemented by the analog electronic components. But today all PID controllers are processed by the microprocessors. Programmable logic controllers also have the inbuilt PID controller instructions. Due to the flexibility and reliability of the PID controllers, these are traditionally used in process control applications.

3.5.1.1 Working of PID Controller

PID controller maintains the output such that there is zero error between process variable and set point/ desired output by closed loop operations.

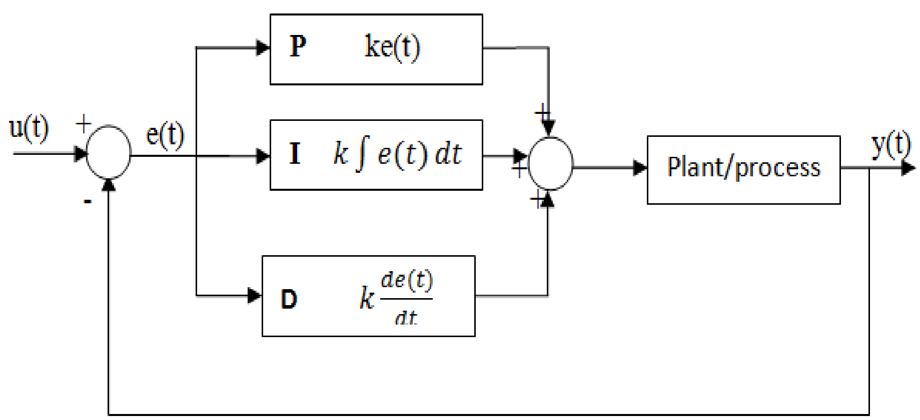

Fig 3-9: Schematic diagram of PID controller

Feedback signal from the process plant is compared with a set point or reference signal $u(t)$ and corresponding error signal $e(t)$ is fed to the PID algorithm [24]. According to the proportional, integral and derivative control calculations in algorithm, the controller produces combined response or controlled output which is applied to plant control devices.

PID uses three basic control behaviors:

P- Controller:

Proportional or P- controller gives output which is proportional to current error e (t). It compares desired or set point with actual value or feedback process value. The resulting error is multiplied with proportional constant to get the output. If the error value is zero, then this controller output is zero.

This controller requires biasing or manual reset when used alone. This is because it never reaches the steady state condition. It provides stable operation but always maintains the steady state error. Speed of the response is increased when the proportional constant K_P increases.

PI- Controller

Due to limitation of p-controller where there always exists an offset between the process variable and set point, I-controller is needed, which provides necessary action to eliminate the steady state error. It integrates the error over a period of time until error value reaches to zero. It holds the value to final control device at which error becomes zero.

Integral control decreases its output when negative error takes place. It limits the speed of response and affects stability of the system. Speed of the response is increased by decreasing integral gainK_i.

In above figure, as the gain of the I-controller decreases, steady state error also goes on decreasing. For most of the cases, PI controller is used particularly where high speed response is not required.

While using the PI controller, I-controller output is limited to somewhat range to overcome the integral wind up conditions where integral output goes on increasing even at zero error state, due to nonlinearities in the plant.

PID-Controller

PI-controller doesn’t have the capability to predict the future behavior of error. So it reacts normally once the set point is changed. D-controller overcomes this problem by anticipating future behavior of the error. Its output depends on rate of change of error with respect to time, multiplied by derivative constant. It gives the kick start for the output thereby increasing system response. It improves the stability of system by compensating phase lag caused by I-controller. Increasing the derivative gain increases speed of response. So finally by combining these three controllers, we can get the desired response for the system.

3.5.1.2 Tuning Methods of PID Controller

Before the working of PID controller takes place, it must be tuned to suit with dynamics of the process to be controlled. Designers give the default values for P, I and D terms and these values couldn't give the desired performance and sometimes leads to instability and slow control performances. Different types of tuning methods are developed to tune the PID controllers and require much attention from the operator to select best values of proportional, integral and derivative gains. Some of these are given below.

Trial and Error Method: It is a simple method of PID controller tuning. While system or controller is working, we can tune the controller. In this method, first we have to set K_i and K_d values to zero and increase proportional term (K_p) until system reaches to oscillating behavior. Once it is oscillating, adjust K_i(Integral term) so that oscillations stops and finally adjust K_d to get fast response.

Process reaction curve technique: It is an open loop tuning technique. It produces response when a step input is applied to the system. Initially, we have to apply some control output to the system manually and have to record response curve.

After that we need to calculate slope, dead time, rise time of the curve and finally substitute these values in P, I and D equations to get the gain values of PID terms.

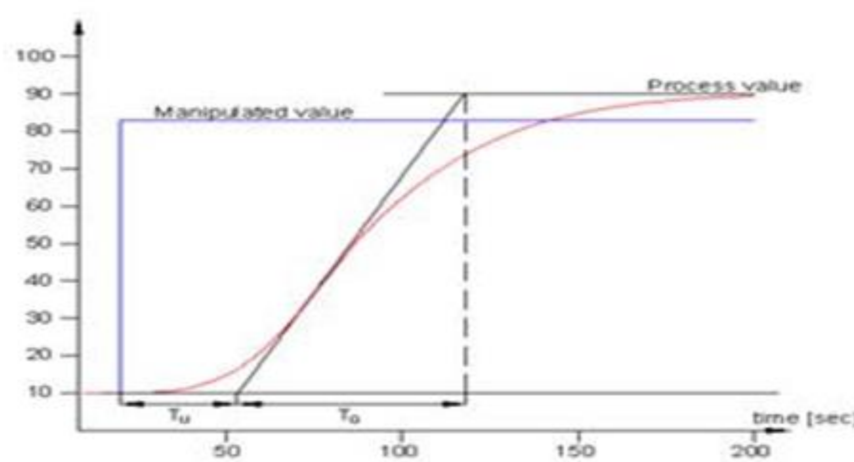

Fig 3-10: Process reaction curve [24]

Zeigler-Nichols method: Zeigler-Nichols proposed closed loop methods for tuning the PID controller. Those are continuous cycling method and damped oscillation method. Procedures for both methods are same but oscillation behavior is different. In this, first we have to set the p-controller constant, K_p to a particular value while $K_i$and $K_d$values are zero. Proportional gain is increased till system oscillates at constant amplitude.

Gain at which system produces constant oscillations is called ultimate gain (Ku) and period of oscillations is called ultimate period (Pc). Once it is reached, we can enter the values of P, I and D in PID controller by Zeigler-Nichols table depend on the controller used like P, PI or PID, as shown below in Table 3-1.

Table 3-1: Zeigler-Nichols table

Controller	k_c	Ti	Td
P	${k_u}/{2}$		
PI	${k_u}/{2.2}$	${p_u}/{1.2}$	
PID	${k_u}/{1.7}$	${p_u}/{2}$	${p_u}/{8}$

The parameter value for each controller is given in Table 3-2.

Table 3-2: PID controller parameters

Controller	Controller parameters		
	K_p	T_i	T_d
Level	2	1/3	3.3
Feed water valve	3	3.3	-
Pressure	15	1.25	-

3.5.2 Optimal Control Theory

Optimal control theory deals with the problem of finding a control law for a given system such that a certain optimality criterion is achieved.

It is an extension of the calculus of variations, and is a mathematical optimization method for deriving control policies. The method is largely due to the work of Lev Pontryagin and Richard Bellman in the 1950s, after contributions to calculus of variations by Edward J. McShane. Optimal control can be seen as a control strategy in control theory [25].

A control problem includes a cost functional that is a function of state and control variables. An optimal control is a set of differential equations describing the paths of the control variables that minimize the cost function.

3.5.2.1 Linear Quadratic Regulator

The theory of optimal control is concerned with operating a dynamic system at minimum cost. The case where the system dynamics are described by a set of linear differential equations and the cost is described by a quadratic function is called the LQ problem. One of the main results in the theory is that the solution is provided by the linear–quadratic regulator (LQR). The LQR is an important part of the solution to the LQG (linear–quadratic–Gaussian) problem. Like the LQR problem itself, the LQG problem is one of the most fundamental problems in control theory [25].

General description

The settings of a controller governing either a machine or process are found by using a mathematical algorithm that minimizes a cost function with weighting factors supplied by a human (engineer). The cost function is often defined as a sum of the deviations of key measurements, desired altitude or process temperature, from their desired values. The algorithm thus finds those controller settings that minimize undesired deviations. The magnitude of the control action itself may also be included in the cost function.

The LQR algorithm reduces the amount of work done by the control systems engineer to optimize the controller. However, the engineer still needs to specify the cost function parameters, and compare the results with the specified design goals. Often this means that controller construction will be an iterative process in which the engineer judges the "optimal" controllers produced through simulation and then adjusts the parameters to produce a controller more consistent with design goals.

The LQR algorithm is essentially an automated way of finding an appropriate state-feedback controller. As such, it is not uncommon for control engineers to prefer alternative methods, like full state feedback, also known as pole placement, in which there is a clearer relationship between controller parameters and controller behavior. Difficulty in finding the right weighting factors limits the application of the LQR based controller synthesis [26].

Derivation of linear quadratic regulator

The finite horizon, linear quadratic regulator (LQR) is given by [27].

$$\dot{x} = Ax + Bux \in \mathbb{R}^n \square, u \in \mathbb{R}^n, x_o given$$

$$\tilde{J} = \frac{1}{2}\int_0^T (x^T Qx + U^T Ru)dt + \frac{1}{2}x^T(T)P_1 x(T) \quad (3.11)$$

Where$Q \geq 0$,$R > 0$,$P_1 \geq 0$ are symmetric, positive (semi- definite) matrices.

In the finite-horizon case the matrices are restricted in that Q and R are positive semi-definite and positive definite, respectively. In the infinite-horizon case, however, the matrices Q and R are not only positive-semi definite and positive-definite, respectively, but are also constant. These additional restrictions on Q and R in the infinite-horizon case are enforced to ensure that the cost functional remains positive.

Solve via maximum principle:

$$H = x^T Qx + u^T Ru + \lambda^T(Ax + Bu)$$

$$\dot{x} = \left(\frac{\partial H}{\partial \lambda}\right)^T = Ax + Bux(0) = x_0$$

$$-\dot{\lambda} = \left(\frac{\partial H}{\partial x}\right)^T = Qx + A^T\lambda(T) = P_1 x(T)$$

$$0 = \frac{\partial y}{\partial x} = Ru + \lambda^T B \Longrightarrow U = -R^{-1}B^T\lambda \quad (3.12)$$

This gives the optimal solution. Apply by solving two point boundary value problems.

Alternative guess the form of the solution becomes $\lambda(t) = P(t)x(t)$. Then

$$\dot{\lambda} = \dot{P}x + P\dot{x} = \dot{P}x + P(Ax - BR^{-1}B^T P)x$$

$$-\dot{P}x - PAx + PBR^{-1}BPx = Qx + A^T Px \quad (3.13)$$

This equation is satisfied if we can find $P(t)$ such that

$$-\dot{P} = PA + A^T P - PBR^{-1}B^T P + QP(T) = P_1 \quad (3.14)$$

Remarks:

1. This Ordinary differential equation is called Riccati ODE.

2. Can solve for $P(t)$ backwards in time and then apply

$$u(t) = -R^{-1}B^T P(t)x. \tag{3.15}$$

This is a (time-varying) feedback control which tells us how to move from any state to the origin.

3. Variation: set T=∞and eliminate terminal constraint:

$$J = \int_0^\infty (x^T Q x + u^T R u) dt$$

$$u = -R^{-1}B^T P x = k \Longrightarrow \quad \text{P is constant.}$$

$$0 = PA + A^T P - PBR^{-1}B^T P + Q \tag{3.16}$$

This equation is called the algebraic Riccati equation. The Riccati controller allows tradeoff between regulation performance and control effort. It's regarded as a robust controller since it attains infinite marginal gain and offers a phase margin $\delta \geq 60^\circ$ which is aligned with practical guidelines for control system design. The resulting optimal feedback gain should drive the closed-loop system without external input from any initial state to the zero state minimizing the cost function

In MATLAB, the controller gain is obtained by typing:

$$K = lqr(A, B, Q, R) \tag{3.17}$$

Where A is the state matrix obtained from the state equation of the system in equation (3.5 to 3.8), B is the input matrix, and Q and R are weighting matrices chosen by trial and error until the optimal performance is obtained. The sample drum boiler dynamics state space matrices are taken from the plant data and it may vary for different plant because of its different operation conditions, measuring devices and so on. This thesis focused mainly to analyze and compare the performance of the system for given plant data using the present classical controller and an optimal controller.

Calculation of the values of state space matrices A, B, C and D can be performed by linearization of the nonlinear model at typical operating points of the drum whose state algebraic equations can be summarized into the generalized description in equation (3.18).

$$\dot{\mathrm{x}} = f(\mathrm{x}, \mathrm{u})$$

$$y = g(\mathrm{x}, \mathrm{u}) \tag{3.18}$$

The matrices are computed with the help of Taylor series approximation as seen in equation (3.19).

$$a_{ij} = \frac{\partial f_i}{\partial x_j}\bigg|\, x_{o,}u_o \qquad , b_{ij} = \frac{\partial f_i}{\partial u_j}\bigg|\, x_{o,}u_o$$

$$c_{ij} = \frac{\partial g_i}{\partial x_j}\bigg|\, x_{o,}u_o, d_{ij} = \frac{\partial g_i}{\partial u_j}\bigg|\, x_{o,}u_o, \qquad (3.19)$$

Where x_o and u_o are state and input value at equilibrium point respectively.

The resulting linearized model can be described in state-space form of equation (3.20) given below.

$$\dot{\mathrm{x}} = \mathrm{Ax} + \mathrm{Bu} + \mathrm{GZ}$$

$$\mathrm{y} = \mathrm{Cx} + \mathrm{Du} \qquad (3.20)$$

Where G is the disturbance matrix, Z is disturbance parameter.

Choosing the values of ***Q*** and ***R*** matrices in principle is similar to tuning of PID-controller parameters where the weighting matrices are varied until a satisfactory response is reached. Tuning a Riccati controller first carries investigations concerning the range of values for each system state and actuating variable. Once these limits are established, an initial guess can take place by constructing diagonal matrices with the normalized values as seen in equation (3.21)

$$Q = \begin{bmatrix} q_{11} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & q_{nn} \end{bmatrix}, R = \begin{bmatrix} r_{11} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & r_{nn} \end{bmatrix}$$

$$q_{ii} = \frac{1}{\sqrt{x_i^{max}}}, r_{ii} = \frac{1}{\sqrt{u_i^{max}}}, i = 1,2,3, \dots., n \qquad (3.21)$$

The state space matrices and weight matrices used in thesis are presented on appendix (C).

3.5.2.2 Neural Network State Estimator

Online estimation of state variables that are difficult or expensive to measure has been a widely studied problem. But those measurements are needed in a variety of engineering applications such as condition monitoring, fault diagnosis and process control. An observer can be designed to produce an estimate $x^{\wedge}(k)$of the state $x(k)$ by making use of relevant process inputs, outputs and process knowledge in the form of mathematical model. The design of any good state estimator necessitates the development of a nonlinear model of the plant [28].

Applications of neural network

An artificial neural network is an information processing paradigm that composed of large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. Basically, the most applications of neural networks fall into the following categories;

- Prediction: use input values to predict some output in future
- Classification: use input patterns to determine the classification
- Data association: similar to classification, but it also recognizes data that contains errors.
- Data conceptualization: analyze the inputs so that grouping relationships can be inferred
- Data filtering: smooth an input signal, or noise reduction
- Process modeling and control: creating a neural network model for physical plant then using that model to determine the best control setting for the plant

Operations of a Single Artificial Neuron

The basic model of a single artificial neuron consists of a weighted summer and an activation function as shown in Fig 3-11.

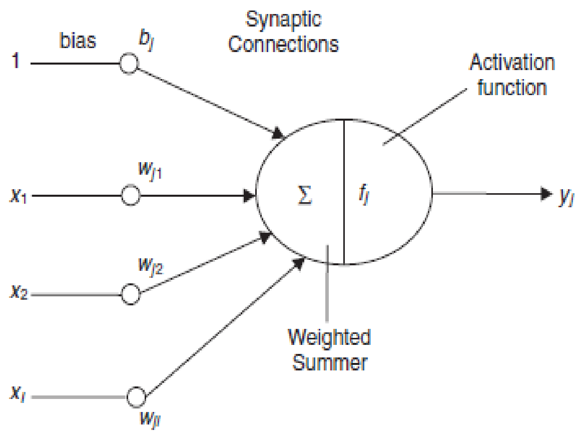

Fig 3-11: Basic model of a single artificial neural network [28]

The figure shows a neuron in the j^{th} layer, where

1. x_1……..x_j are inputs
2. w_{j1}…….w_{ji} are weights
3. B_j is a bias
4. F_j is the activation function
5. y_j is the output

The weighted sum s_j is therefore

$$S_j(t) = \sum_{i=1}^{N} w_{ji} x_i(t) + b_j \qquad (3.22)$$

Equation (3.18) can be written in matrix form

$$S_j(t) = W_J X + b_j \qquad (3.23)$$

The activation function f(s) (where s is the weighted sum) can take many forms such as hard limit (hardlim), logsig, tansig, purlin etc.

The output signal y_j is obtained as

$$y_j = f(s_j) \qquad (3.24)$$

Learning in neural network

Learning in the context of neural network is the process of adjusting the weights and biases in such a manner that for given inputs, the correct responses, or outputs are achieved. Learning algorithms include:

1. Supervised learning: the network is presented with training data that presents the range of input possibilities, together with the associated desired outputs. The weights are adjusted until the error between the actual and desired outputs meets some given minimum value.
2. Unsupervised learning: also called open-loop adaption because the technique does not use feedback information to update the networks parameter

In this thesis, an approach to design an artificial neural network with a feed forward architecture to estimate the state of a nonlinear drum boiler dynamic system has been applied. The training data are taken from the plant and trained with back propagation learning algorithms.

Back Propagation Algorithms

Back propagation was created by generalizing the Widrow-Hoff learning rule to multiple layer networks and nonlinear differentiable transfer functions. Input vector and corresponding output vectors are used to train a network until it can approximate a function, associate the input vectors or classify input vectors in an appropriate way as defined by the user. A very valuable consequence of this definition is that every continuous function is Borel-measurable [29] [30]. Hence every linear or nonlinear continuous function is realizable with a feed forward sigmoid neural network.

The back propagation learning rules are used to adjust weights and biases of networks to minimize the sum squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect error. This is called a gradient descent procedure. Change in each weight and bias are proportion to the effect of that element on the sum squared error of the network.

Trained back propagation networks tend to give reasonable answers when presented with inputs that they have never seen, if these inputs are similar to training data. This generalization property makes it possible to train a network on a representative set of input/ target pairs and get good results for new inputs without training the network on all possible input/output pairs.

In this work the plant state parameter values are obtained at equilibrium condition and the controller is designed to keep those variables at their desired value shown in Table 3-1.

Table 3-3: Drum-boiler operating points

Operation at equilibrium	State parameters				Input parameters	
	$P(bar)$	$V_{wt}(m^3)$	$\alpha_r(\%)$	$V_{sd}(m^3)$	$q_f(\frac{kg}{s})$	$q_s(\frac{kg}{s})$
Value	5.5	20.391	0.0138	1.067	6	6

Chapter Four

4. ANN System Design and Simulation Study

4.1 Introduction

In this chapter, parameters used for evaluating the performance of the designed controller are introduced. After the formation of the sets of the initial conditions, the results of the performed simulations are presented in the form of figures. Finally, the results will be discussed for comparison between conventional PID and neural network based linear quadratic regulator controller.

4.2 MATLAB SIMULINK Model

Models for the three different conditions of obtaining drum pressure and level outputs are designed on matlab/simulink library. Model of plant without controller which generates open loop response for non-linear dynamics of boiler drum is designed. Secondly plant model with PID controller is designed. Finally model which linearize the plant dynamics and generate expected state parameters'(neural network estimator) and better track the response making the error signal close to zero (LQR) as discussed earlier in section (3.6.2) is designed. The outputs of each model are observed and described in section (4.3) for different time intervals such that at stating, the system response shows the transient response which determines the stability of the system and speed of response. As time goes increasing the result shows the steady state response and which determines the accuracy of the system.

4.2.1 Boiler Drum Model

Mathematical modeling of the drum dynamics presented on section (3.5) is generated by writing code on matlab. The boiler drum model is designed on MATLAB/SIMULINK environment as shown in Fig 4-1 below.

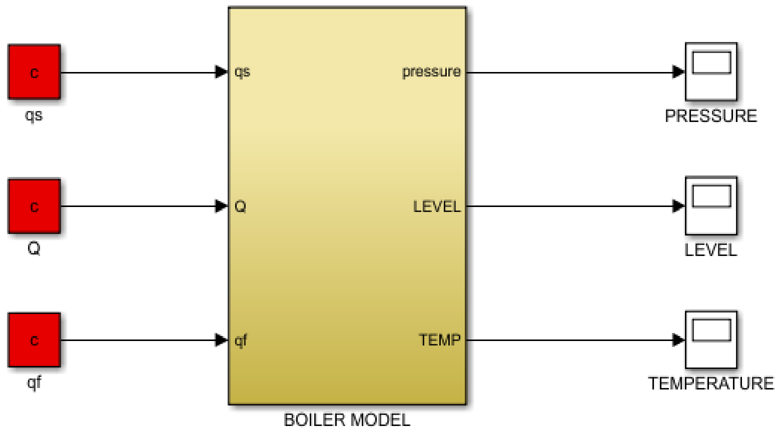

Fig 4-1: Block diagram of boiler drum model

The manipulated variables $q_s$and q_f are given to the plant (drum) as input and the output parameters are pressure and level. The third input parameter is the heat flow rate ($\dot{Q}$) which is the rate of heat transfer to the liquid surface from hot gas produced inside the furnace or evaporator. MATLAB script for the boiler drum model is presented on (appendix D1).

Derivation of heat flow rate

In thermodynamics, heat transfer takes place between systems undergoes change of process from one equilibrium state to another.

The basic requirement for heat transfer is the presence of a temperature difference. The tempe rature difference is the driving force for heat transfer.Conduction is the transfer of energy fro m the more energetic particles of a substance to the adjacent less energetic ones as result of int eractions between the particles. The rate of heat flow between two systems is measured in watt (joules per second) and calculated by:

$$\frac{\Delta Q}{\Delta t} = -kA\frac{\Delta T}{x}, \tag{4.1}$$

Where $\frac{\Delta Q}{\Delta t}$ is the heat flow rate, ΔT = T2 – T1 is temperature difference across the wall, k is thermal conductivity factor of metal, A is the surface area of contacts, and *x* is the thickness of material. T2= temperature of steam/water mixture inside the drum and T1=external temperature applied

4.2.2 Open Loop Plant model with Actuators and Valves

The overall open loop plant model with its actuators and control valves is shown in Fig 4-2. The input variables q_s and q_f are generated from the steam control valve and feed water control valve respectively and these valves are driven by electrical motors. The electrical motors are also excited by the difference of reference input signal to the system and the output signal back to the system using feedback elements. Feed water pump used to drive water to the drum and it is kept open.

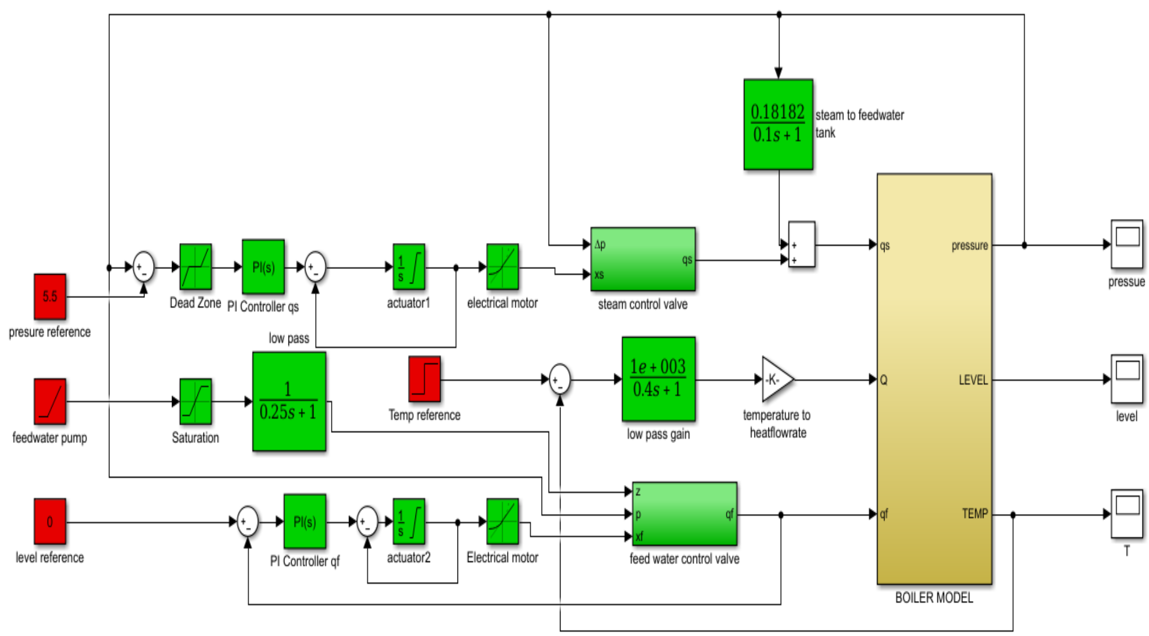

Fig 4-2**:** Block diagram of boiler drum model with actuators and valves

Block diagram description

1. Steam Drum

A steam drum is a standard feature of a water-tube boiler inside which the water stored evaporated and changed to steam. The magnitude of input variables can determine the water level and pressure of the drum. The difference in densities between hot and cold water helps in the accumulation of the "hotter"-water/and saturated-steam into the steam-drum. The saturated steam is drawn out from the top section of the drum called drum outlet. The steam and water mixture enters the steam drum through riser tubes; drum internals consisting of demister separate the water droplets from the steam producing dry steam.

2. Steam control valve

The steam outlet valve is used to control the flow of saturated steam outgoing to the super heater or process. Most often butterfly valve is preferable for pressure control systems because it can be used for isolating or regulating flow. The closing mechanism takes the form of a disk. Operation is similar to that of a ball valve, which allows for quick shut off. Butterfly valves are generally favored because they are lower in cost to other valve designs as well as being lighter in weight, meaning less support is required. The disc is positioned in the center of the pipe; passing through the disc is a rod connected to an actuator on the outside of the valve. Rotating the actuator turns the disc either parallel or perpendicular to the flow.

3. Feed-Water Pump

A boiler feed-water pump is a specific type of pump used to pump feed-water into a steam boiler. These pumps are normally high pressure units that take suction from a condensate return system and can be of the centrifugal pump type or positive displacement type.

Feed-water pumps range in size up to many horsepower and the electric motor is usually separated from the pump body by some form of mechanical coupling. Large industrial condensate pumps may also serve as the feed-water pump. In either case, to force the water into the boiler, the pump must generate sufficient pressure to overcome the steam pressure developed by the boiler. This is usually accomplished through the use of a centrifugal pump. Another common form of feed-water pumps run constantly and are provided with a minimum flow device to stop over-pressuring the pump on low flows [31].

4. Feed-Water Control Valves

The feed-water control valve performs the critical function of controlling the feed-water flow rate over a wide range of service conditions from mild to severe. During normal operation, the feed-water control valve controls near the full-open position, and the pressure drop across the valve is small. During startup and shutdown the feed-water control valve restricts feed-water flow by controlling near the closed position. The pressure drop across the valve is high, which can cause severe capitations and noise. Over time, these severe service conditions will damage a control valve unless the valve is designed to withstand them. Even a properly designed valve will not work well unless it is connected to a correctly sized actuator.

5. Electric Motor

Electric motors are used to produce linear or rotary force (torque). In the block above, electric motors are used for opening and closing of the mass flow valves with the actuator. An actuator is a component of a machine that is responsible for moving or controlling a mechanism or system. An actuator requires a control signal and a source of energy. The control signal is relatively low energy and may be electric voltage or current, pneumatic or hydraulic pressure, or even human power. The supplied main energy source may be electric current, hydraulic fluid pressure, or pneumatic pressure. When the control signal is received, the actuator responds by converting the energy into mechanical motion. An electric actuator is powered by a motor that converts electrical energy into mechanical torque. The electrical energy is used to actuate equipment such as multi-turn valves. It is one of the cleanest and most readily available forms of actuator because it does not involve oil.

6. Low pass filter

Practically the measurement sensors produce noise at high frequency which is an unwanted disturbance in an electrical signal. Different types of noise are generated by different devices and different processes. For instance thermal noise is unavoidable signal generated by process at non-zero temperature. This noise gets amplified due to the derivative action leading to very large unusable controller output. Low pass filters are used to attenuate high frequency noise. A filter is a frequency discriminating electrical network which passes one band of frequencies while rejecting others. By so doing, it alters the amplitude and phase characteristics of a signal with respect to frequency. It changes the relative amplitudes of the various frequency components and/ or their phase relationships.

Low pass filters permit all signals of frequencies below a cut-off frequency, fc to pass through them while others above that frequency are rejected. Three low pass filters are used with cutoff frequency of 10, 5 and 2.5 rad/sec. To ensure optimal performance, the immunity of a system to noise effects must be high. For optimal performance, circuit parameters are adjusted to achieve minimum noise.

7. Saturator

In electronics , a limiter is a circuit that allows signals between specified input power or level to pass unaffected while attenuating (lowering) the peaks of stronger signals that exceed this threshold. Saturator is used to prevent bursting of feed water valve due to higher difference between drum pressure and feed water pump pressure. The feed water are kept at high pressure, saturation takes place when reaching maximum capacity of valve and are commonly used as a safety device.

8. Dead zone

The dead zone block generates zero output within a specified region. We can specify the lower limit (LL) and upper limit (UL) of the dead zone as the start of dead zone and end of dead zone parameters, respectively. The block output depends on the input (U) and the values for the lower and upper limits. The upper limit and lower limits are adjusted to avoid frequent oscillation near pressure set point.

4.2.3 Plant with PID Controller

The drum pressure and water level set values should be always kept constant. Each output is controlled with its separate decoupled control loop, without considering any sort of interaction between both outputs. The complete plant model with PID controller is shown in Fig 4-3.

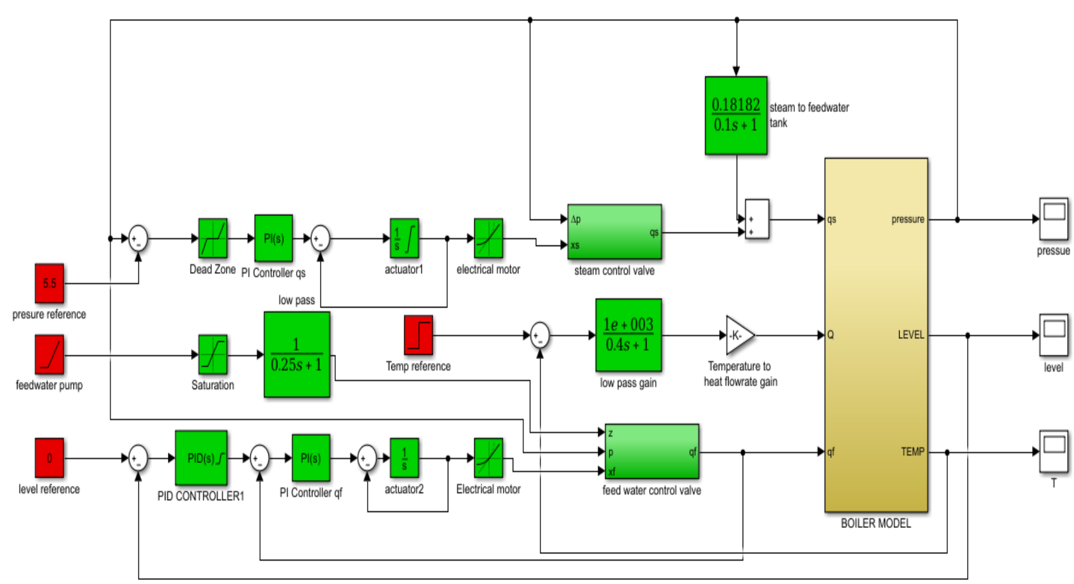

Fig 4-3**:** System model with PID controller

The level controller currently implements the 2-element structure, which employs a cascaded control architecture using level and feed-water flow rate as process variables.

The outer loop compares the current level with the specified reference; the computed error signal generates using a PID controller the new set value for feed-water flow rate. The inner loop analyzes the current flow with the amount established by the outer loop, in order to adjust accordingly the control valve percentage opening using a PI-controller.

The pressure controller senses the pressure decrease within the drum as less heat is being supplied, thus it tries to close the butterfly valve to restore pressure back to its set point. Once the valve starts closing, the water level drops due to the shrinking effect of steam bubbles.

The controllers react on the pressure rise within the drum caused by the additional heat supplied, therefore opening the corresponding valve to relief drum pressure allowing more steam to leave from the drum outlet in the process.

4.2.4 Artificial Neural Network Model

The state estimation problem is addressed using artificial neural networks seen in section (3.6.2.2). The derived neural network estimator gives state estimates during the system is subjected to unknown noises and parameter variations. A feed forward state estimator neural network is modeled in matlab as indicated in Fig 4-4.

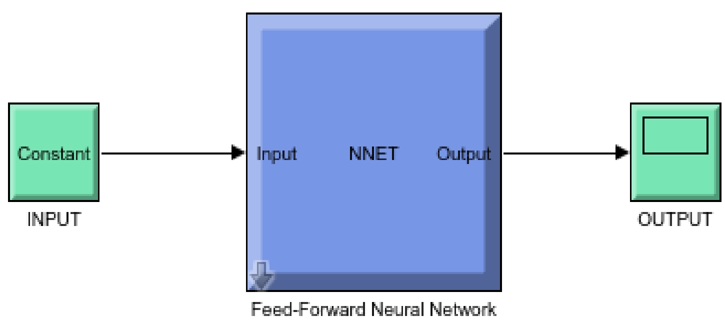

Fig 4-4: Neural network state estimator model

The input signals to boiler drum such as; steam flow rate (q_s), feed water flow rate (q_f) and heat flow rate ($\dot{Q}$), the drum output pressure (p) and drum water level (l) are used as input to the neural network and the estimated outputs: p,V_{wt} ,α , and V_{sd} are obtained from the neural network model and given to the plant as state parameters. A two layer feed forward artificial neural network algorithm was developed as seen in Fig 4-5. The front page and validation test blocks of two layer feed forward neural network are presented on appendix (E)

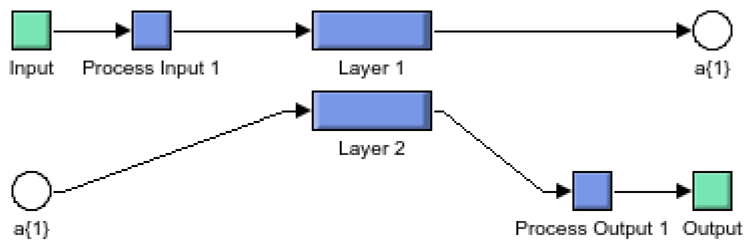

Fig 4-5: Block diagram representation of two layer feed forward NN estimators

4.2.5 Simulation Model of Drum Integrated with Neural Network Estimator

After designing the boiler drum open loop model and neural network models, the two models are integrated together to get the linearized state parameters approximations used for state feedback control system as shown in Fig 4-6.

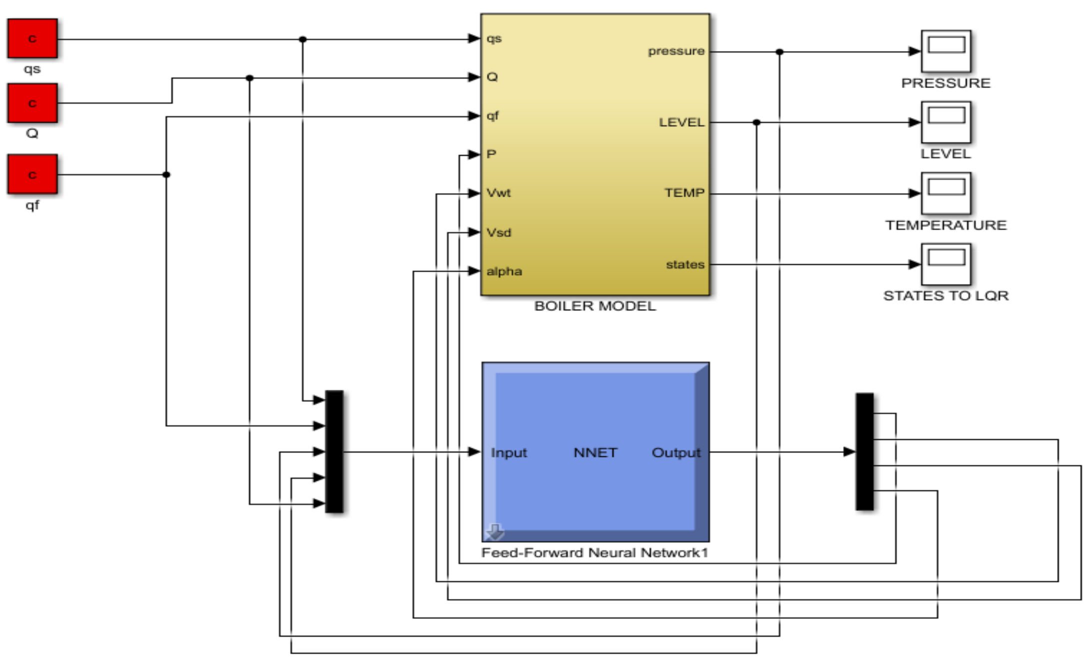

Fig 4-6: plant model integrated with neural network estimator

The three input (q_s,q_f,$\dot{Q}$) and the two output (P,L) of the plant model are given as input to the neural network estimator and four outputs from the estimator are feedback to the plant model as feedback state variables.

4.2.6 Plant with NN Estimator and LQR Controller

The final simulation model of the system with neural estimator and LQR is modeled by combining models of each of the three parts that are boiler drum model, neural network state estimator model and LQR model together. Fig 4-7 presents the combined model of the system with its controller. The states of plant is given to the LQR controller, which is an optimal control regulator that better tracks a reference trajectory by predicting future outputs at every time step in order to minimize a global criterion/cost function. By estimating future outputs based on past outputs, we are able to better regulate offset in tracking. In this design LQR is used to track the level and pressure response to their set point. The output level, pressure and temperature are then with the closed loop system.

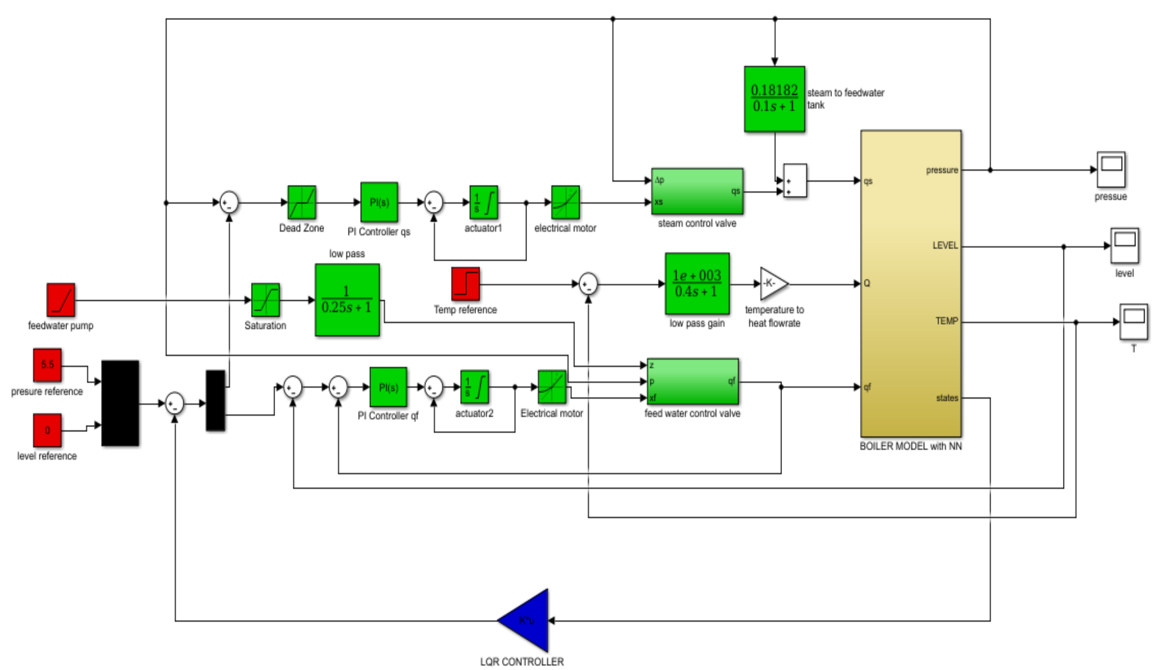

Fig 4-7**:** Optimal control design model with NN and LQR

4.3 Result Analysis

4.3.1 Open Loop Response

The open loop plant model is simulated with MATLAB by applying an external heat source of 450 degree kelvin to the system and the system response is analyzed below.

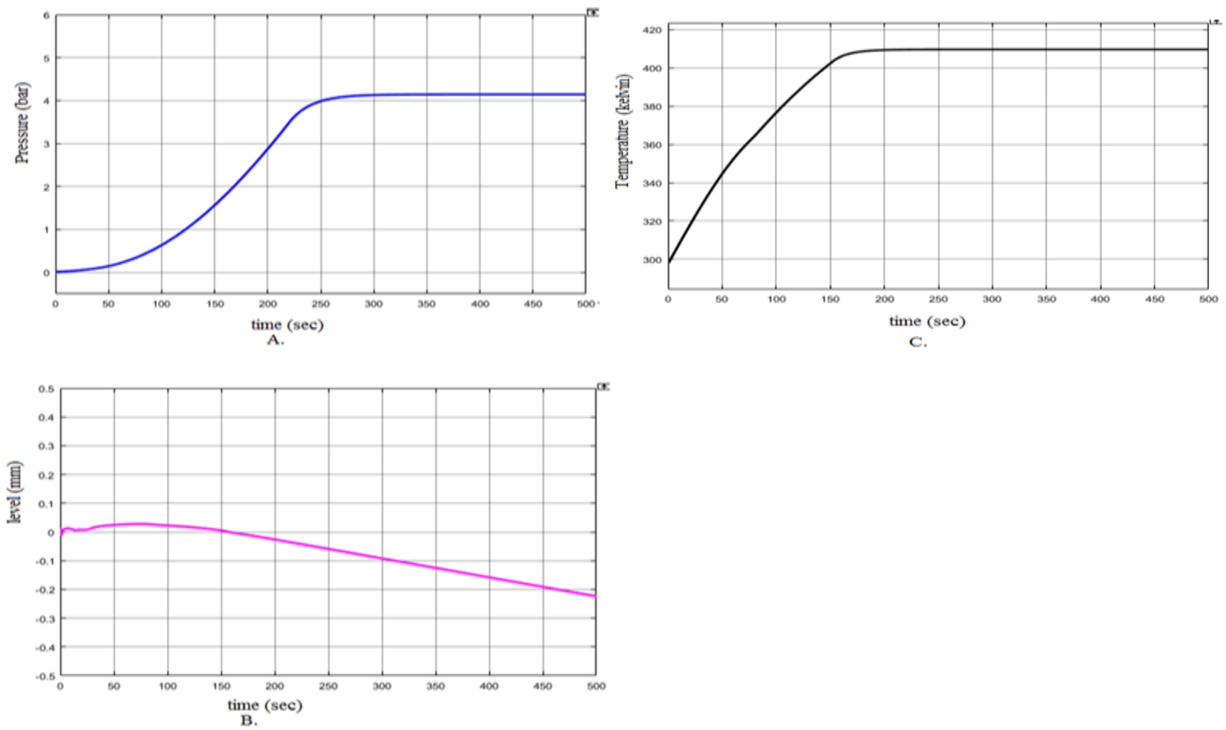

Fig 4-8:Transient response of open loop plant model (A) pressure, (B) level, (C) temperature

Fig 4-8 (A) indicates pressure starts from zero because there is no heat supply to the system, pressure decreases to zero. When applying, Fig 4-8 (C) indicates that temperature inside the drum increases linearly with time as input signal increases starting from 310 degree kelvin. The non-zero initial value at starting are inherited from feed water temperature developed by heating inside the economizer tubes before entering to the drum. The pressure controller senses the pressure within the drum as less heat is being supplied initially, thus it tries to close the steam control valve to restore pressure back to its set point. Pressure grows up to 4.2 bar as step input temperature increases from zero to 450 K. Water Level in Fig 4-8 (B) starts from zero reference value and increases slightly at starting with low heat transfer to the drum and reaches to 0.04 mm at time t=74 sec., and then decrease down when internal temperature indicated in Fig 4-8 (C) increases. Then pressure increases and once the steam valve starts closing, the water level *l* drops due to the shirking effect of steam bubbles. PI controller is placed to regulate the mass flow rates and maintain stability of the system. Increasing time to infinity yields the result indicated on Fig 4-9, the pressure graph (A) reaches its steady state value of 4.2 bar, but the water level (B) goes to negative value implying the drum is going be to empty. Also it can be noted that even the pressure becomes constant, level continues to fall down. This is due to the nonlinear properties of the drum dynamics as well as the temperature rise due to fuel gas flame surrounding the drum and its water tubes make water to evaporate. The level response depends on a combination of complicated dynamics related to distribution of water and steam. The drum temperature rise to 412 degree and becomes constant.

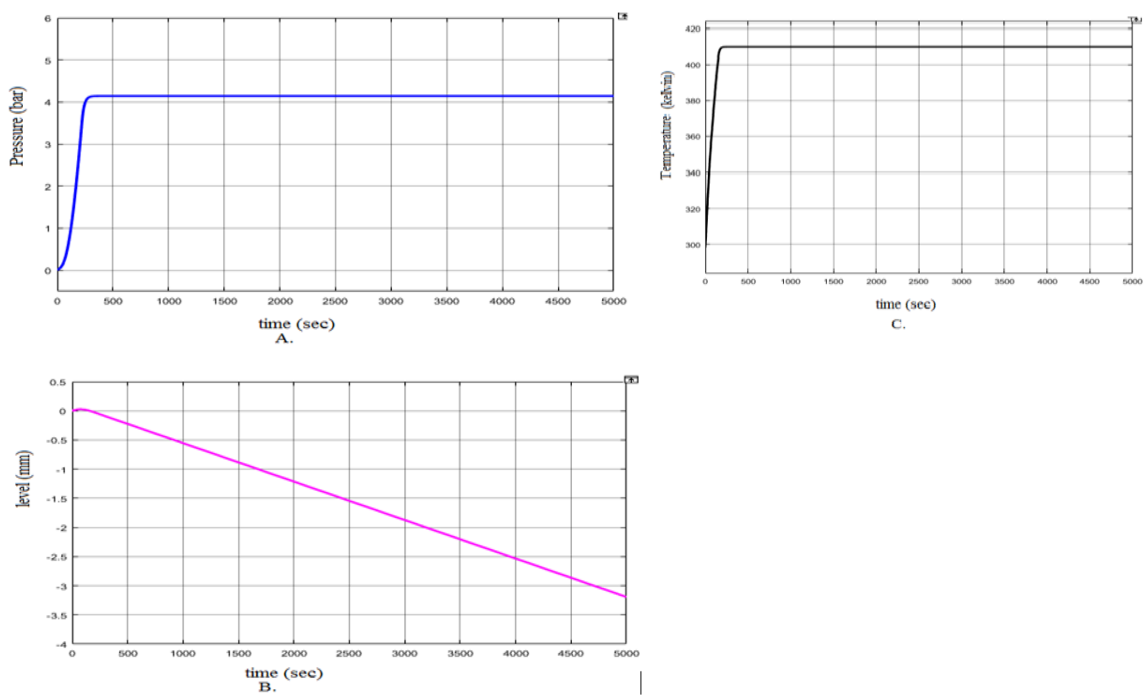

Fig 4-9: Simulation result for open loop plant model for increasing time to 50000 sec. (A) pressure, (B) level, (C) temperature

Effect of temperature on drum pressure and water level

The pressure law states that for a constant volume of gas in a sealed container the temperature of the gas is directly proportional to its pressure. This is due to the particles of gas in the container move with a greater energy when the temperature is increased. This means that they have more collisions with each other and the sides of the container and hence the pressure is increased. If V is a constant, then P/T will be a constant, Where V= Volume, P= Pressure and T= Temperature of the closed vessel.

Increasing the temperature increases evaporation of water due to water molecules move fast enough to escape their liquid state and become vaporous. The vapor steam floats above and thus the drum water level fall below the set point. Water level is inversely proportional with temperature. Increase the external input temperature increase drum pressure and decreases the water level and vice versa.

4.3.2 Response of Plant Model with PID Controller

To reduce the effect of non-linearity and to obtain a constant water level at the specified reference value, we need to design a controller. The classical PID controller was designed as described in section (4.2.3) and its response is simulated and validated here.

At starting time in Fig 4-10 (A), it is considered that there is no heat source applied to the system so that drum pressure drops to zero. The feed water control valve allows inflow of water inside the drum in full opening position thus the level graph starts from zero initially and grow up fast. As time increases, pressure response starts from zero initially and grows slightly with increasing temperature and level drops down after reaching the value of 0.16 mm. Increasing drum pressure, water control valve closes the water flow to the drum thus minimizing feed water flow rate. Since temperature inside the drum is increasing, water evaporates and changes to steam thus level of water decrease. The temperature graph also starts from 310 k at initially and grow up due to increase of external temperature so that heat transfer to the water steam mixture.

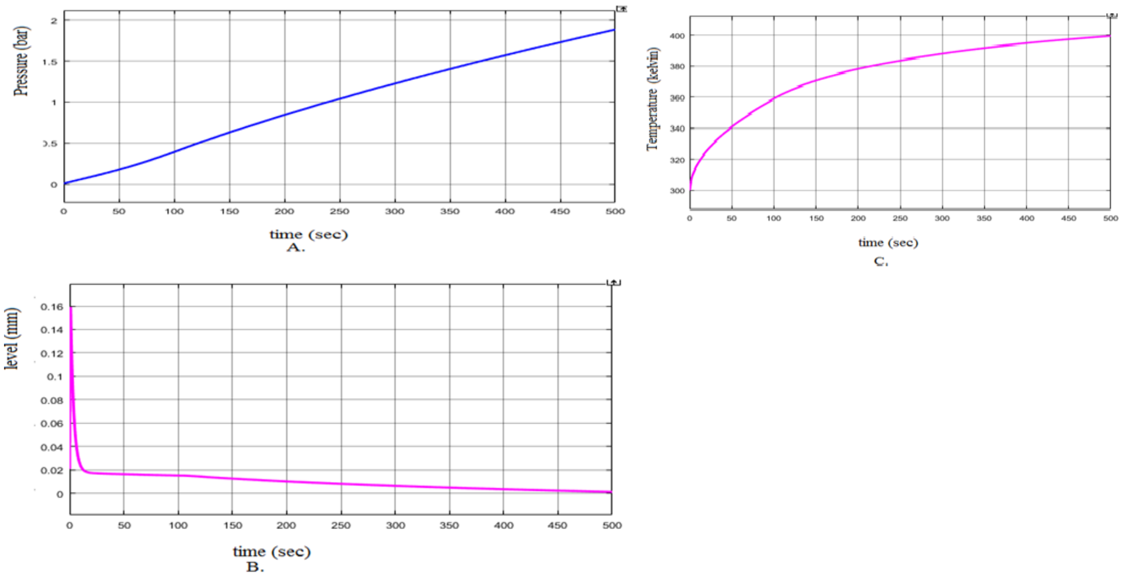

Fig 4-10:Transient response of plant model with PID controller (A) Pressure, (B) level, (C) temperature

When time goes high, pressure graph increases with some oscillation because of integral action and reaches to the steady state value of 5.45 bar and keeps constant at input temperature reaches to 450 kelvin. It is also shown that level graph drops but the PID controller take action to compensate the level by tracking to its set point. So that level again increase. It is observed from the result the limitation on PID control is that as time increases the response becomes oscillatory with slightly increasing amplitude and the response is slow. Temperature graph (C) follows pressure by increasing to its maximum value of 435 degree kelvin and stay constant.

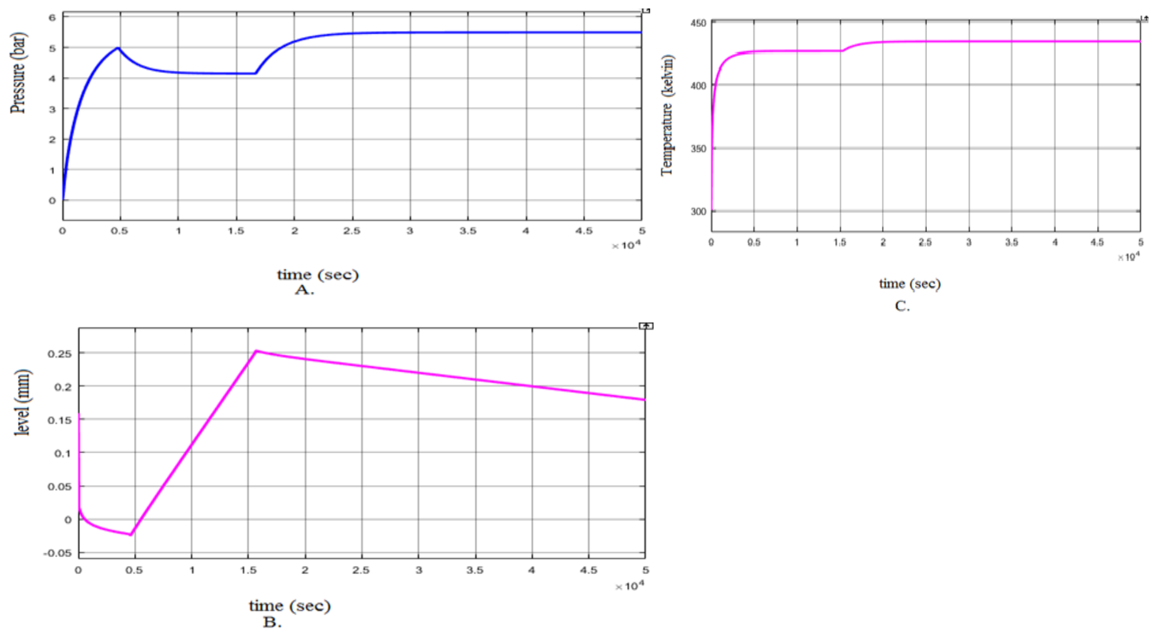

Fig 4-11: Steady state response of model PID controller at t=50000 sec. (A) pressure, (B) level, (C) temperature

4.3.3 Neural network validation test

An artificial neural network is designed by extracting data from open loop plant model and trained in feed forward neural network algorithms with back propagation learning approach. After training the neural network, the network validation is checked with input and state value which is never seen by the network during offline training. The input and actual state validation data are presented on Table 4-1.

Table 4-1: Neural network validation test input and plant actual state value

S. no	Input variables					Actual state value			
	Qs	Qf	P	L	Q	P	Vwt	alpha	Vsd
1	0.083011	0	5.500003	-0.0021	757388.6	5.500003	20.391	0.013781	1.072192
2	0.145467	0	5.50001	-0.00175	1361670	5.50001	20.391	0.013767	1.075542
3	0.281909	0	5.500046	-0.00188	2806337	5.500046	20.39099	0.013732	1.08358
4	0.568059	0	5.50029	-0.0021	6673027	5.50029	20.39097	0.013648	1.105329

5	0.800559	9.70E-05	5.501037	-0.00201	11636900	5.501037	20.39091	0.013557	1.134051
6	0.842765	0.000164	5.501347	-0.0019	12955751	5.501347	20.39089	0.013537	1.141925
7	0.984777	0.000184	5.505826	0.000719	21694576	5.505826	20.39066	0.013478	1.201237
8	0.991	0	5.507007	0.001504	22774165	5.507007	20.3906	0.013488	1.210847
9	0.99453	0	5.508095	0.002237	23556893	5.508095	20.39056	0.0135	1.218781
10	0.995561	0	5.508527	0.00253	23819918	5.508527	20.39054	0.013506	1.22174
11	0.999284	0.003524	5.510978	0.004198	24921720	5.510978	20.39044	0.013543	1.237115
12	1.006946	0.007956	5.54	0.01942	15792535	5.54	20.38916	0.013714	1.43237
13	1.006946	0.007956	5.54	0.01942	15792535	5.54	20.38916	0.013714	1.43237
14	1.022948	0.01435	5.542661	0.019581	13818399	5.542661	20.38897	0.013611	1.466906
15	1.473083	0.120547	5.551744	0.008276	5241260	5.551744	20.38744	0.012315	1.715205
16	1.581678	0.173278	5.552326	0.002855	4359752	5.552326	20.38698	0.011917	1.771522
17	1.809405	0.568009	5.552363	-0.02008	3432318	5.552363	20.38535	0.01061	1.920504
18	1.859905	1.197847	5.55191	-0.0357	3573146	5.55191	20.38464	0.009932	1.970319
19	1.865803	1.430444	5.551798	-0.03944	3628109	5.551798	20.38455	0.009789	1.976925
20	1.862341	7.589543	5.55047	-0.07794	4303771	5.55047	20.38724	0.008706	1.908808
21	1.855567	8.025431	5.550201	-0.08376	4427898	5.550201	20.3884	0.008598	1.875764
22	1.78035	8.463932	5.548887	-0.12528	-0.12528	5.548887	20.39883	0.007888	1.626041
23	2.159323	8.89264	5.547398	-0.26366	6446531	5.547398	20.76253	0.005198	1.02846

		2							2
24	2.321625	9	5.546834	-0.2414	6789400	5.546834	20.9113	0.00542	1.028172
25	2.737949	9	5.545389	-0.18221	7668917	5.545389	21.33803	0.006006	1.028695
26	3.735525	9	5.541927	-0.01102	9776449	5.541927	22.96314	0.00737	1.030022
27	3.767498	9	5.541816	-0.0034	9843998	5.541816	23.04978	0.007413	1.030063
28	4.861356	9	5.54149	0.020994	10042295	5.54149	23.33505	0.007539	1.030182
29	4.886081	9	5.541404	0.028049	10094531	5.541404	23.41967	0.007572	1.030213
30	5.924166	9	5.541272	0.03957	10174994	5.541272	23.55985	0.007623	1.030261

After applying the plant sample input data to network, neural network estimated the outputs those are the estimated state values and the error signal is calculated by subtracting estimated state value from actual state value as given in Table 4-2.

Table 4-2: Neural network estimated state value and error signal

S. no.	Estimated state value				Error=Actual state value -Estimated state value			
	P	Vwt	Alpha	Vsd	P	Vwt	Alpha	Vsd
1	5.499975	20.39228	0.013724	1.073302	2.78972E-05	-0.00128	5.68635E-05	-0.00111
2	5.500019	20.39099	0.013743	1.075665	-8.4297E-06	1.06E-05	2.40719E-05	-0.00012
3	5.500077	20.39096	0.013741	1.083732	-3.1298E-05	3.57E-05	-8.1324E-06	-0.00015
4	5.500321	20.39098	0.013707	1.10532	-3.1104E-05	-6.2E-06	-5.9326E-05	8.89E-06
5	5.501011	20.39086	0.013613	1.134018	2.55505E-05	4.67E-05	-5.6192E-05	3.28E-05
6	5.501313	20.39083	0.01358	1.141954	3.40345E-05	5.54E-05	-4.3753E-05	-2.9E-05
7	5.50588	20.3906	0.013431	1.201239	-5.4095E-05	5.12E-05	4.72579E-05	-2.1E-06
8	5.507044	20.39056	0.013455	1.210831	-3.615E-05	4.21E-05	3.24822E-05	1.59E-05
9	5.508104	20.39054	0.013486	1.218783	-9.0593E-06	1.9E-05	1.42102E-05	-1.6E-06
10	5.508524	20.39059	0.013499	1.221715	3.00589E-06	-4.6E-05	6.453E-06	2.58E-05
11	5.51091	20.39062	0.013573	1.237103	6.792E-05	-0.00017	-3.0884E-05	1.19E-05

12	5.540006	20.38918	0.013716	1.432403	-5.5272E-06	-2.3E-05	-2.621E-06	-3.3E-05
13	5.540006	20.38918	0.013716	1.432403	-5.5272E-06	-2.3E-05	-2.621E-06	-3.3E-05
14	5.542623	20.38887	0.013602	1.466922	3.82268E-05	9.8E-05	9.53377E-06	-1.6E-05
15	5.551766	20.38748	0.012319	1.715171	-2.2262E-05	-4.2E-05	-3.9201E-06	3.39E-05
16	5.552379	20.38708	0.011936	1.771474	-5.3213E-05	-0.0001	-1.9086E-05	4.79E-05
17	5.552397	20.38529	0.010625	1.920485	-3.4706E-05	6.35E-05	-1.5174E-05	1.88E-05
18	5.551832	20.38472	0.009922	1.970308	7.7744E-05	-8.3E-05	9.62186E-06	1.11E-05
19	5.5517	20.38464	0.009777	1.976964	9.87902E-05	-9.5E-05	1.15077E-05	-4E-05
20	5.550658	20.38713	0.008799	1.908838	-0.00018762	0.000111	-9.2629E-05	-3E-05
21	5.55015	20.38844	0.008584	1.875596	5.11867E-05	-3.9E-05	1.40881E-05	0.000168
22	5.550198	20.30982	0.007907	1.716685	-0.00131093	0.089001	-1.9086E-05	-0.09064
23	5.547337	20.76238	0.005212	1.02837	6.04662E-05	0.000156	-1.321E-05	9.19E-05
24	5.546756	20.91122	0.00544	1.028149	7.77584E-05	8.61E-05	-2.063E-05	2.36E-05
25	5.545413	21.33803	0.00601	1.028689	-2.4664E-05	3.74E-06	-4.3264E-06	6.11E-06
26	5.541931	22.96326	0.007376	1.030085	-4.153E-06	-0.00012	-5.3319E-06	-6.3E-05
27	5.541824	23.04995	0.007426	1.030155	-8.1089E-06	-0.00017	-1.2785E-05	-9.2E-05
28	5.54149	23.33421	0.007598	1.029649	-8.4756E-08	0.000834	-5.8813E-05	0.000534
29	5.541393	23.41785	0.007654	1.028973	1.13273E-05	0.001821	-8.146E-05	0.00124
30	5.541231	23.5552	0.007755	1.026764	4.16258E-05	0.004649	-0.0001318	0.003497

From table it is noticed that the maximum magnitude of deviation of estimated value from the actual plant state is: pressure error=0.00131, Vwt error=0.089001, Alpha error=0.00013 and Vsd error=0.09064. This implies estimated value is very close to the actual value that the neural network has learned the general behavior of the plant and is able to approximate the plant state parameters successfully.

4.3.4 Response of system with NN Estimator and LQR

Finally simulation result of the desired optimal controller for boiler drum water level control with neural network estimator and linear quadratic regulator is validated and presented on Fig 4-12.

Applying neural network estimator to the system helps to approximate the plant state parameters for non-linear system subjected to uncertainty and unknown parameter variations. The neural network is trained offline with feed forward algorithm and back propagation learning method. Then LQR is designed to track the level and pressure response to their desired set point. LQR improves the system performance by predicting future output based on past output and minimizing the control effort.

Fig 4-12 shows the system response: (A), pressure response of boiler rise up from zero with smooth response as input temperature increases and reaches steady state response of 5.45 bar. In Fig 4-12 (b), level graph start initially from zero and then drops to -0.00139 mm. Then it turns back with small oscillation and finally reaches its steady state value at 0.0322 mm. The oscillation resulted from non-linear complex drum dynamics; neural network reads the plant actual data and approximates state parameters by solving the estimation functions with offline trained data. Then LQR estimates the output level and pressure value, tracks the response toward desired point value of 0 and 5.5 respectively. In Fig 4-12 (C) it is shown temperature graph initially grow smoothly and after small oscillation, settles to 435 degree.

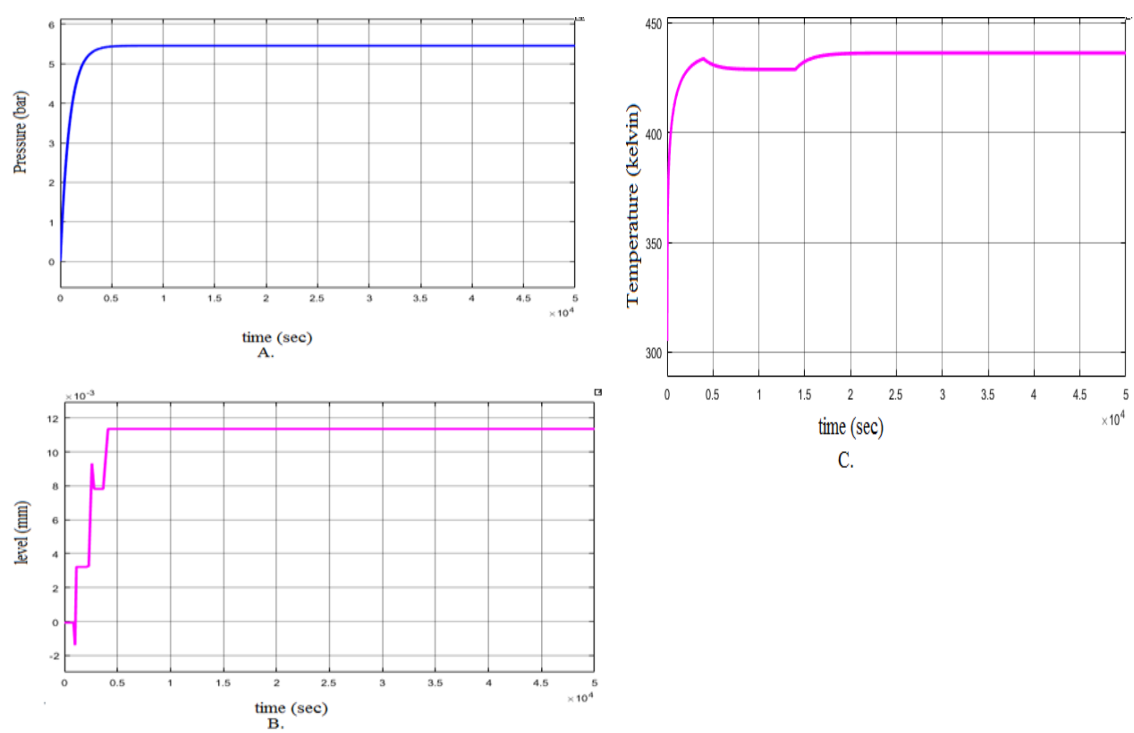

Fig 4-12**:** Simulation result for plant model with NN estimator based LQR controller. (A) Pressure, (B) level, (C) Temperature

4.4 Discussion

As observed from the results of open loop model response, pressure and temperature starts from zero and rise as external input is applied. The water level increases initially because no heat is applied to the drum and hence pressure inside the drum is zero, feed water valve compares the pressure difference between feed water pump and boiler drum and opens the feed water control valve. With increasing time, the drum pressure and temperature rise so the water level drops. Increasing the simulation time Fig 4-9 resulted pressure settle at 4.2 bar. The water level drops down and reached about -3.2 mm at t=50000 second. This implies level is falling down beyond the limit. When the level continues to fall, the drum might become empty and will be fired. Level of water is affected by other factors in addition to heat flow rate, keeps falling after pressure becomes constant.

Applying PID controller to the system in Fig 4-10 pressure first rises from zero and increases with increasing input temperature and level drops down. The result obtained in Fig 4-11 indicates pressure and internal temperature of reaches to their final value of 5.45 bar and 435 kelvin respectively. Level graph drops slightly and PID controller reacts to take action to return it to the set point. But the PID action is slow and oscillatory with slowly increasing amplitude. In practice PID controller is suitable for linear and single input single output (SISO) systems.

Finally the result indicated in Fig 4-12 shows applying an ANN and LQR controller yields pressure increases smoothly and settles to steady state value of 5.45 bar. Level and temperature graph increases with small oscillation and settle to their steady state value of 0.00322 mm and 436 degree kelvin respectively. ANN state estimator takes the plant data and generates the approximated state parameter and LQR controller tracks the system response to the set point.

Comparing result from model with PID controller and with neural network based LQR controller, the proposed controller has a good final response tracking and fast response. In this chapter negative sign indicates level is below the reference (zero) value.

Chapter Five

5. Conclusion and Recommendation for Future Works

5.1 Conclusions

This thesis described different types of steam boilers and their principle of operation. Water tube type steam boiler is selected because of its advantage of working under high pressure process like thermal power plant. Then different stages in steam generation and components used are listed and explained briefly.

Nonlinear mathematical model which describes the dynamical process of steam generation using steam drum boiler units and its control valves is implemented. PID controller is designed with the plant model and the pressure and water level performance of the drum analyzed.

The model is implemented within MATLAB/SIMULINK environment and examined intensively throughout various scenarios to ensure its validity and reliability. Further it is pointed out clearly the drawbacks of the existing control strategy.

Proposed optimal multivariable feedback control strategy designed to improve the process operation performance ensuring steady-state accuracy and set value tracking. Additionally a neural network state estimator, which guarantees good estimation of the state variables required for feedback is designed and realized.

Simulation results show that PID controller reaches its steady state value of pressure of 5.45 bar and water level oscillates about the set value with comparably slow response. The NN based LQR controller achieves steady state value of pressure and level value of 5.455 bar and 0.00322 mm respectively. Comparing the two controllers described, the proposed neural network based linear quadratic regulator achieved good performance.

5.2 Recommendation for future Works

The comparison results show that the proposed model can capture the drum dynamics to a great extent. However, a relatively small deviation from the set value is still noticed.
The error arises due to the assumptions made in order to simplify the complete process complex dynamics and simulation. Even though the deviation is existed, the model current response can be regarded as satisfactory.

To overcome the problems discussed, it's required to design an advanced and reliable controller which is able to solve the problems and achieve the exact desired point.

In the future, I recommend that the nonlinear model shall be realized within the real plant Distributed Control System (DCS) to act as an observer of the process, thus offering in return a great opportunity to test and examine the model more closely before being combined with the suggested state-feedback controller. From a practical perspective, the proposed strategy can be integrated in parallel with the existing controller, without many modifications within the DCS.

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Appendix

Appendix A: Nomenclature

A1: Physical units

Symbol	Unit	Description
A	m2	Area
C_p	J/kg K	Metal specific heat capacity
h	J/kg	Specific enthalpy
k_v	kg/hr	Valve sizing coefficient
m	kg	Mass
P	bar	Pressure
$\dot{Q}$	W	Heat flow rate
T_{sat}	◦C	Saturation temperature
V	m^3	Volume
V^o	m^3	Volume in hypothetical situation
T_d	s	Residence time of steam in drum
ρ_s	kg/m3	Steam Density
ρ_w	kg/m3	Water Density
q_s	kg/s	Steam flow rate
q_f	kg/s	feed water flow rate
q_r	kg/s	flow momentum in riser tube
V_{sd}	m^3	Steam bubble volume
V_t	m^3	Total drum volume
V_{wt}	m^3	Total water volume
h_s	J/kg	Specific enthalpy of steam
h_w	J/kg	Specific enthalpy of water
h_c	J/kg	Specific enthalpy of condensation

A2: Dimension less units

Symbol	Description
k	Friction coefficient
m	Head loss

x	Valve opening percentage
z	Compressibility factor
α_r	Steam-mass fraction
α_v	Steam-volume fraction
β	Empirical coefficient
ζ	Normalized length

APPENDIX B: Drum-boiler state equations coefficients

$$e_{11} = V_{wt}\frac{\partial \rho_w}{\partial p} + V_{st}\frac{\partial \rho_s}{\partial p}$$

$$e_{12} = \rho_w - \rho_s$$

$$e_{21} = V_{wt}\left(h_w\frac{\partial \rho_w}{\partial p} + \rho_w\frac{\partial h_w}{\partial p}\right) + V_{st}\left(h_s\frac{\partial \rho_s}{\partial p} + \rho_s\frac{\partial h_s}{\partial p}\right) - V_T + m_tC_p\frac{\partial t_{sat}}{\partial p}$$

$$e_{22} = \rho_w h_w - \rho_s h_s$$

$$e_{31} = \left(\rho_w\frac{\partial h_w}{\partial p} - \alpha_r h_c\frac{\partial \rho_w}{\partial p}\right)(1-\overline{\alpha}_v)V_r + \left(\rho_s\frac{\partial h_s}{\partial p} + (1-\alpha_r)h_c\frac{\partial \rho_s}{\partial p}\right)\overline{\alpha}_v V_r$$
$$+ (\rho_s + (\rho_w - \rho_s)\alpha_r)h_cV_r\frac{\partial \overline{\alpha}_v}{\partial x} - V_r + m_rC_p\frac{\partial t_{sat}}{\partial p}$$

$$e_{33} = \big((1-\alpha_r)\rho_s + \alpha_r\rho_w\big)h_cV_r\frac{\partial \overline{\alpha}_v}{\partial p}$$

$$e_{41} = V_{sd}\frac{\partial \rho_s}{\partial p} + \alpha_r(1+)V_r\left(\overline{\alpha}_v\frac{\partial \rho_s}{\partial p} + (1-\overline{\alpha}_v)\frac{\partial \rho_w}{\partial p} + (\rho_s-\rho_w) + \frac{\partial \overline{\alpha}_v}{\partial p}\right)\frac{1}{h_c}\left(\rho_sV_{sd}\frac{\partial h_s}{\partial p}\right.$$
$$\left. + \rho_wV_{wd}\frac{\partial h_w}{\partial p} - V_{sd} - V_{wd} + m_dC_p\frac{\partial t_{sat}}{\partial p}\right)$$

$$e_{43} = \alpha_r(1+\beta)(\rho_w+\rho_s)V_r\frac{\partial \overline{\alpha}_v}{\partial p}$$

$$q_{dc} = \sqrt{\frac{2\rho_w A_{dc(\rho_w-\rho_s)g\overline{\alpha}_v V_r}}{K}}$$

$$q_{ct} = \frac{h_w - h_{fw}}{h_c} q_f + \frac{1}{h_c}\left(\rho_w V_{wt} \frac{\partial h_w}{\partial p} + \rho_s V_{st} \frac{\partial h_s}{\partial p} - V_t + m_t C_p \frac{\partial t_{sat}}{\partial p}\right) \frac{dP}{dt}$$

$$q_r = q_{dc} - V_r \left(\overline{\alpha}_v \frac{\partial \rho_s}{\partial p} + (1 - \overline{\alpha}_v) \frac{\partial \rho_w}{\partial p} + (\rho_w - \rho_s) \frac{\partial \overline{\alpha}_v}{\partial p} \frac{dP}{dt}\right) + (\rho_w - \rho_s) V_r \frac{\partial y}{\partial x} \frac{dy}{dx}$$

$$\overline{\alpha}_v = \frac{\rho_w}{\rho_w - \rho_s}\left(1 - \frac{\rho_s}{(\rho_w - \rho_s)\alpha_r} ln\left(1 + \frac{\rho_w - \rho_s}{\rho_s} \alpha_r\right)\right)$$

$$\zeta = \alpha_r \frac{\rho_w - \rho_s}{\rho_s}$$

$$\frac{\partial \overline{\alpha}_v}{\partial \alpha_r} = \frac{\rho_w}{\rho_s \zeta}\left(\frac{ln(1+\zeta)}{\zeta} - \frac{1}{1+\zeta}\right)$$

$$\frac{\partial \overline{\alpha}_v}{\partial p} = \frac{1}{(\rho_w - \rho_s)^2}\left(\rho_w \frac{\partial \rho_s}{\partial p} - \rho_s \frac{\partial \rho_w}{\partial p}\right)\left(1 + \frac{\rho_w}{\rho_s(1+\zeta)} - \frac{\rho_w + \rho_s}{\rho_s \zeta} ln(1+\zeta)\right)$$

Appendix C: Sample state space and weight matrices

C1: State space matrices

$$A = \begin{bmatrix} -7.148e-5 & 1.051e-14 & 0 & 0 \\ -5.094e-11 & -9.723e-21 & 0 & 0 \\ 1.021e-9 & -2.684e-21 & -0.1827 & 0 \\ 1.752e-6 & 7.424e-18 & -297.3 & -0.3333 \end{bmatrix}$$

$$B = \begin{bmatrix} -21.09 & -216.6 \\ 0.001085 & -0.001255 \\ 5.386e-6 & 5.534e-5 \\ -0.01486 & 0.2023 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -4.86e-4 & 68.027 & 2035 & 68.027 \end{bmatrix}$$

C2: LQR weighting matrices

$$Q = \begin{bmatrix} 1.23e-12 & 0 & 0 & 0 \\ 0 & 0.25 & 0 & 0 \\ 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 1e-4 \end{bmatrix}$$

$$R = \begin{bmatrix} 50 & 0 \\ 0 & 150 \end{bmatrix}$$

APPENDIX D: MATLAB script

D1. Drum-boiler model MATLAB code

```
function [y1,Y2] = DrumBoiler_SWM (Q,qf,qs,P,Vwt,Alpha,Vsd)
Vd=20.204; %Drum volume (m3)
Vr=20; %Drum riser volume (m3)
Vdc=0.9; %Drum down-comer volume (m3)
Vt=Vd+Vr+Vdc; %Total drum volume (m3)
Ad=14.7; %Drum area (m2)
Adc=0.0637; %Down-comer area (m2)
mr=1300; %Riser mass (Kg)
md=1363; %Drum mass (Kg)
mt=mr+md+98888; %Total metal mass (kg)
K=25; %Friction coefficient in down-comer
Td=3; %Residence time of steam in drum(s)
Beta=0.3; %Empirical coefficient
Vsd0=2; %Steam bubbles volume in the hypothetical situation (m3)
Cp=550; %Metal specific heat capacity (Pascal.m3/Kg.K)
%% Liquid/Vapour mixture properties
P=P*1e-5; %Pascal to Bar
%% Temperature
Tfw=104; %Feed-water (C)
T_Sat=XSteam('Tsat_p',P); %Saturation (C)
dT_Sat_dP=IAPWS_IF97('dTsatdpsat_p',P*0.1) * 1e-6; %(K/Pa)
%% Density
rhoV=XSteam('rhoV_p',P); %Steam (Kg/m3)
rhoL=XSteam('rhoL_p',P); %Water (Kg/m3)
%Partial derivative with pressure
drhoL_dP=(2*P*0.0148-3.7836)*1e-5; %Water (Kg/J)
drhoV_dP=(2*P*0.0010+0.4450)*1e-5; %Steam (Kg/J)
%% Specific Enthalpy
```

```
hfW=XSteam('hL_T',Tfw)*1e3; %Feed water (J/Kg)
hL=XSteam ('hL_p',P)*1e3; %Water (J/Kg)
hV=XSteam ('hV_p',P)*1e3; %Steam (J/Kg)
hC=hV-hL; %Condensation (J/Kg)
%Partial derivative with pressure
dhL_dP=IAPWS_IF97('dhLdp_p',P*0.1)*1e-3; %Water (J/Kg.Pa)
dhV_dP=IAPWS_IF97('dhVdp_p',P*0.1)*1e-3; %Steam (J/Kg.Pa)
%% Coefficients Values
Eta=(Alpha*(rhoL-rhoV))/rhoV;
AlphaV=(rhoL/(rhoL-rhoV))*(1-((rhoV/((rhoL-rhoV)*Alpha))*log(1+(((rhoL-
rhoV)*Alpha)/rhoV))));
dAlphaV_dP=(1/((rhoL-rhoV)^2))*(rhoL*drhoV_dP-rhoV*drhoL_dP)*(1+(rhoL/(rhoV
*(1+Eta)))-(((rhoV+rhoL)*log(1+Eta))/(rhoV*Eta)));
dAlphaV_dAlpha=(rhoL/(rhoV*Eta))*(((1/Eta)*log(1+Eta))-(1/(1+Eta)));
qdc=sqrt((2*rhoL*Adc*(rhoL-rhoV)*9.81*AlphaV*Vr)/K);
Vwd=Vwt-Vdc-(1-AlphaV)*Vr;
%% State equations coefficients
e11=rhoL-rhoV;
e12=Vwt*drhoL_dP+(Vt-Vwt)*drhoV_dP;
e21=rhoL*hL-rhoV*hV;
e22=Vwt*(hL*drhoL_dP+rhoL*dhL_dP)+(Vt-Vwt)*(hV*drhoV_dP+rhoV*dhV_dP)-Vt +
mt*Cp*dT_Sat_dP;
e32=(rhoL*dhL_dP-Alpha*hC*drhoL_dP)*(1-AlphaV)*Vr+((1-
Alpha)*hC*drhoV_dP+rhoV*dhV_dP)*AlphaV*Vr+(rhoV+(rhoL-
rhoV)*Alpha)*hC*Vr*dAlphaV_dP-Vr + mr*Cp*dT_Sat_dP;
e33= ((1-Alpha)*rhoV + Alpha*rhoL)*hC*Vr*dAlphaV_dAlpha;
e42=Vsd*drhoV_dP+(1/hC)*(rhoV*Vsd*dhV_dP + rhoL*Vwd*dhL_dP-Vsd-Vwd +
md*Cp*dT_Sat_dP)+Alpha*Vr*(1+Beta)*(AlphaV*drhoV_dP + (1-
AlphaV)*drhoL_dP+(rhoV-rhoL)*dAlphaV_dP);
e43=Alpha*(1+Beta)*(rhoV-rhoL)*Vr*dAlphaV_dAlpha;
e44=rhoV;
```

```
%% State variables
dP_dt=(1/(e11*e22-e12*e21))*(e11*Q + qf*(hfW*e11-e21)+qs*(e21-hV*e11));
dVwt_dt=(1/(e11*e22-e12*e21))*(qf*(e22-hfW*e12)+qs*(hV*e12-e22)-e12*Q);
dAlpha_dt=(1/e33)*(Q-Alpha*hC*qdc-e32*dP_dt);
dVsd_dt=(1/e44)*(((rhoV/Td)*(Vsd0-Vsd))+((hfW-hL)*qf/hC)-e42*dP_dt-e43*dAlpha_dt);
Level=(Vwd+Vsd)/Ad-0.875;
%% Model outputs
Y1=[dP_dtdVwt_dtdAlpha_dtdVsd_dt];
Y2=[Level];
end
```

D2: Feed forward Neural Network code

```
%Artificial Neural Network for State Estimation of Drum Boiler
%10:5:1 structure of multilayer feed forward neural network training
dlc=ni'; % input training data
lo=no'; %output training data
net = feedforwardnet(10); %10 neuron input layer and 1 neuron_ output FFNN
%net = layrecnet(1:2,10);%Recurrent Neural Network
%net = elmannet(1:2,10);Elman Neural Network
net.layers{1}.transferFcn = 'tansig';%input layer activation transfer %function
net.layers{2}.transferFcn = 'purelin';%output layer activation transfer %function
net.divideFcn='dividetrain';
net = configure(net,dlc,lo);
net = init(net);
net.trainParam.min_grad = 1e-10;
net.trainParam.epochs = 1000;
%Neural Network Based level control of boiler drum level
disp('boiler level control system...');
net = train(net,dlc,lo);
%%%%%%%%%%%%%%%%%%%%%%%%%%%
gensim(net,-1);% Generate Simulink model of Feed forward Neural Network
```

APPENDIX E: nntraintool and validation test

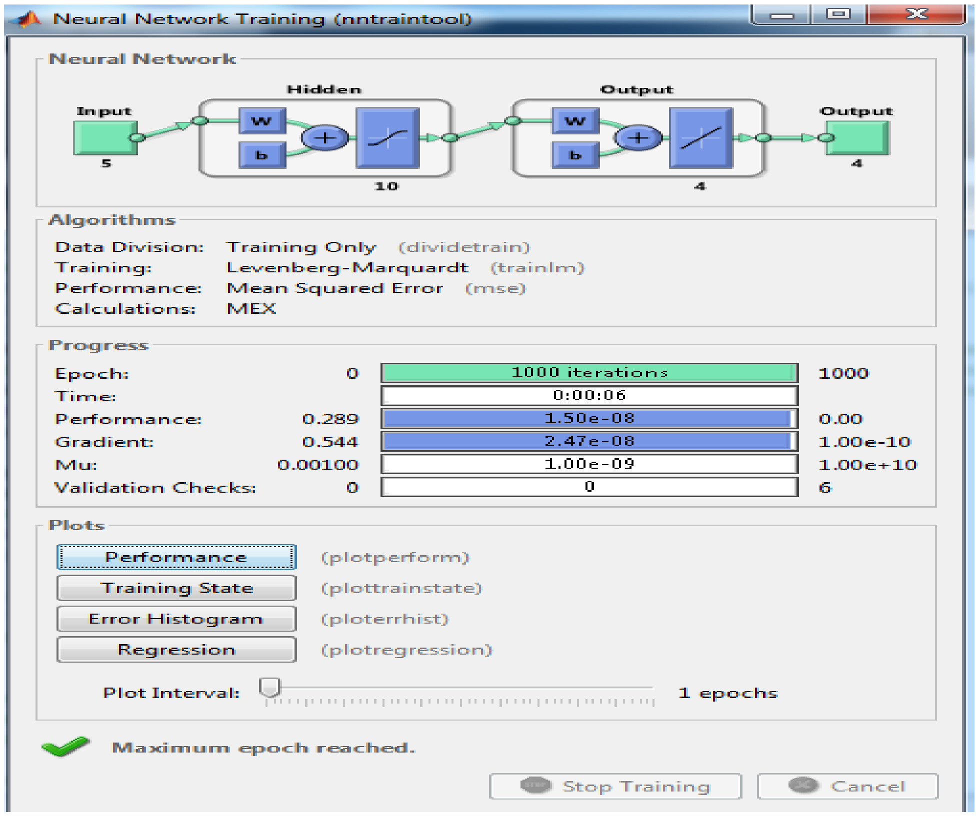

Fig E-1: Neural Network Training Front Page

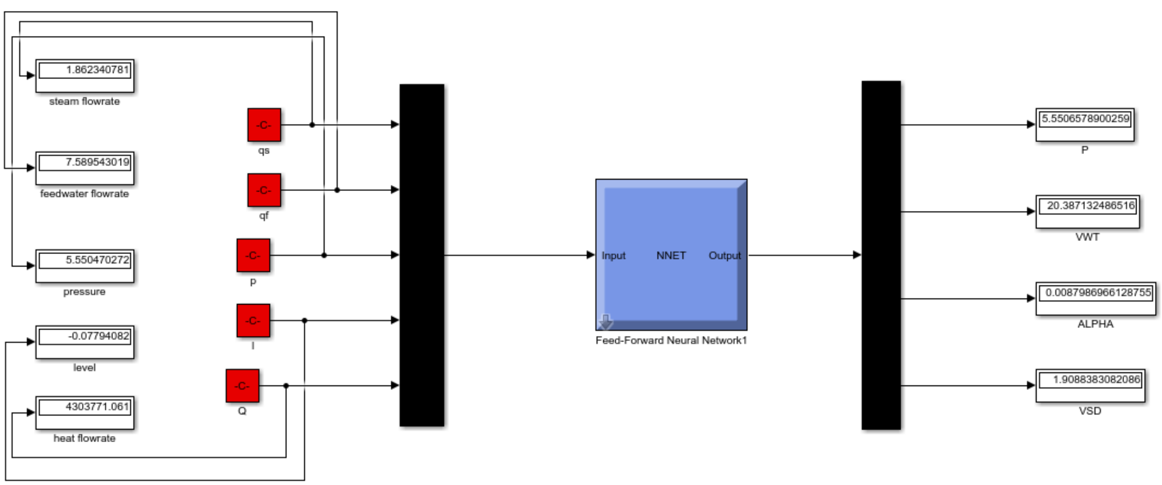

Fig E-2: Neural network validation test block diagram