TECHNICAL AND VOCATIONAL TRAINING INSTITUTE (TVTI)

School of Graduate studies

FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY

(DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

PERFORMANCE ANALYSIS OF RADIAL BASIS FUNCTION NEURAL NETWORK BASED MODEL PREDICTIVE CONTROL FOR BIOMASS BOILER PROCESS

MSc Thesis for the Partial Fulfillment of

Master of Science in Electrical Automation and Control Technology Management

By,

OUSMAN ESSA (MTR/769/13)

Supervisor,

Dr. SARAVANAKUMAR GURUSAMY

January, 2023

Addis Ababa, Ethiopia

Performance analysis of Radial Basis Function Neural Network (RBFNN) Based Model Predictive Control for Biomass boiler process

A Thesis paper submitted to

TECHNICAL AND VOCATIONAL TRAINING INSTITUTE (TVTI)

FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY
(DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

In partial fulfillment for the Degree

MASTER OF SCIENCE IN ELECTRICAL AUTOMATION AND CONTROL TECHNOLOGY MANAGEMENT

By,

Ousman Essa (MTR/769/13)

Supervisor,

Dr. Saravanakumar Gurusamy

January, 2023

Addis Ababa, Ethiopia

DECLARATION

I here by certify that the work that is being provided in this thesis entitled “Performance analysis of Radial Basis Function Neural Network Based Model Predictive Control for Biomass boiler process” is the original work of my own, and that is not presented on a master’s thesis elsewhere. The necessary acknowledgment has been given to every source of information that was used or this thesis work, regardless of whether the source was from this university or elsewhere.

Name: - Ousman Essa (MTR/769/13)

Signature:-

Place:- Addis Ababa

Date of Submission: 27/01/2023

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

Dr. Saravanakumar Gurusamy

Advisor Name

Signature

27/01/2023

Date

TECHNICAL AND VOCATIONAL TRAINING INSTITUTE (TVTI)
FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY
AND INFORMATION AND COMMUNICATION TECHNOLOGY

(DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

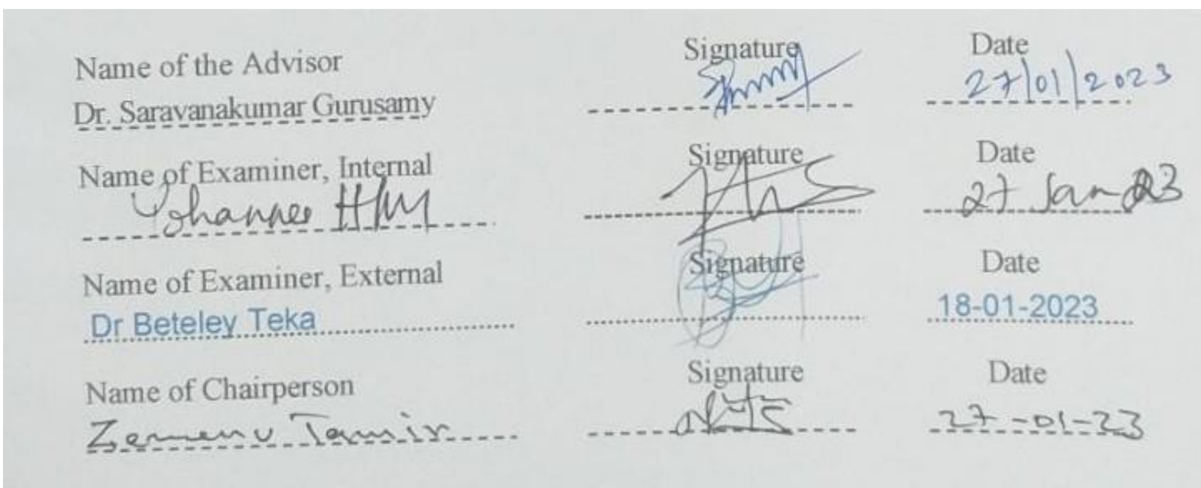
Thesis on

Performance analysis of Radial Basis Function Neural Network (RBFNN) Based Model Predictive Control for Biomass boiler process

By,

OUSMAN ESSA (MTR/769/13)

APPROVED BY THESIS ADVISORY COMMITTEE



Name of the Advisor Dr. Saravanakumar Gurusamy	Signature	Date 27/01/2023
Name of Examiner, Internal Yohannes HM	Signature	Date 27 Jan 23
Name of Examiner, External Dr Beteley Teka	Signature	Date 18-01-2023
Name of Chairperson Zemenu Tamir	Signature	Date 27-01-23

Acknowledgment

First and foremost, I thank Allah for assisting me in completing this study in this manner; it brings me great pleasure to convey my heartfelt appreciation to everyone who has supported and helped to make this thesis possible.

I want to express my sincere thanks to my advisor Dr. Saravana Gurusamy for his unconditional support for this work and for being a kind, supportive, and inspirational guide to me.

The Wenji Shoa sugar factory employees are also to be thanked for their readiness to assist me by supplying the essential measurement data.

My warmest gratitude goes to my family, especially my lovely wife and friends, for their moral support and motivation.

Abstract

As the world population has increased, electricity demand and consumption have risen rapidly in recent years. As a result, fossil fuel costs have risen and the associated air pollution has become a global issue. A biomass boiler power plant is one of the most effective solutions to this problem. The boiler plant is a multi-input, multi-output, time-varying and nonlinear system by nature. The majority of biomass boiler controllers use classical PID controllers. The inability of these classical controllers to control time-varying and nonlinear systems is the source of the plant's poor performance. To make the controller better, first determine the system model of the nonlinear, MIMO and time-varying system by employing a data-driven Radial Basis Function Neural Network model and then input the model result into the model predictive controller. The Model Predictive Controller is responsible for controlling the system's present state and determining the system's future state based on the system's historical and current states. The suggested method may be validated by simulating the system in MATLAB/SIMULINK and contrasting the results with those obtained using a traditional state space estimator in conjunction with model predictive control. The proposed system has achieved 0.094 sec, 0.368 sec and 0.0422 sec of rise time and also 0.02072 sec, 0.6841 sec and 0.673 sec settling time for temperature, pressure and water level respectively. It was clear from the results that the proposed system would be fastly stable and sufficient control ability would be accomplished as a whole the dynamic responses had been enhanced.

Keywords: - Biomass Boiler, RBFNN, MPC

Table of Contents **Pages**

List of Figure

List of Table

Acronyms

ANN……………….……………………………...Artificial Neural Network

ARX…………………..…………………..…...Auto-Regressive exogenous

DSP………………………………………..…..Digital Signal Processing

FPGA…………………………………………….Field Programmable Gate Array

GA…………………..…………………...……Genetic Algorithm

GHG…………………..……….………….....…Green House Gas

LMIs…………………..………………………....Linear matrix inequalities

LSO…………………………………………..…..Local Search Optimisation

MIMO……………….……………….…..……….Multi-Input Multi-Output

MISO……………….……………….…..……….Multi-Input Single-Output

MLP…………………..……………..………….Multilayer Perceptron

MPC ………………………………..……....Model Predictive Control

MW……………………………………………Mega Watt

NLARX…………………………….…..……….. Non Linear Auto-Regressive exogenous

NN……………………………………..……Neural Network

PI……………………………………..………. Proportional Integral

PID…………………………………..…..………. Proportional Integral Derivative

PSI ……………………………………………….Pounds per Square Inch

PSO……………………………………………….Particle Swarm Optimisation

RBFNN ………………………...……………..Radial Basis Function Neural Network

Sec………………………………………………..Second

TPH……………………………………………….Tone Per Hour

CHAPTER ONE
INTRODUCTION

Electricity demand and consumption have expanded dramatically over the last several decades due to the development of industry and the world population. As a consequence of the significant rise and fluctuation in fossil fuel costs, as well as the environmental concerns about the greenhouse gas (GHG) impacts by uses of fuel. Biomass is the best alternative energy source, a significant choice among other renewable energy sources in several nations [1]. Biomass is quite essential. Because it offers the advantages of conserving energy resources, releasing no greenhouse gas and protecting the environment. Wood, sugar cane, grasses and other plant products are used to generate biomass energy and a low-carbon fuel or energy source. Biomass products convert into energy, for electricity, heat, power or transportation is the result of biomass energy production [2].

Biomass power plants are one of the popular methods for generating power from biomass input. The biomass boiler plant converts the biomass input into useful heat. The plant produces high pressure steam that can drive turbine generators. The total efficiency of biofuels combined with heat and power plants for industrial or municipal heaters ranges between 70% to 90% [3]. However, the boiler users claim that their boilers' efficiency is higher than that (usually 90%-95%).

The boiler generates steam used for chemical processing in many factories and power plants. The boiler is a critical component in the application. Steam flow rate, temperature, and pressure all have an impact on its performance. During plant operation, the amount of steam produces varies. As a result, output variables such as steam pressure, temperature, and drum water level must be maintained at their respective values [4]. In sugar production factories, PID control is a common type of boiler controller. On the other hand, PID control is limited to systems with a single input and a single output. It is a complicated task to develop PID control for a multivariable system.

Radial basis function (RBF) networks offer the benefits of being simple to construct, having high generalisation, being resistant to input noise and having the capacity to train online. RBF networks are adequate for designing flexible control systems due to their features [5]. The RBF network's roots can be attributed to the accurate interpolation of many data points in a multi-dimensional space. The RBF network is a widespread approximator and a preferred alternative to Multilayer

Perceptron’s (MLP) due to its more straightforward construction and considerably faster training procedure [6].

MPC can predict the behavior of the system using an estimation procedure and optimise the expected to generate the best decision. The control decides at the current time. Models are essential in all forms of MPC. It is to analyse the previous record of measurements to estimate the most expected initial state of the system since the optimal control operation depends on the initial state of the dynamic system. The goal of the state estimate challenge is to evaluate the previous data record and match these measurements with the model to establish the desired value of the existing decisions [7].

1.1 Statement of the Problem

Ethiopia is a biomass energy rich country. However, there remains a significant gap in the use of renewable energy. Biomass boilers are used in sugar plants for chemical processing and electricity generation. However, they are used in conventional control systems such as PID and PLC with PI controllers. These controllers are more applicable for linear and MISO systems,

As a result, the biomass boiler is inefficiently used. The operation of biomass boilers is one of nonlinear systems by nature. According to a review of the literature, most academics have looked at a variety of studies to answer the problem of conventional control systems. However, there are still certain gaps that need to be filled. Either influential parameters such as temperature, pressure, and water level are not taken into consideration, future system states are not predicted, or models of the system are not well-trained.

To fill this gap, it is proposed to utilise the biomass boiler model with RBFNN based MPC that employs a smart control technique to improve performance (by controlling temperature, pressure, and water level), efficiency (the machine is trained by using RBFNN), and anticipate the future state (model predictive control).

1.2 Objectives of the Thesis

1.2.1 Main objective

The primary goal of the thesis is to simulate and analyse the performance of Radial basis function neural network based model predictive controller for the biomass boiler process.

1.2.2 Specific objectives

- To derive the mathematical model of the Biomass Boiler process using measured Biomass Boiler input and output data of sugar plant
- To analysis the performance of RBFNN based model of the biomass boiler process
- To analysis the performance of MPCs based on RBFNN models
- To compare the performance of state space estimator with MPC and Radial basis function neural network based MPC system.

1.3 Scope

This work is limited by developing a Radial Basis Function neural network to approximate a nonlinear plant system and model predictive controller for a biomass boiler based on plant data. Furthermore, the biomass boiler system is restricted in its ability to convert biomass heat into steam. For this work, the measurable variables found on the waterside of the biomass boilers are considered. which means input variables: primary airflow, secondary airflow, Water flow and Fuel flow (bagasse). output variables: the pressure of the Drum, Steam temperature, and level of the Drum in this study. MATLAB/SIMULINK is used to test the overall system efficiency and figure out how to improve the biomass boiler.

1.4 Significance of the Thesis

This study focuses on modeling and controlling the biomass boiler. The system model is developed using the system measured data by the RBFNN technique, and its control method is model predictive control. This is very important for sugar plants to represent the nonlinear boiler. Model predictive control has a significant benefit for closely linked and Multimodal processes because it can manage interdependency and constraints of the system, which can save energy. MPC is an effective control strategy for minimising resource waste and controlling interaction loss in the biomass boiler plant of a sugar refinery. This new Thesis work demonstrates how to model and control a biomass boiler.

1.5 Limitations of the Thesis

There are different techniques to control biomass boiler outputs. In this case, the Radial basis function neural network is carried out to estimate the system model and apply MPC to control the outputs parameters and simulated in MATLAB/SIMULINK. This work implemented using only MATLAB/ SIMULINK simulation without practical implementation.

1.6 Thesis outline

CHAPTER ONE: In This chapter consists introduction to biomass boiler systems, a statement of the problem, objectives, scope, significance and limitations of the study

CHAPTER TWO: This chapter includes an introduction about the boiler, discussing different literatures related to biomass boiler and identifying the gap from the worked works of literature and a summary of the literature.

CHAPTER THREE: Explanation of the methodology of the study, discussion about ANN, RBFNN, development of biomass boiler modeling by using RBFNN and state space estimation.

CHAPTER FOUR: MPC Controller design for biomass boiler process

CHAPTER FIVE: In this chapter models and controller behavior figure out by MATLAB code and Simulink. analysis of RBFNN model and state space estimation model, analysis of MPC controller based on RBFNN model and conventional state space model. discuss the result of the system.

CHAPTER SIX: This chapter presents the conclusion from the work carried out on this thesis and suggests further studies.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction about boiler

A boiler is a type of steam generator that uses various inputs. It converts water to steam using combustion. Its the primary heat source for a variety of industrial applications, including heating the process, chemical processing, and the production of electricity. Two primary systems make up a boiler. The first is the water steam side of the boiler, which produces hotter steam from the supplied water. Water is entered through water pipes, heated by transference, and then converted to hot steam. The combosition of fuel and air gas are the other boiler operation, often known as the boiler's fireside. This system generates the heat and then delivered it to the water. The fuel and air are the necessary system inputs to burn the fuel. Flue gas and ash are the system's outputs [8]. Figure 2.1 illustrates a schematic representation of a typical boiler system.

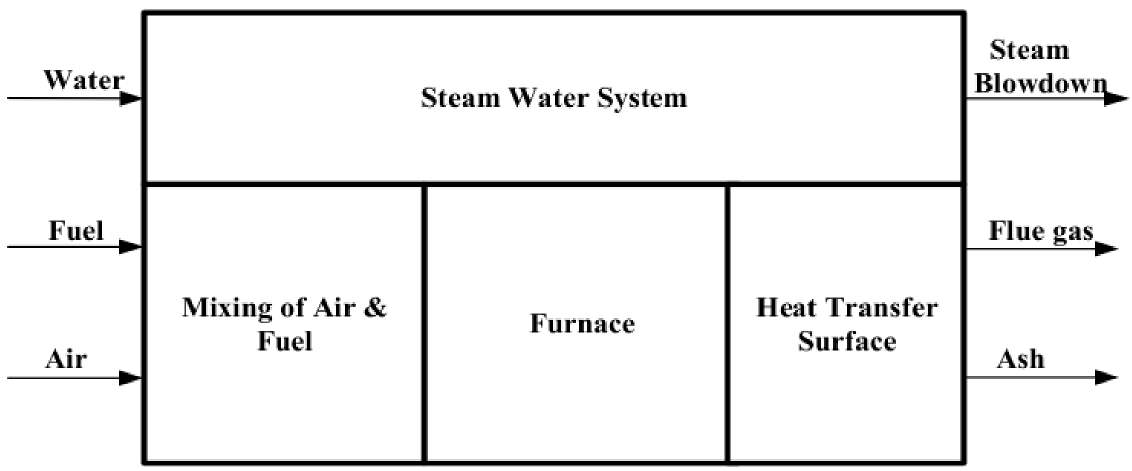


Figure 2.1: Basic boiler diagram [8]

2.2 Biomass Boiler Control Mechanism

Two design considerations determine the boiler control system.

1. Control system's configuration: the way that the system's elements are linked together. Open-loop systems and Closed loop systems are the two basic types of control system configurations. the system control is determined by the variables that are manipulated and controlled variables.

2. Control methodology choice: A variety of control techniques are available for biomass boiler control. In the studied literature reviews, the following control approaches were investigated.
    a) PID control
    b) Model reference adaptive control
    c) Fuzzy logic control
    d) Neural network control

2.3 Review related work

Many researchers work on boiler control. Those researchers control and improve the efficiency of boiler in different approaches as follows

2.3.1 Improve combustion efficiency

Researchers try to improve the boiler efficiency by enhancing the combustion efficiency but not controlling the safety of boilers like temperature, and drum level. A predictive control algorithm is used in the boiler to improve system combustion efficiency, controlled variables are main steam pressure, flue gas oxygen content, and furnace pressure [9]. Radial Basis Function based mathematical modeling of the carbon content of fly ash, exhaust gas temperature, and their related input variables is used to improve the utility boilers combustion process, and The thermal boiler model is created uses the neural network trained data, which also used to enhance the boiler combustion model [10]. Optimising combustion is a core strategy for lowering fuel costs. Oxygen concentration in the boiler exhaust gases is measured in real-time operation to improve the system's combustion A boiler's combustion airflow rate was controlled by a fuzzy controller [11]. They provided many approaches to optimising boiler combustion, but reducing only fuel costs is not enough for effective boiler steam generation, additional controllable parameters must be included to ensure a safe and efficient boiler system in addition to fuel cost reduction.

2.3.2 MISO approach

Some researchers' work demonstrated a safe and efficient boiler system using a variety of approaches and techniques of control while just considering one parameter. Backpropagation neural networks were used to demonstrate a modeling system for calculating and improving the water level in boiler drums [12]. The level process of a steam generator is a highly nonlinear system, that uses a mix of PID and Radial Base Function, The performance of neural network level control is excellent [13].

The control methods used a mix of fuzzy and PID techniques. This optimisation strategy has a strong learning capacity and can replace experienced operators. The fuzzy PID control method for the drum water level has been created. It has great control adaptability [14].

According to [15], the boiler drum water level system in a power plant is highly nonlinear, unpredictable, and time-varying with conventional methods, controlling the boiler drum is problematic. The water level of the boiler drum is controlled using an internal model control method based on neural networks. The genetic algorithm is proposed to train neural networks to learn the dynamics and inverse dynamics of the system.

The boiler drum water level should be within the specified range for safe and efficient operation. A model predictive controller controls the system's several input variables by taking into account various input and output constraints [16]. Previous works have been limited to controlling boiler water levels.

For the heating system of a biomass hot water boiler, a fuzzy inference approach is used to achieve online tuning of PID parameters, and a fuzzy PID control strategy is proposed [17]. The advantages of the PID algorithm are combined by using a fuzzy controller with proportional, integrative, and derivative behavior. Fuzzy with PID is used to control medium-scale biomass boiler water temperature control. The proposed algorithm only controls the fuel feeding rate as manipulated variable [18]. They had given a presentation on the fuzzy inference method used to achieve online tuning of PID parameters for interior temperature management, but no other parameters are taken into account.

According to [19], A model predictive control strategy based on trained radial basis function networks has a good ability to control the steam temperature of a boiler. Both a recurrent radial basis function network and a self-organising mechanism are used to represent local transfer functions. it is also used to forecast the boiler future control action. The RBFN regularly reviews boiler dynamics in real time and modifies the model to account for various uncertainties

A multi layer perception (MLP) artificial neural network architecture and backpropagation (BP) were used to forecast the quantity of steam produced by the biomass boiler [20].

As a whole MISO for boiler control and optimisation, the generating power and steam are not efficient. Controlling a single parameter does not provide effective safety and control since other parameters might have a significant impact on boiler efficiency and safety.

2.3.3 MIMO approach

The boiler is an example of a time-varying system with several inputs and outputs. This system needs wide approaches to efficient steam generation. Some researchers work to improve the boiler efficiency multi-input multi-output system approach.

The boiler's real time operation is predicted by using an artificial neural network (ANN) approach. From several experiments the boiler of thermal power data is used to train and test data by developing ANN. the backpropagation algorithm is used as an ANN train. ANNs have been effectively used to predict the different properties of a coal-fired water tube boiler, such as power, outlet steam pressure, and efficiency of the boiler [21].

The multi variable RBFARX model is proposed to describe the dynamics of MIMO, nonlinear systems. The system's working points can be linearised since they change over time. Based on the estimated model, a predictive control strategy is created to control such a nonlinear system. The RBF-ARX model estimation approach is provided using offline data. Steam pressure, main steam temperature and reheat steam temperature are controlled variables. which are used to show the performance of the suggested technique. this research study on a thermal power plant [22] [23]. One of the key limitations of the two studies is not control the water level in the drum.

When the operating pressure of steam-consuming equipment surpasses the working pressure, dangers may arise. More accurate modeling of the boiler and its pressure relationships is required. The steam pressure, water level in the drum and electrical output are output variables. the plant Output variables include the pressure of the steam, drum water level, and generate electrical power. The input variables are the fuel flow rate, the output steam flow rate, and the flow rate of the water entering the boiler. To control this multivariable system a recurrent type-2 fuzzy based model reference adaptive control system is used [24].

By considering fuel flow, feedwater flow, two actuator flows, and control valve position as inputs, the performance of the drum pressure, power output, and drum level were improved by a fuzzy logic controller with PI [25]. This paper worked on a power plant boiler, so power output is taken into account, but the temperature isn't considered and future changes aren't predicted.

The MPC method was utilised to control the boiler turbine process by manipulating three variables: the position of fuel flow, steam control and feed water flow as well as controlling three variables: drum pressure, output power, and drum water level variation. A Taylor series expansion was used to generate a linearised model [26]. The limitation of this proposed work is not to control the drum temperature.

Fuzzy modeling is a technique for converting a nonlinear system model to a linear system. The model predictive controller controls the coupling of variables. based on a biomass boiler operation takes into account four inputs (water flow, fuel flow, airflow1, and airflow2) as well as three outputs such as pressure, temperature, and water level in the drum [27]. But the proposed fuzzy logic control system depends completely on human knowledge and skill. Machine learning or neural networks aren't recognized by these systems.

2.4 Summary of the Literature Review

As previously stated, studies focus their investigation on coal and fuel used boilers in power plants. There have been very few studies on biomass boilers.
A classic control method is used by many biomass boilers. For nonlinear and multivariable systems with forecasting future states, the existing control mechanisms such as PID, fuzzy PID, and adaptive PI controllers with MISO system are inefficient and inaccurate. In addition some researchers focus on constrained output and combustion-based work without considering MIMO had a limitation to efficient steam generation. As they explain in the books and the worked papers the model predictive control has its features and advantages over classical PID controllers. MPC can control a multivariable system. MPC controls the outputs simultaneously by taking into account all the interactions between system variables. Another strength of MPC is that it can handle constraints. Constraints are important because violating them can lead to undesired consequences. Because of this MPC is chosen as a controller. A. Getenet, (2019) considers MIMO with model predictive control using Fuzzy logic but the approach is limited on human knowledge and experience. Peng et al.(2011) this work is done in a power plant, power output is considered but a crucial parameter boiler temperature is ignored. Radial basis function (RBF) networks offer the benefits of being simple to construct, having high generalization ability and being resistant to input noise The RBF

network's roots can be attributed to the accurate interpolation of many data points in a multi-dimensional space. RBFNN has its advantage and ability to model the system from measured data. because of this RBFNN is selected to model the system.

As a result, this thesis work proposes performance analysis of biomass boiler control by Radial Basis Function Neural Network based model predictive controller. Biomass for sugar factories is not only generating power also steam is utilised for chemical processing. Temperature, pressure and drum level are critical parameters to safe and efficient steam generation by a biomass boiler.

CHAPTER THREE

MATHEMATICAL MODELING

3.1 Identification of variables for biomass boiler

Biomass boilers by nature MIMO system and nonlinear system so it is difficult to analyse the plant or process. Modeling of the system, algorithm and controller approach is by applying system identification of a system. Collecting the measure input and output data from Wonji Shoa sugar factory. The data applying to the black box modeling method, the biomass boiler model is derived from the system identification box. The boiler is a MIMO system as shown in Figure 3.1.

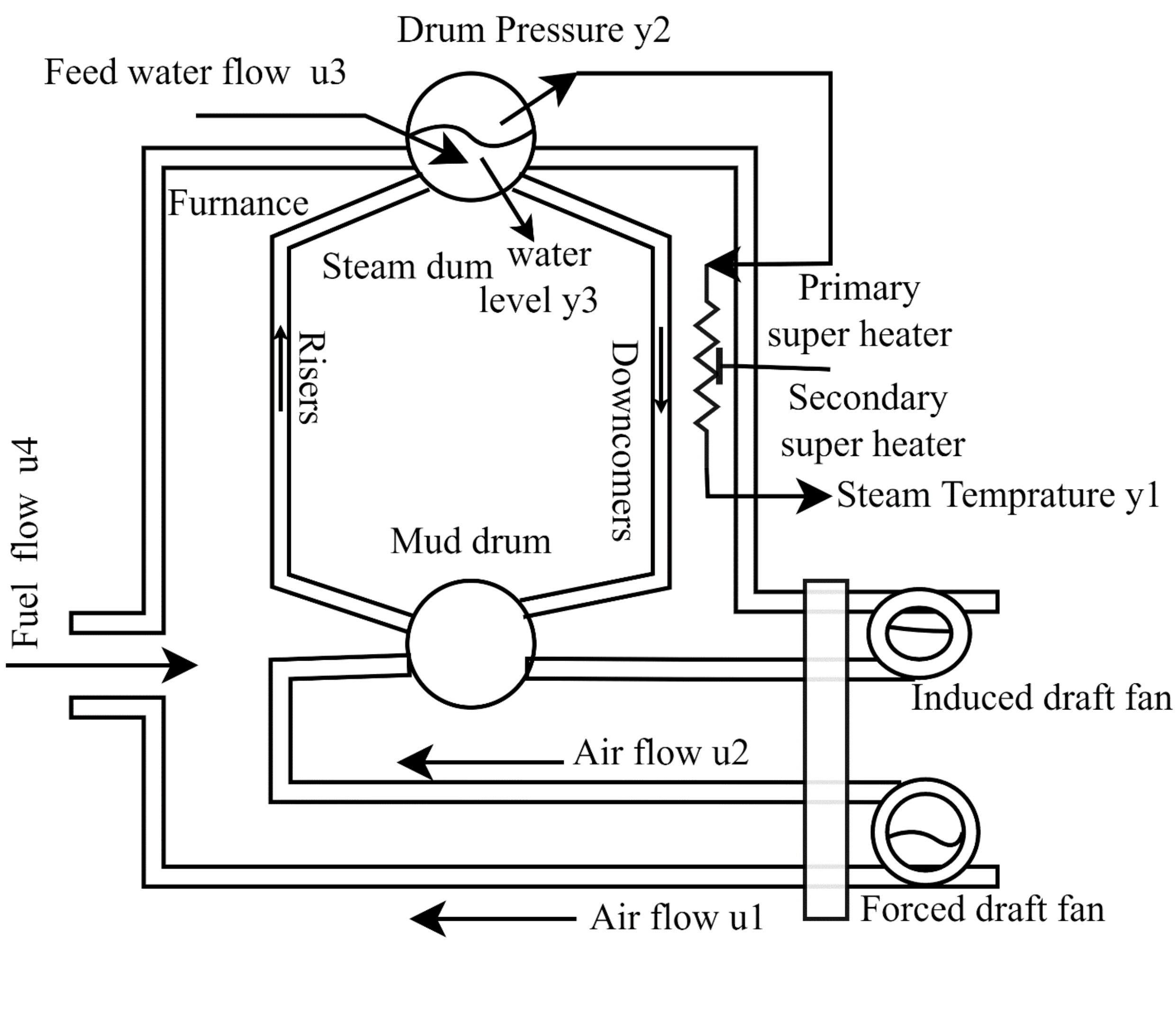


Figure 3.1: Schematic digram of MIMO Biomass Boiler [28]

This is difficult to determine with the usual mathematical model system behavior. As a result, the Black-box modeling approach may be used to identify the biomass boiler system.

There are different modeling identification methods

1. **Black-box modeling: -** The modeling approach depends only on a collection of data that was obtained through measurements and also supposes no understanding of the system dynamics.
2. **White-box modeling:** - A description of the system is built using the physics laws that control the process.
3. **Gray-box modeling**:- A specific system information is employed to improve the empirical modeling. Some system characteristics, such as system order, responsiveness, stability, degree of freedom, and basic nonlinearity properties, may aid to good system identification [29].

This study Radial basis function system identification would be used for Biomass Boiler modeling techniques. Choosing input and output variables for the system that will be modeled is the first phase in the system identification process. This study has four manipulated inputs (water flow, fuel flow, airflow 1, airflow 2) and three controlled output variables (pressure, temperature and water level in the drum). The following justification is the significance of these elements in the production of steam:

Drum Pressure control: Steam made from biomass boiler is used for various industrial activities and generating electricity. In sugar factory biomass boiler provides both services. High pressure steam drives a steam turbine can drive well. Because high pressure steam has a low volume, this means it can pass through pipes easily. But if it is low pressure carries out the water and gives us low efficiency. However to get good performance Boiler pressure needs to be controlled. Controlling this parameter can also be achieved by controlling various variables.

Steam Temperature control: Temperature plays a major role in biomass boiler steam. This temperature needs to be reached and controlled to the desired level. If it is too hot the fuel cost will increase. In addition, it is too hot can be even more dangerous. Heating as much as the desired value allows us to reduce fuel costs as much as possible.

Drum level control: It's one of the most critical aspects of steam production is the drum water level. The water level in the drum needs to be kept within a certain range. Unless it falls below the drum water level range superheater or the turbine can cause significant damage and maintenance costs will increase. This can lead to factory shutdown.

Generally, These three output parameters have a significant effect on the biomass boiler so we should be controlled at the desired set point. If we do not control it as much as the setpoint, it leads to high maintenance costs, and downtime and cause human injury and even death.

3.2 Block diagram of RBFNN based MPC for biomass boiler process

The system block diagram describes the connection of the process in an asystematic way. Figure 3.2 describes the modeling of the system from measured data by using RBFNN and then control the RBFNN model by model predictive control.

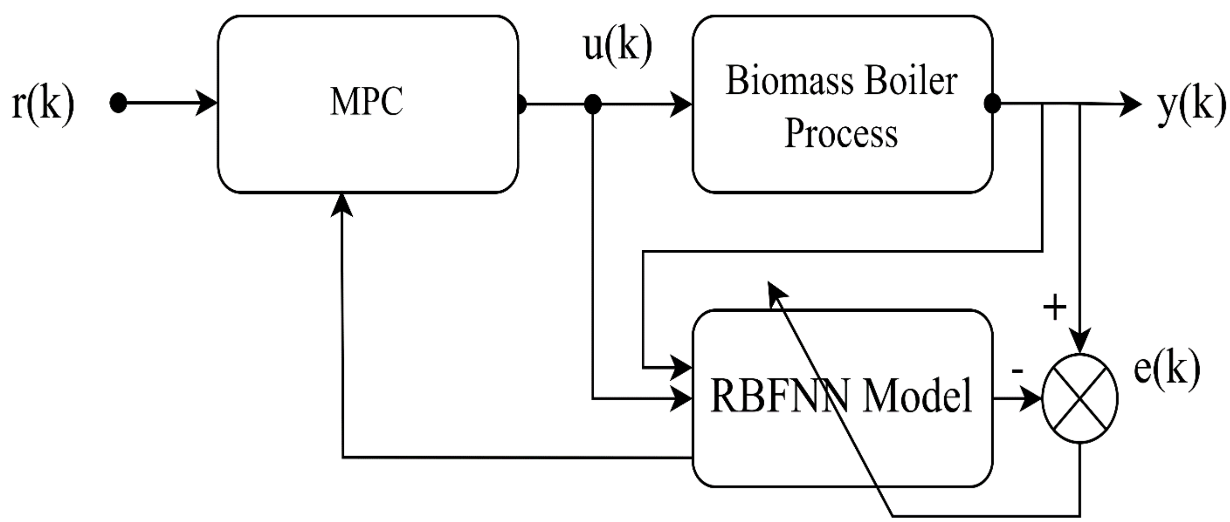


Figure 3.2: Block diagram of RBFNN based MPC for biomass boiler process

Where *r(k)*: reference of the desired output

u(k): manipulated variables (Airflow1, Air flow2, Water flow and Fuel flow) outputs

y(k): controlled variables (Temperature, Pressure and Water level in the drum) outputs

e(k): Difference between the output of the model and the controlled output

3.3 System Identification

The data for this study was obtained from the operation of the biomass boiler system by the previous researcher [27]. The output parameter in the process of a biomass boiler is fundamental and requires consideration, i.e temperature, pressure and water level in the drum. The system parameter must be balanced, they shouldn't be either too high or too low. This may occur as a result of temperature, pressure, and water level in the drum being either too high or too low the system devices may burn or quality and output production rate will be affected. This study aims to model the system using measurable input and output data before using a model predictive controller. Therefore, a strong system identification technique like linear or nonlinear models is needed to create a satisfactory model of the system.

3.3.1 Structure of Nonlinear ARX Model (NLARX)

The Non-Linear Auto-Regressive with Exogenous (NLARX) input model structure is applied in this process. Nonlinear ARX models use a simultaneous combination of a nonlinear and linear block to describe nonlinear structure. The nonlinearity predictor block utilises a combination of nonlinear and linear functions to transfer the regressor to the model output [30]. Wavelet Network (wavelet), Sigmoid Network (sigmoid), Custom Network, and Neural Network can all be used to estimate nonlinear ARX. Because it may be applied for different type of nonlinear mapping, One of the most optimal estimators or model structure in the control system is known to be neural networks [31]. It shows that it can deal with any restricted input-output mapping problem. According to research using neural networks to forecast and control universal nonlinear systems as evidence. The advantages of this neural system include how quickly it processes information and how robust it is [32]. This study examines the effectiveness of NLARX when simulating a biomass boiler MPC control using a customised network (Radial Basis Function) model.

3.4 System Modeling using Artificial Neural Networks

Over the years, a wide variety of mathematical models characterising behaviors of the boiler's to external demand have been produced. Whereas traditional model driven approaches some times unsuccessful. Without needing to understand the physical nature of the problem, one of the data-driven approaches of such computational intelligence, such as Methods of Artificial Neural Network Modeling should be applied. This method has the ability to immediately address all of its complicated outputs. It enables us to investigate correlations between the related model's input-output parameters by adapting adequately chosen sample empirical measured data [22]. As a result, it is widely accepted that artificial neural networks are excellent universal approximators for stochastic connections between any number of variables.

An information processing architecture known as artificial neural networks (ANNs) was motivated by the ability of the brain to store and analyse complicated information. It is created to explore behavior of complex systems, static-dynamic, complicated processes by computer simulation using pattern recognition, categorisation, and adaptation. An ANN structure is made up of a vast number of linked neurons that communicate with one another components of the system. Artificial neurons have layered structures like as biological neurons, and they are linked by synaptic values or weighted connections which are similar to a biological synapse [24].

Three layers are required for each ANN: an input layer, a minimum of one hidden layer, and an output layer. Every ANN neuron gets information from neighboring neurons as well as environmental stimuli. It then modifies its internal state (activation) in accordance with these inputs and activations to generate output.

Neural networks' primary feature is their ability to generalise connections between manipulated (input) and controlled (output) variables provided in an appropriate manner (structure of matrices), in addition to suggested rules obtained for every input parameter by this oversimplified black box model. The relationship conceptual process is implemented using a set of measured experimental input-output data. which is a network learning operation. whereas the learning algorithm modifies the neuron weight values until the cost function typically represented by a Mean squared error is satisfied to ensure system global error minimisation. When learning is complete, the output weights are fixed. Based on the established rules, the trained network output data is identical to the applied input data. because the generalised weights were kept in the learned information. Since it seeks to understand the relationship between the input-output data patterns and precisely realise their essential structure, such a combination of weights is known as an ANN model [26].

3.5 Radial Basis Function Neural Network

A neural network (NN) is made up of interconnected artificial neurons. which processes information using a mathematical or computational model [33]. Radial basis functions serve as the activation functions in neural networks, which are single hidden layer NNs. Only a small number of connections can be used by the RBF-NN to modify the output of the network within a small input space region. Therefore, compared to other feed forward Neural network models RBFNN has better speeds of adaption.

To develop and apply RBFNN, the proper number of hidden neurons, the width and centers of the RBFs (which indicate the pattern spread), and the weights for the output layer must be determined. The activation function can be moved left or right using a bias value, which is important for effective training. Additionally, it contributes to achieving a more accurate data fit or a good predictive function as an NN output. In each iteration of a learning process the RBF center location, width, and linear weights for each output neuron are modified. Learning is said to be completed when all RBF centers are positioned as closely as possible to the input vector and the output error of the network is within the allowable limitations. As a result, every functional dependence between parameters can be approximated as a linear combination with sufficient width of RBFNN [34]. The RBFNN is also an example of ANN error backpropagation mechanism. During the learning process only the weights between the hidden and output layers must be modified by using an error signal. As all RBF-ANN inputs are given directly without any weight to the hidden layer. As a result, RBF-ANN has a substantially shorter learning curve than multi-layer feed-forward back-propagation ANNs the most popular ANNs for all kinds of real-world applications. Figure 3.3 shows the RBFNN structure, which incorporates an input layer, a hidden layer and an output layer. The neurons in the hidden layer has Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron. The RBFNN inputs are nonlinear, but the output is linear. Because of their nonlinear approximation properties, the RBFNNs are able to model complex functins.

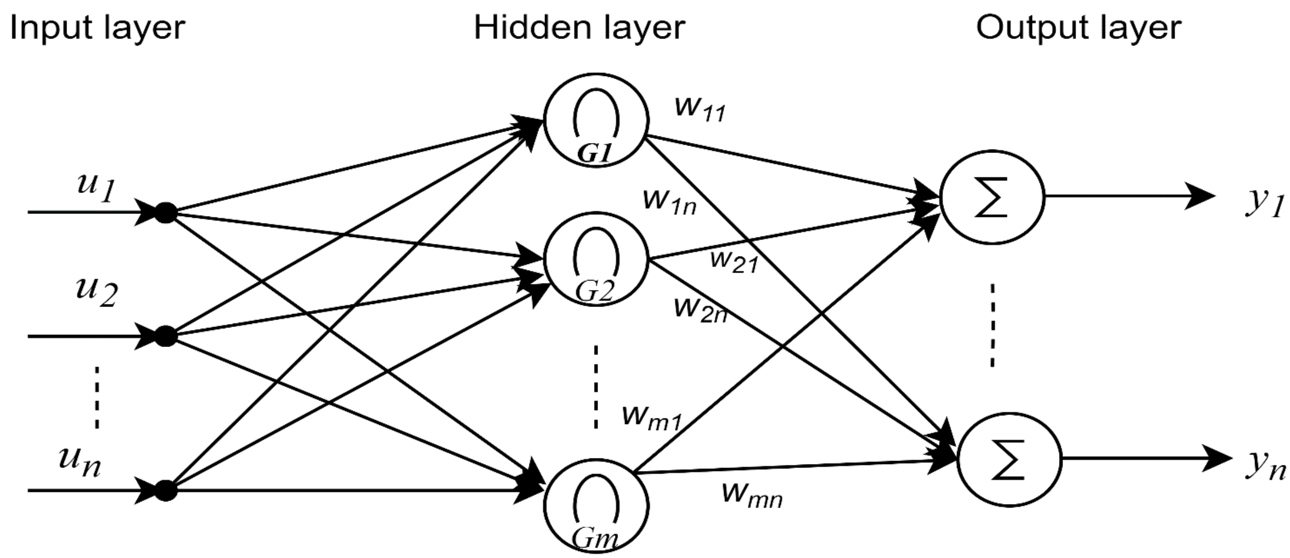


Figure 3.3: Architecture of RBFNN [34]

The three layers of RBFNNs:-

1. Input layer:- the system original data entered into the system, which is made up of artificial input neurons, where it is later processed by other layers of artificial neurons.
2. Hidden layer:- The optimum number of neurons for this layer is changeable and it is determined by the training. The basic building block of every neuron is a radial basis function that is centered on a point whose dimension is equal to the number of predictor variables. Each dimension may have a varied impact on the RBF function's width (radius). As a result of the training procedure, the centers and widths are determined. When given a vector of input values from the input layer a hidden neuron computes the test case's Euclidean distance from the neuron's center point and then uses the width values to apply the RBF kernel function to this distance.
3. Output layer:- The output of each neuron in the hidden layer is multiplied by the weight assigned to it and delivered to the summation, which adds the weighted values and provides the aggregate as the network's output [35].

To use an RBFNN the hidden layers activation function, the number of processing units, a standard for modeling a given behavior, and a training technique for establishing the network's parameters must be specified. The method of determining RBFNN weights is known as network training. The suggested training algorithm aims to extract a least mean square estimator from the defined models.

The training technique determines the following parameters:

1. The number of neurons in the hidden layer.
2. The coordinates of the center of each hidden layer RBF function.
3. The width (radius) of each RBF function in each dimension.
4. The weights are placed on RBF function outputs before they are sent to the output layer.

The network parameters are optimised for a series of input-output pairs, referred to as training data to fit the outputs of the network to the supplied inputs. The cost function, which is typically believed to represent the mean square error is used to evaluate the fit [36]. When the RBFNN has been trained, it can be used for data whose underlying statistics are similar to those of the training set.

The following steps constitute the RBFNN training process:

1) Apply the training data set's input vector to the input layer.
2) Calculate the hidden layer's output.
3) Calculate the RBF network output vector, compare it to the desired performance, and then modify the weight vector to close the gap.
4) Repetition of steps 1 through 3 for every vector in the set.
5) Keep going through steps 1 through 4 until the error trends to zero.

3.6 RBF NN System Modeling

By using the experimental data interaction of nonlinear MIMO systems RBFNN approaches have excellent capabilities for modeling and system identification. RBF modeling are often used in several sectors for nonlinear and time varying systems. The concept of developing a Single Input Single Output RBF-ARX model is used to construct the multivariable form of the model in this section [37]. Consider the following discrete-time MIMO nonlinear and time varying system:

$$y(k) = f(\Phi(k-1)) \tag{3.1}$$

$$\Phi(k-1) = \left[y(k-1), \dots y(k-n_y), u(k-1), \dots u(k-n_u) \right] \tag{3.2}$$

Where $y(k-1) = \left[y_1(k-1), \dots y_m(k-1) \right]^T$ is the output (temperature, pressure and drum level) vector and $u(k-1) = \left[u_1(k-1), \dots u_n(k-1) \right]^T$ is the input (airflow1, air flow2, water flow and fuel flow) vector that comprises the manipulated variables. n_y and n_u are the appropriate maximal lags in output and input. Various functions have been used to estimate the unknown nonlinear map f(·) that optimises the possibility of the model.

In this paper, an RBFNN will be adopted since it has a simple structure as shown in Figure 3.3. When the Gaussian function is chosen as the radial basis function:

$$G_j = \exp\left(-\frac{\| u - m_j \|^2}{2\sigma_j^2}\right) \tag{3.3}$$

The function shows Euclidean distance between the elements of the input vector $u(k)$ and the corresponding centroid of Gaussian m_j (Euclidean norm of RBF)

$$d_j(u) = \| u - m_j \| \tag{3.4}$$

RBFNN can be written as follows:

$$y_i(k) = \sum_{j=1}^{L} G_j w_{ji} = \sum_{j=1}^{L} w_{ji} \exp\left(-\frac{\| u - m_j \|^2}{2\sigma_j^2}\right) \text{ for i=1, 2,….,m.} \tag{3.5}$$

Where $y(k-1) = \left[y_1(k-1), \ldots y_m(k-1) \right]^T$ is the output vector and $u(k-1) = \left[u_1(k-1), \ldots u_n(k-1) \right]^T$ is the input vector of RBFNN.

Where w_{ji} is the synaptic weight,

G_j is the Gaussian function,

m_j and σ_j are the center and width of G_j respectively, and

L is the number of the Gaussian functions, which is also equal to the number of the hidden layer nodes.

As previously mentioned, RBFNN is generated and trained using a built-in radbas function in the Matlab programming environment. The method of this Matlab programme added neurons one at a time with the given width of the Gaussian RBF function distributed to the hidden layer in order to achieve both the predefined maximum number of neurons and the specified value of mean squared error (MSE) target. An empty hidden layer is the starting point for the iterative approach of continuous networking and training of the data.

Each iteration step performed a network simulation following the addition of a new hidden neuron.

The input vector with the highest MSE for the network is obtained and a Gaussian RBF (radbas) neuron with constant bias and weights corresponding to the vector is added to the hidden layers. To minimise the MSE of the network, the linear layer biases and weights are redesigned. The network's MSE is reduced until the target is met or the maximum number of neurons is achieved by repeating this process [38].

As a criterion, The mean squared error should be computed for each ANN-based system model. A set of training input-output pairs $(x^{(t)}, y^{(t)})$, k=1,2,....,N are given.

where $x^{(t)}(k) = [x_1^{(t)}(k),....,x_n^{(t)}(k)]^T$ and $y^{(t)}(k) = [y_1^{(t)}(k),....,y_m^{(t)}(k)]^T$,

The nonlinear MIMO system identification problem involves determining the values of L, w_{ji}, m_j and σ_j to minimise the following performance index (MSE):

$$\mathrm{e} = \sum_{t=1}^{N} || y^{(t)} - y^{(t)} ||^2 \tag{3.6}$$

Where $y^{(t)}$ is the equivalent output of the RBFNN, when the input of the network is $x^{(t)}$.

Finally, use experimental measured data to train RBFNN network. the input and target data used to create training, validation, and testing data sets. The partition is used to test the approximation capabilities of the constructed network, validate the identified RBFNN model, and assess the performance of the model.

3.7 State Space Estimation

State-space representations of a physical process that is composed of inputs and outputs as well as a particular set of state variables. those are linked by first-order differential equations. Estimate State Space Model tool uses time or frequency data to estimate and validate state space models. this approach iteratively reduces prediction error. The approach initialises the model parameters before updating them through iterative searching to reduce the prediction errors for black-box estimation. state space estimation techniques is used as a comparison to demonstrate the performance of the proposed model. A simple ssest code is used to estimate state space model of the measured data. On the other hand matlab has a black box to estimate state space.

State space represents in the form of :

$$x'(t) = Ax(t) + Bu(t),$$
$$y(t) = Cx(t) + Du(t). \qquad (3.7)$$

Where x is the state vector.

x' is the differential state vector.

u is the input vector.

y is called the output vector.

A is the system matrix

B is the input matrix

C is the output matrix and

D is known as the feed-forward matrix.

The first equation is the state equation and the second equation is the output equation respectively.

CHAPTER FOUR

CONTROLLER DESIGN

4.1 Introduction to Model Predictive Control

Model predictive control is an advanced approach of process control that uses a system model to forecast future plant output. It is commonly implemented in industrial applications because of its ability to deal with constraints in the best possible way. As the name indicates the basis for MPC is the prediction of set point tracking performance and disturbance rejection from historical controlled and manipulated variable data. An optimisation process is used to identify the appropriate input values to meet the necessary criteria in the closed loop control response after each prediction. The system output requires increasing the rate of production or optimising a profit function [39].

MPC computations are conducted at each sample time, which is adjustable by the control developer. Such computations are based on present measurements as well as forecasts of future output values. Predictions of MPC are made using two types of MPC computations. These are set point computations and control computations, which involve system constraints and other manually determined considerations. The essential purpose of an MPC controller is to find a series of control actions for manipulated variables so that the system can be optimally followed according to its references [40].

With regard to constraints on the input/output of the process (upper and lower values) MPC controllers are capable of doing in an optimal way. Under this approach, the system should be able to be operated safely by being restricted to a specific area of action, like a valve's limited by its maximum and minimum opening degree.

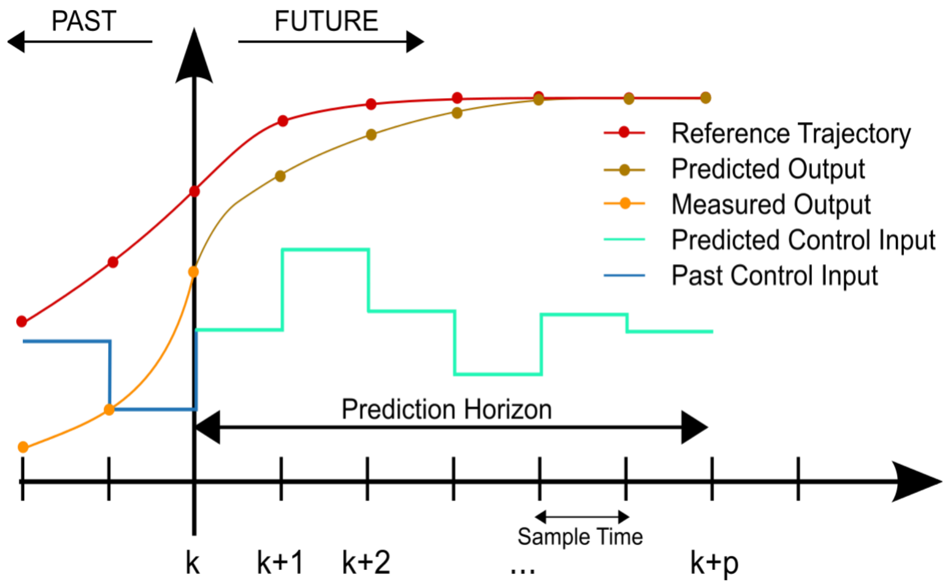


Figure 4.1: Basic concept of MPC[41]

Model predictive control is a technique of selecting control inputs by minimising an objective function. present and predicted future process results are used to develop objective function. Minimising the variation between the predicted process output and the setpoint is the basic computation to achieve optimal control. [41]. Using an objective function based on output predictions, an optimisation issue is solved at each time step k throughout a prediction horizon of P time steps. By modifying the manipulated variable's outputs, the objective function is minimised [42]. As summary, model predictive control has become one of the best studied synthesis techniques. Based on a process model determines the optimal control strategy in accordance with a number of predetermined targets over future time horizon. In reality, it's one of MPC's most main qualities. MPC is based on analysing the anticipated future error resulting from chosen control trajectories in an output feedback approach, in contrast to classical control systems, which decide the actions based the error of previous iterations.

4.2 Major features of Model Predictive Control

1. Depending on forecasts to guide actions:- PID controllers don't consider the future because they don't provide a better understanding of what will happen next theoretically. While model predictive control takes future implementation into account. To prevent problems that could prediction is essential to predict them.

2. Model-based predictions are made:- The output of the model must be dependent on the current measured value as well as the present and future inputs. System predictions are created using a model. the uncomplicated model that is appropriate for the goals and provide sufficient predictions.
3. Choosing the input currently being used: The expected inputs are chosen based on which ones minimise a particular cost function. For the desired performance, the cost function should be as straightforward as possible.
4. Receding horizon control: For a specific time horizon in the future, an MPC resolves optimal control problems. It solves the issue by iteratively addressing a constrained optimisation problem. Choosing the control action based on forecasts of future costs, interruptions, and constraints over a dynamic time horizon.
5. Controller Tuning: Model predictive control provides stable control because the most important factors include providing balanced input sources, balancing the effectiveness of various loops, having high sensitivity, and having more responsiveness. A weighting matrix's tuning is crucial for achieving these balances. If one knows how important each loop's performance is concerning to another, tuning is frequently simple.
6. Dealing with Constraints:-Under uncertain conditions, the control action satisfies the system constraints.
7. Systematic control design for multiple variables:- MPC algorithms have a systematic approach to dealing with multiple-variable (MIMO) systems. It permits MIMO system design to be done systematically.

4.3 Model Predictive Control Algorithms

MPC is a real time continuous optimisation control approach based on the given system models. An objective function is minimised in each control cycle by estimating the system's upcoming dynamic response and executing online repeated optimisation computations. The MPC uses a method of progressive optimisation. Each phase includes the collection of updated data and the minimisation of a cost function based on the expected future outcomes of the plant [43].

Different models like the step response, the ARX, the state space, and the neural network model are used in model predictive control to predict the output of the controlled variables in a finite period of time. Optimisation can reduce the variation between the desired value and the result of the model.

Model predictive control is often used to solve optimisation problems in the following way:

$$\min_{\Delta u(k),\ldots,\Delta u(k+N-1),\, j=0,1,2,\ldots N-1} J \tag{4.1}$$

With

$$J(k)=\sum_{j=1}^{M}(r(k+j)-y_p(k+j))^2+\lambda\sum_{j=0}^{N-1}(\Delta u(k+j))^2 \tag{4.2}$$

Where J is the objective function optimised

r is the reference trajectory of output signal (desired output) at sampling instant k

y_p is the RBFNN model predicted output in (3.5)

Δu is the difference between the manipulated input at each sample time

λ is a weight for the changes the manipulated input

M is the prediction horizon ($1 \le M$)

N is control horizon (0<N<M)

The following constraint are considered

$$u_{\min} \le u(k+j) \le u_{\max}, \quad j=0,1,\ldots,N-1 \tag{4.3}$$

$$\Delta u_{\min} \le \Delta u(k+j) \le \Delta u_{\max}, \quad j=0,1,\ldots,N-1 \tag{4.4}$$

$$y_{\min} \le y(k+j) \le y_{\max}, \quad j=0,1,\ldots,M \tag{4.5}$$

Where $u_{\min}$ and $u_{\max}$ are separately the minimum and maximum constraints on the manipulated inputs. $\Delta u(k+j)=u(k+j)-u(k+j-1)$ and $\Delta u_{\min}$ and $\Delta u_{\max}$ are present minimum and maximum constraints on the manipulated inputs and $y_{\min}$ *and* $y_{\max}$ are constraints on the predicted outputs [44]. Using vector and matrix notation

$$\begin{aligned}
\Delta U &= [\Delta u(k) \ \ldots \ \Delta u(k+N)]^T \\
Y_p &= [y_p(k+1) \ \ldots \ y_p(k+M)]^T \\
R &= [r(k+1) \ \ldots \ r(k+M)]^T
\end{aligned} \tag{4.6}$$

$$\lambda = \begin{bmatrix} \lambda & 0 \cdots 0 \\ 0 & \lambda \cdots 0 \\ \vdots & 0 \ddots \vdots \\ 0 \cdots & 0 \ \lambda \end{bmatrix} \tag{4.7}$$

The cost function (4.2) can be written

$$J = \| R - Y_p \|^2 + \| \Delta U \|_\lambda^2 \tag{4.8}$$

The difference between the model output and the measured data is corrected by output feedback:

$$\begin{aligned} y^c(k+j) &= y_p(k+j) + e_k \\ e_k &= y_k - y_p(k) \end{aligned} \tag{4.9}$$

It is possible to modify the cost function in the Equation (4.8) by

$$J = \| R - Y_p^c \|^2 + \| \Delta U \|_\lambda^2 \tag{4.10}$$

In the optimisation problem, the neural network-based system model brings nonlinear dynamics to the cost function and constraints. To solve this problem sequential quadratic programming (SQP) approach needs to be employed.

4.4 RBFNN MPC with local linearisation

The nonlinear neural network model used in MPC is most likely leads to non-convex, which means that the global optimum solution cannot be ensured. to solve this problem linearisation of the nonlinear model at the present sample point is an effective method. The generated linear model will be applied to forecast the outcomes of the prediction horizon P during the current sampling period. As well as the neural network model will undergo linearisation at a new sample point throughout the succeeding sampling time.

Due to this, this approach technically applies a linear model with time-varying parameters. By using the linear model in MPC the convex nature of the optimisation problem can be ensured. This allows the adoption of an effective SQP algorithm [45].

In (3.5), the RBF neural network model is linearised at the time of the present sample. The Following are the first two terms of the Taylor series expansion that can be used to approximate the predicted output.

$$y(k+i) \approx y_i(x)\Big|_{x=x(k)} + \frac{\partial y_i(x)}{\partial x}\Big|_{x=x(k)}(x(k+i)-x(k)) \tag{4.11}$$

The partial derivative $\frac{\partial y(x)}{\partial x}$ can be calculated from neural network model in (3.5). The predicted output in (4.11) can be arranged as:

$$y(k+i) = e_{NL}(k) + C_{NL}(k)x(k+i) \tag{4.12}$$

With

$$e_{NL}(k) = y_i(x)\Big|_{x=x(k)} - C_{NL}(k)x(k) \tag{4.13}$$

$$C_{NL}(k) = \frac{\partial y_i(x)}{\partial x}\Big|_{x=x(k)} \tag{4.14}$$

The given predicted outcome in (4.12) can be applied to predicting the process output value $y_p(k+j)$ in (4.9).

After the computations are complete, The optimisation problem can be expressed as a quadratic programming problem with constraints.:

$$J_{opt}(k) = [\Delta U(k)]^T H_{QP}[\Delta U(k)] + [f_{QP}(k)]^T[\Delta U(k)] \tag{4.15}$$

$$s.t.\begin{cases} A_{ineq}\Delta U(k) \le B_{ineq} \\ \Delta U_{\min} \le \Delta U(k) \le \Delta U_{\max} \end{cases}$$

CHAPTER FIVE
RESULTS AND DISCUSSION

5.1 Introduction

This chapter discusses and analyses the RBF based NN model of a biomass boiler and a model predictive controller for the biomass boiler process. Additionally, comparing the response of a biomass boiler that is a 4x3 MIMO model with and without using the Radial basis function by applying the same Model predictive controller (controller with the same parameter). The first step in the research process is to model the system without a controller and then validate the model that was built for the system. And also compare the results obtained from RBF neural network based and classical state space estimation The next step is to evaluate the controller and determine how well the controller performs concerning the reference variations.

5.2 Simulink Modeling

The biomass boiler is MIMO and Nonlinear system. The system measured input data shows in Figure 5.1, and output measured data is shown in Figure 5.2, gathered from the Wonji sugar factory and is used to train the model of the system [27].

Table 5.1: Specifications of Wenji Shoa sugar factory biomass boiler

Measured Parameters	Amount
Generated Electric power	17 MW
Steam generated	130 TPH
Rate of feed water	170 TPH
Temperature of feed water	110 °C
Steam temperature	505 °C
Steam pressure	65 PSI

A software program used to model, simulate, and analyse dynamic systems is called MATLAB/Simulink. Simulink has various features, including its capacity to model complicated dynamic systems, graphical workspaces with real-time coding and various toolboxes.

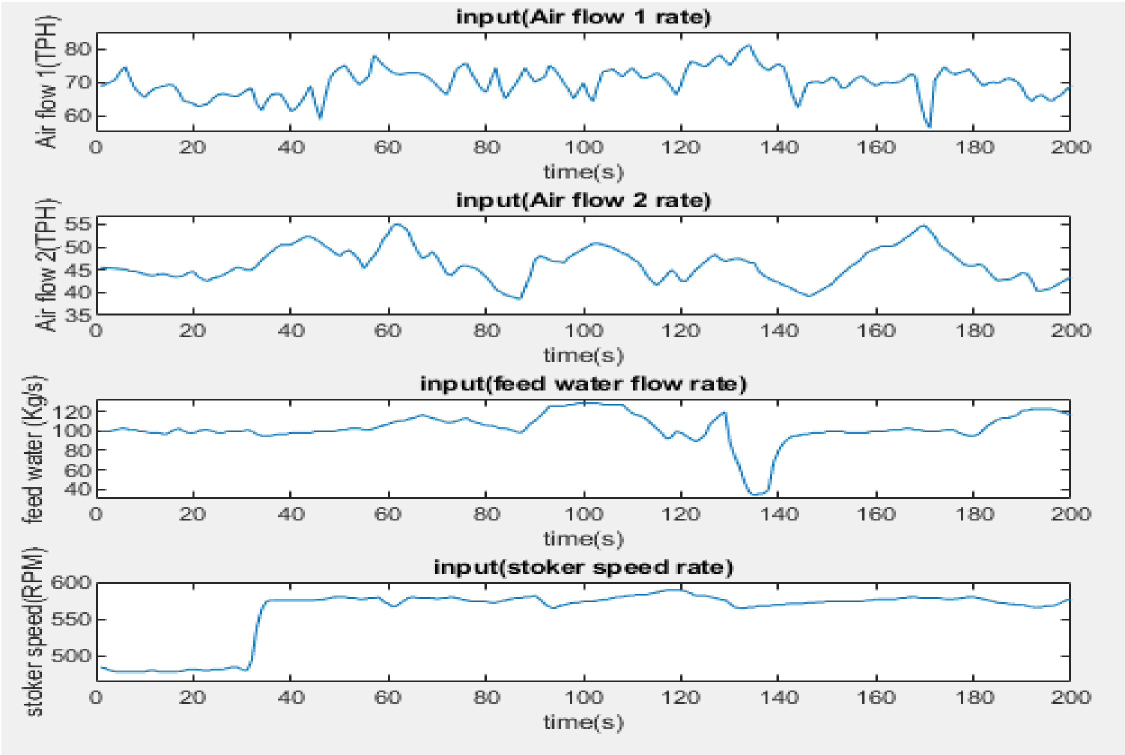


Figure 5.1: Graph of input variables data

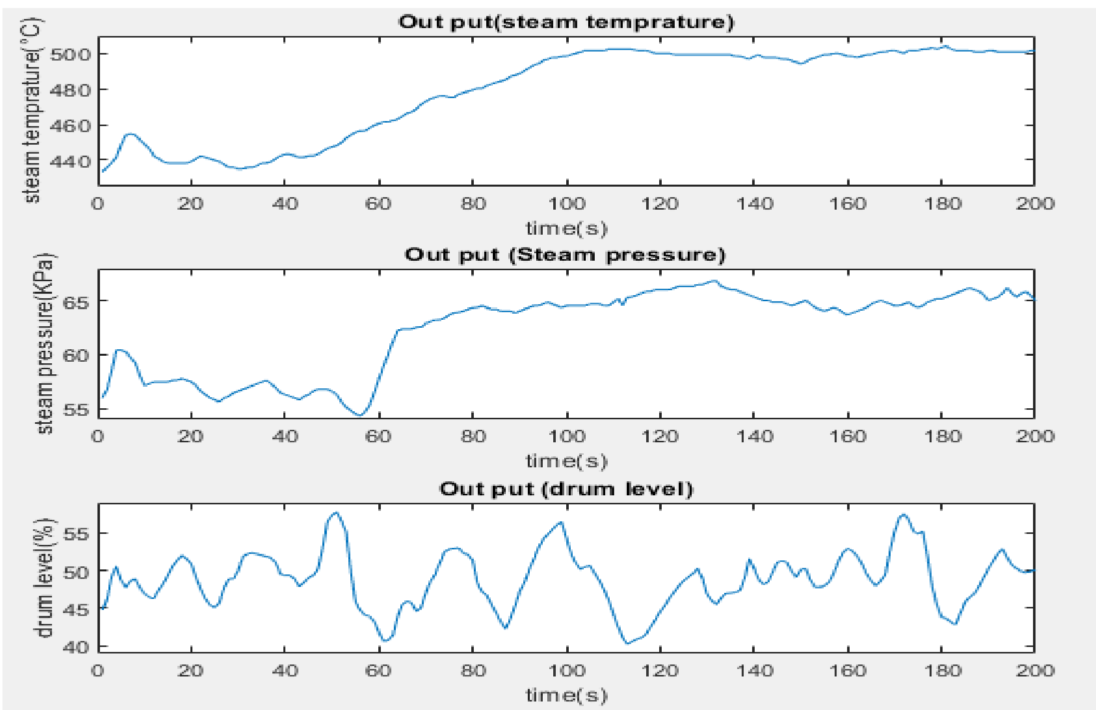


Figure 5.2: Graph of output variables data

5.3 Analysis of the Model

The identified RBF neural network models are simulated in Matlab/Simulink R2021a environment. The biomass boiler process model is determined by estimating a nonlinear ARX model. It uses input and output data from the Wonji Shoa sugar plant and employs the RBF as the activation function for the neural network's hidden layer. Once the nonlinear ARX model has been determined, validation must be performed before designing a controller.

5.3.1 Analysis of RBFNN Training

Since RBFNN training is an iterative process, it may be terminated when the overall training error falls below a predetermined level. The hidden layers can reduce error by using a variety of neurons. The number can gradually be raised or lowered by starting with a minimal number of neurons until a desired training error is attained. This study considers a network with 30 hidden neurons with 1000 alternative initial weight sets. For a proper review of the performance of an RBFNN trained model, the model performance, regression, and model error plots were used. Figure 5.3 presents the mean squared error against RBFNN training, test and best values for an RBFNN model with 30 neurons in the hidden layer. The difference between the validation result and the expected RBFNN outcomes is taken into account when calculating the mean squared error (target). The objective was to optimise the transferred function by iteratively adjusting the weight of the input signal. The illustrated figure demonstrates that the RBFNN performance changes over epochs within around 157 epochs. The MSE maintains at a value of 0.3633.

The Regression figures in Figure 5.4- Figure 5.6 demonstrate the relationship between the system's outputs and the RBFNN outcomes (targets). The R-value shows the link between the outputs and the targets. R values for all graphs are close to 1, as seen in the three figures. The results are a very excellent match for the training, validation, and test data sets.

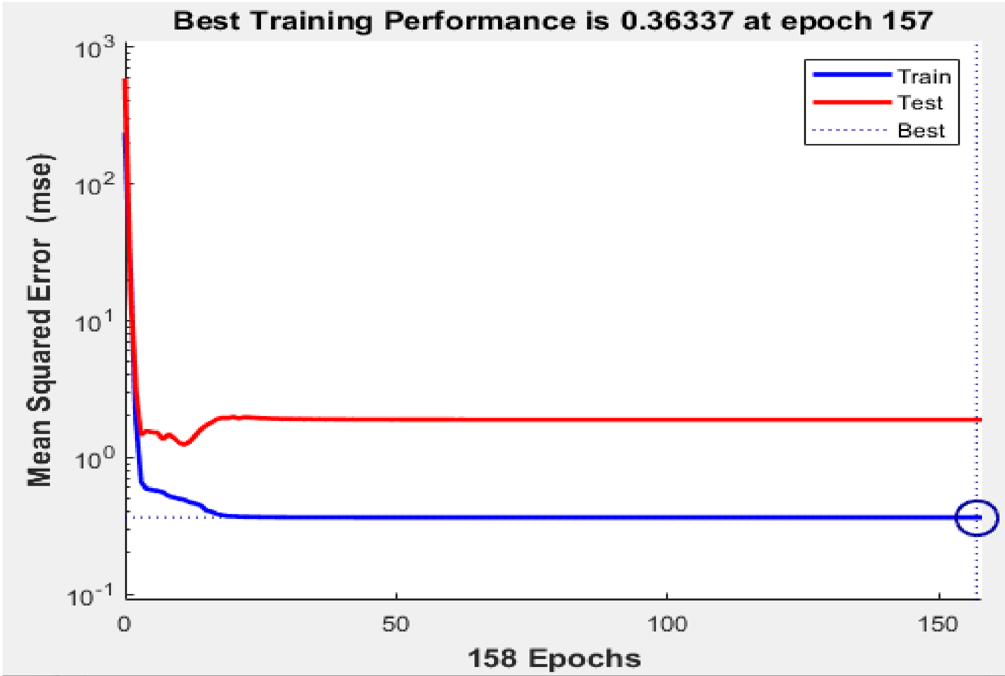


Figure 5.3: Mean Squared Error (MSE) versus the number of Training Epochs

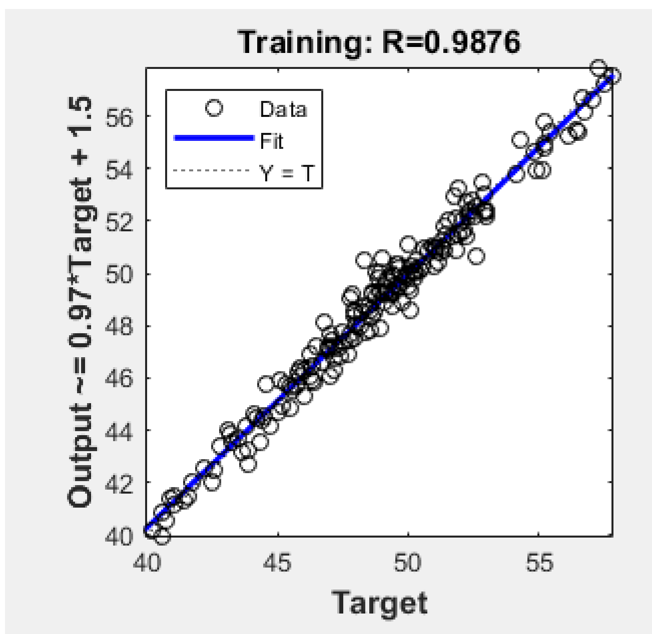


Figure 5.4: linear Regression plot for Training data

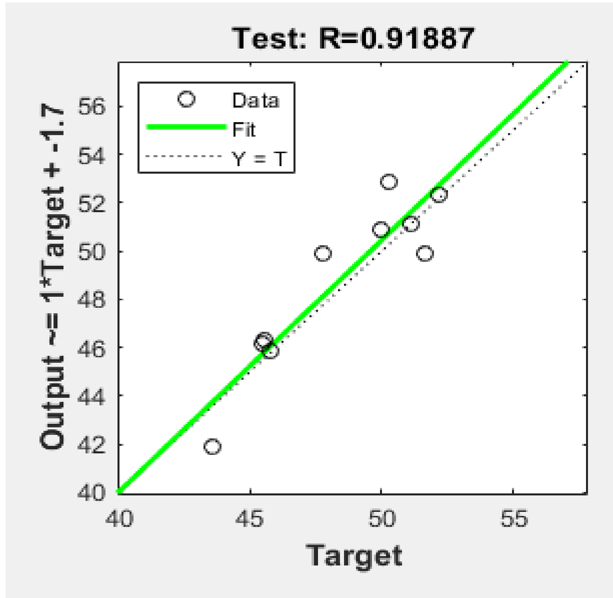


Figure 5.5: Linear regression plot for test data

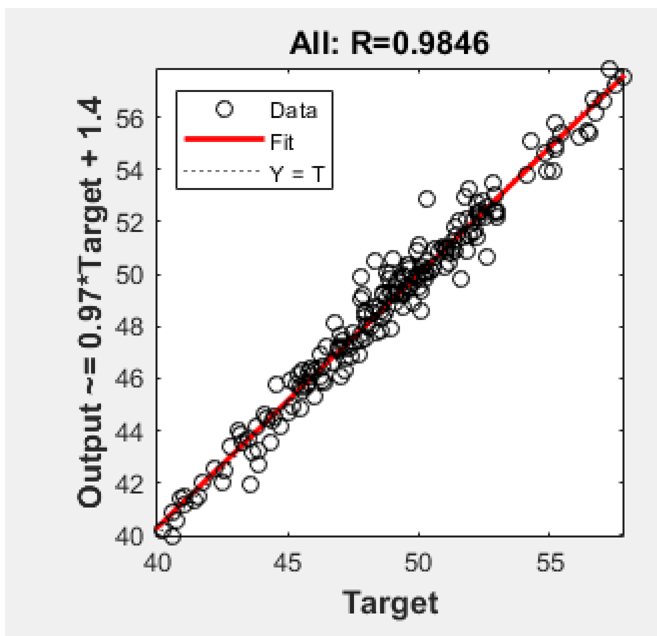


Figure 5.6: Linear regression plot for All data

The histogram of errors between desired values and predicted values during neural network training is known as the error histogram. Since these error numbers show how the goal values and anticipated values vary, it might be the value is negative.

According to the error (predicted versus actual) histogram, which is displayed in Figure 5.7 the majority of predicted values have extremely small errors that range from 08991-0.889.

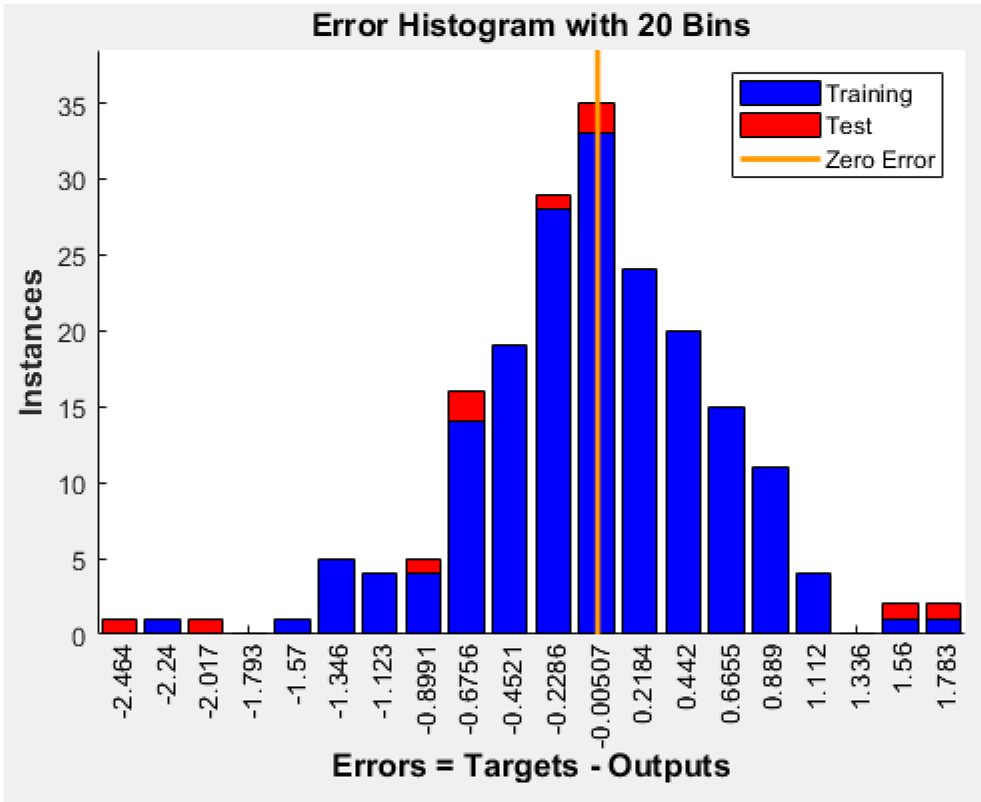


Figure 5.7: Error histogram in the RBFNN training process.

5.3.2 Analysis of RBFNN model and state space model

A linear state space model has also been estimated to make a comparison. Figure 5.8 and Figure 5.10 shows the Simulink model of biomass boiler system with and without RBF respectively. By random sample selection of inputs from the actual measured data, it is possible to see the response of the estimated model to know how it behaves. The resulting model output will be compared to the actual measured outputs.

Figure 5.9 and Figure 5.11 shows the estimated model outputs for randomly selected inputs. The randomly chosen inputs are 70.38 TPH, 42.85 TPH, 113.26 Kg/s and 571.91 RPM for airflow1, airflow2, water flow and stocker speed, and outputs are 501.81 °C, 66.19 PSI and 46.45 % for temperature, pressure and drum level respectively.

As shown in Figure 5.9, steady-state responses for the RBFNN model are 508.5 °C, 65.58 PSI and 48.17 % for temperature, pressure and water level, respectively.

In addition, Figure 5.11 shows steady state responses for the system model without using radial basis function are 470.6 °C, 60.49 PSI and 42.87% for temperature, pressure and water level respectively.

Table 5.2: Comparison of model outputs

Controlled variables	Measured outputs	RBFNN	ssEstimated
Temperature in °C	501.81	508.56	470.6
Pressure in PSI	66.19	65.58	60.49
Drum level in %	46.45	48.1	42.87

The actual measured data fit estimation data by [97.75; 95.73; 82.59]% for temperature, pressure and drum water level, respectively when the system is estimated by using a Radial basis function neural network. On the other hand, when the system model is estimated without using Radial basis function neural network, the actual measured data fit estimation by [97.26; 93.52; 77.64]% to temperature, pressure and drum water level, respectively. From the above results, the model with RBF neural network best fits the actual measured data. As a result, the RBF neural network-based estimation model better approximates the actual plant.

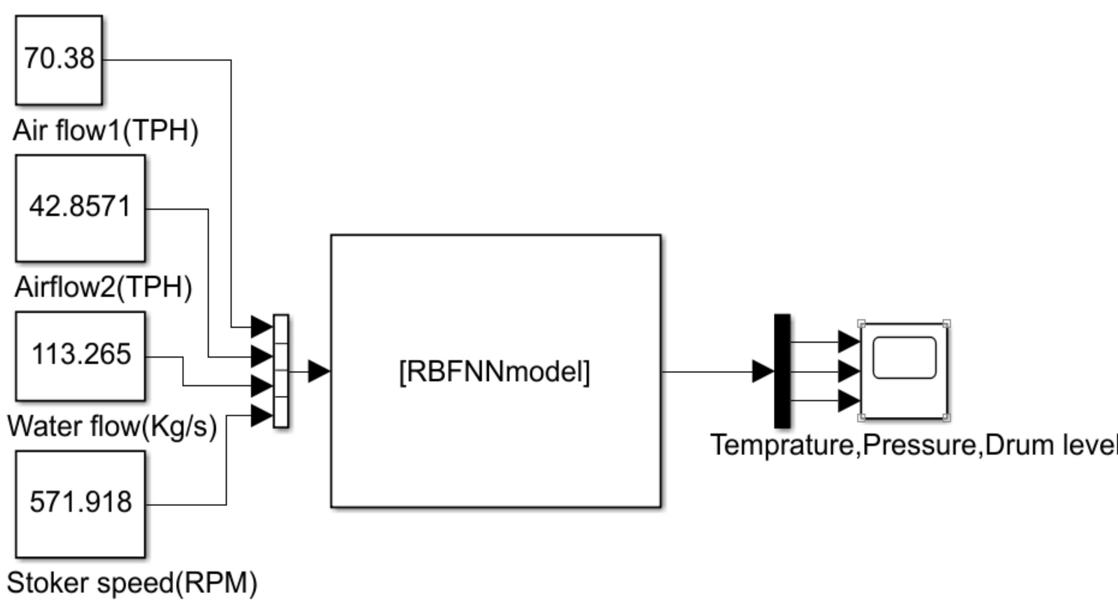


Figure 5.8: RBF neural network simulink model of Biomass Boiler with measured inputs

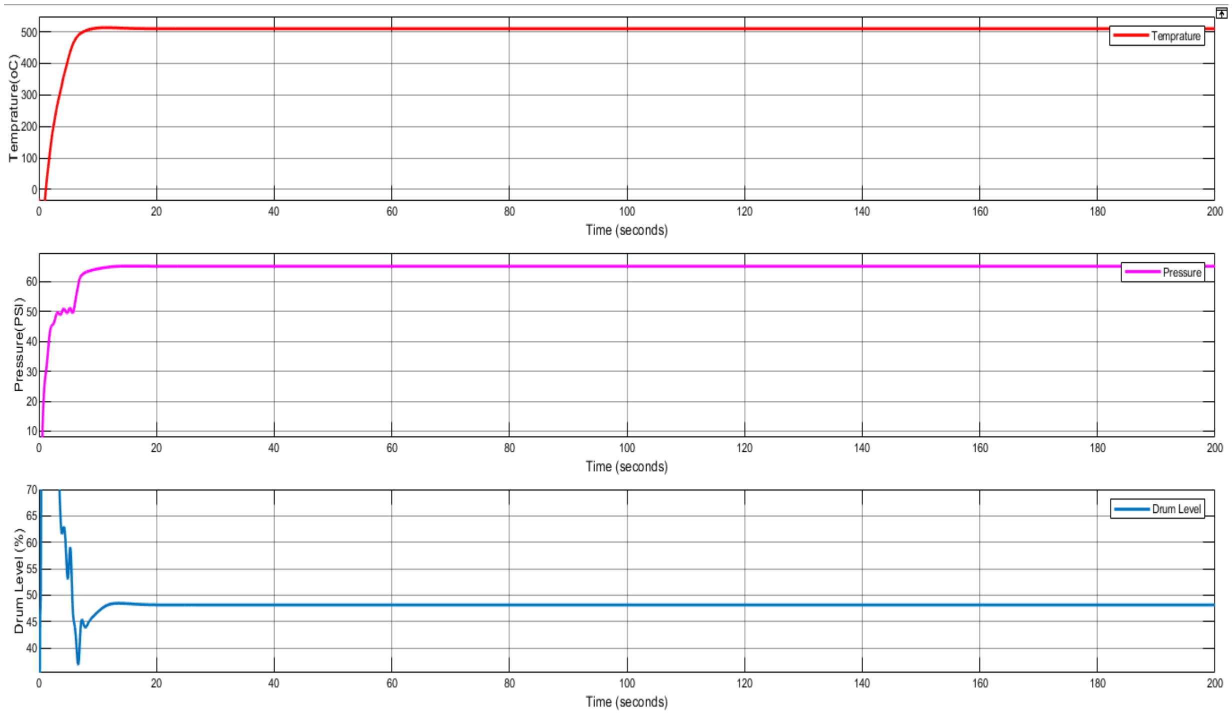


Figure 5.9: Response of RBFNN model of Biomass Boiler for measured inputs

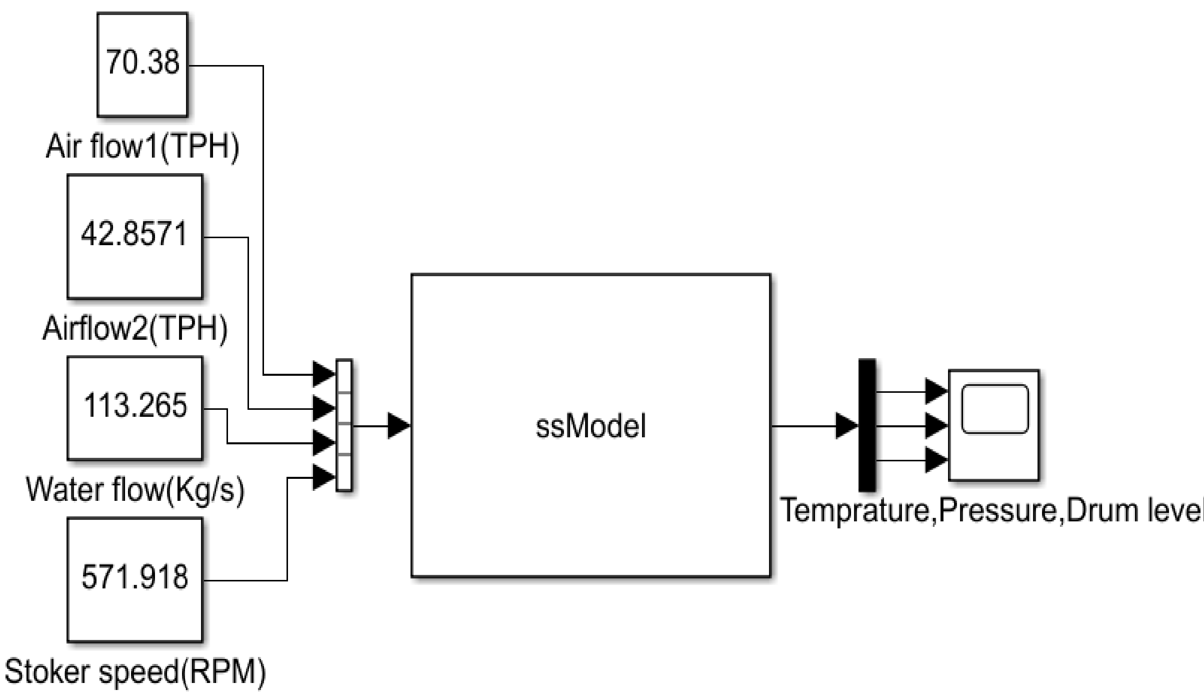


Figure 5.10: Simulink model of Biomass Boiler without RBF with measured inputs

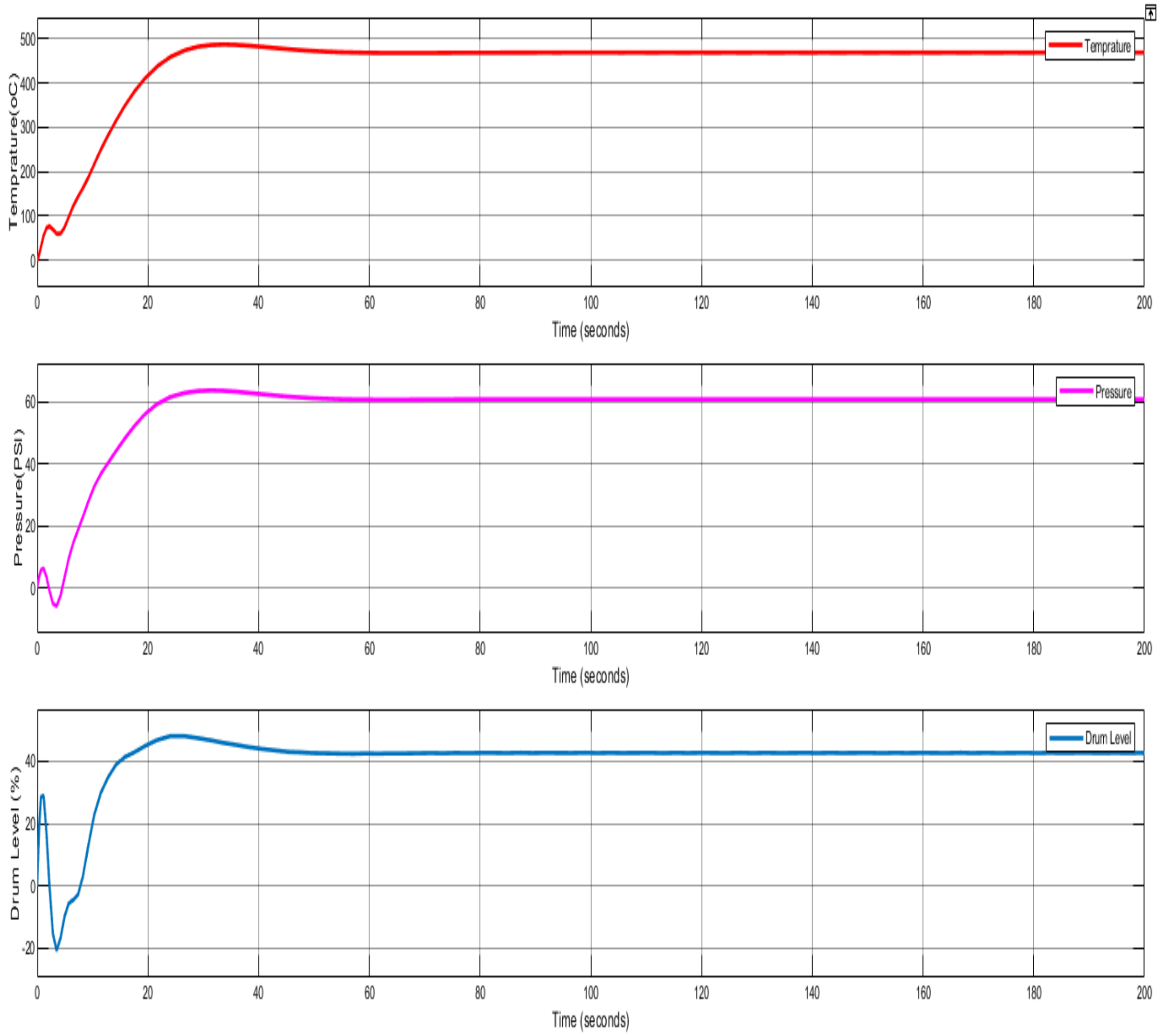


Figure 5.11: Response of Biomass Boiler model without RBF for measured inputs

5.4 Response of closed loop system

The entire system simulation block is made up of several components, one of which is a model predictive controller for two different RBF neural network models of biomass boiler systems (with and without RBF). Figure 5.12 shows the closed-loop Simulink model of the biomass boiler system with and without the RBF neural network. Once developed in MATLAB/Simulink, the schematic diagram can be simulated using various algorithms. These algorithms determine the internal state variables of the blocks by computing their corresponding ordinary differential equations representing their models in MATLAB. The algorithm is crucial for reducing calculation time and improving simulation accuracy.

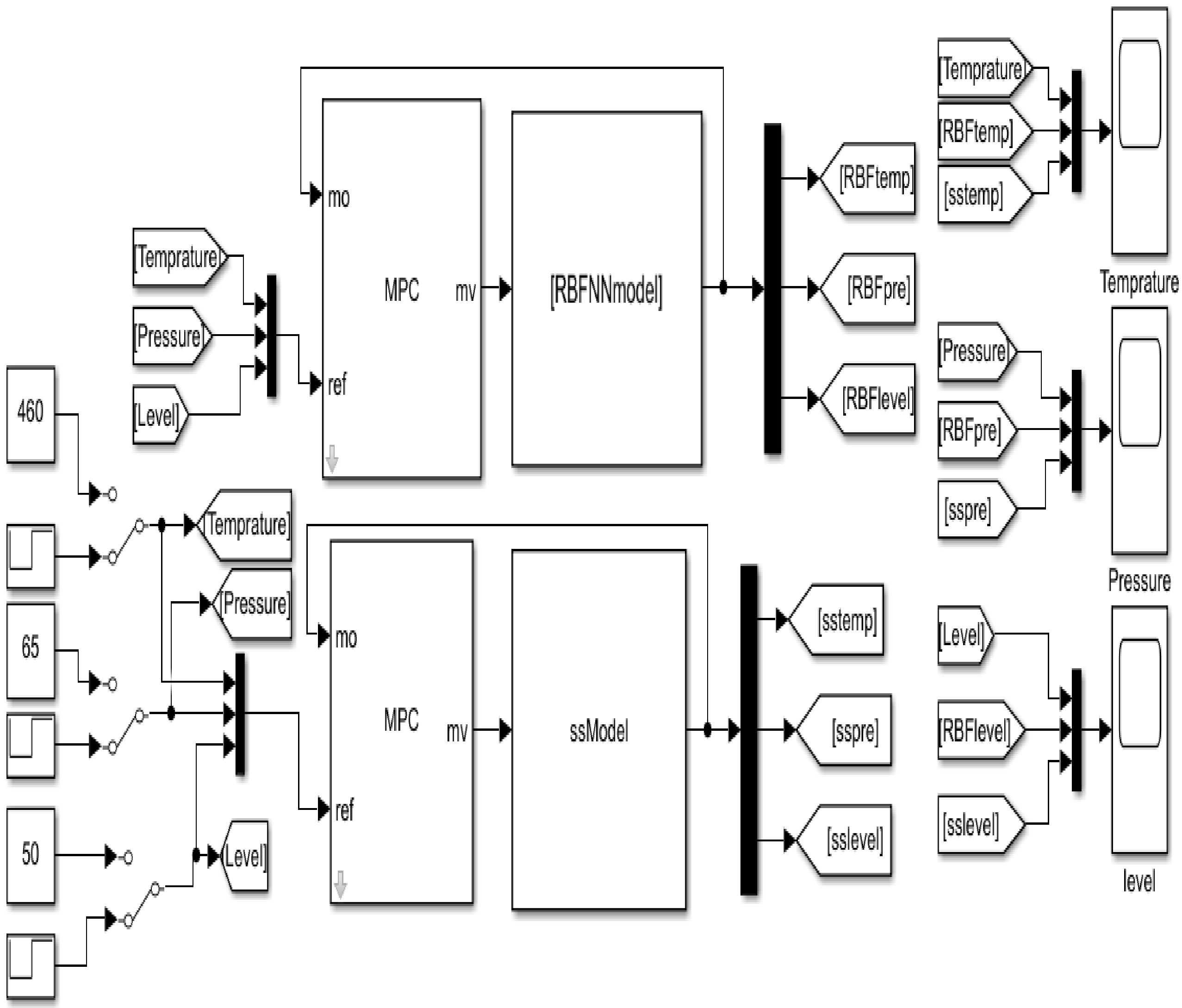
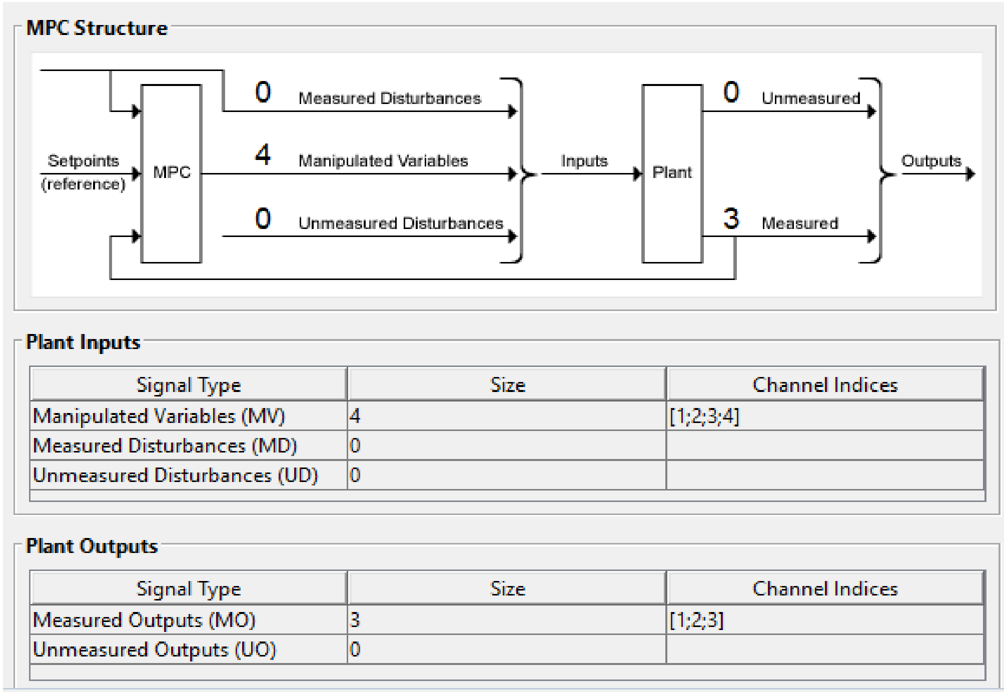


Figure 5.12: Closed loop Simulink model of Biomass Boiler with and without RBF

The Model Predictive Controller parameters are manually configured using the MATLAB Model Predictive Controller Designer toolbox. Figure (5.16-5.18) shows the manually adjusted MPC parameters: prediction horizon = 30 and control horizon = 7 for both controllers to obtain the closed loop response. The simulation results are carried out at 460°C, 60PSI and 50% for temperature, pressure and water level reference respectively. This study compares the closed-loop performance of an RBF neural network model for a biomass boiler to a typical state space model. Figure 5.14 shows that the cost function of the MPC graph is fastly decreased and within 1 second. which means the optimal cost function can be achieved quickly in this study.



Plant Inputs

Signal Type	Size	Channel Indices
Manipulated Variables (MV)	4	[1;2;3;4]
Measured Disturbances (MD)	0	
Unmeasured Disturbances (UD)	0	

Plant Outputs

Signal Type	Size	Channel Indices
Measured Outputs (MO)	3	[1;2;3]
Unmeasured Outputs (UO)	0	

Figure 5.13: MPC structure of the system

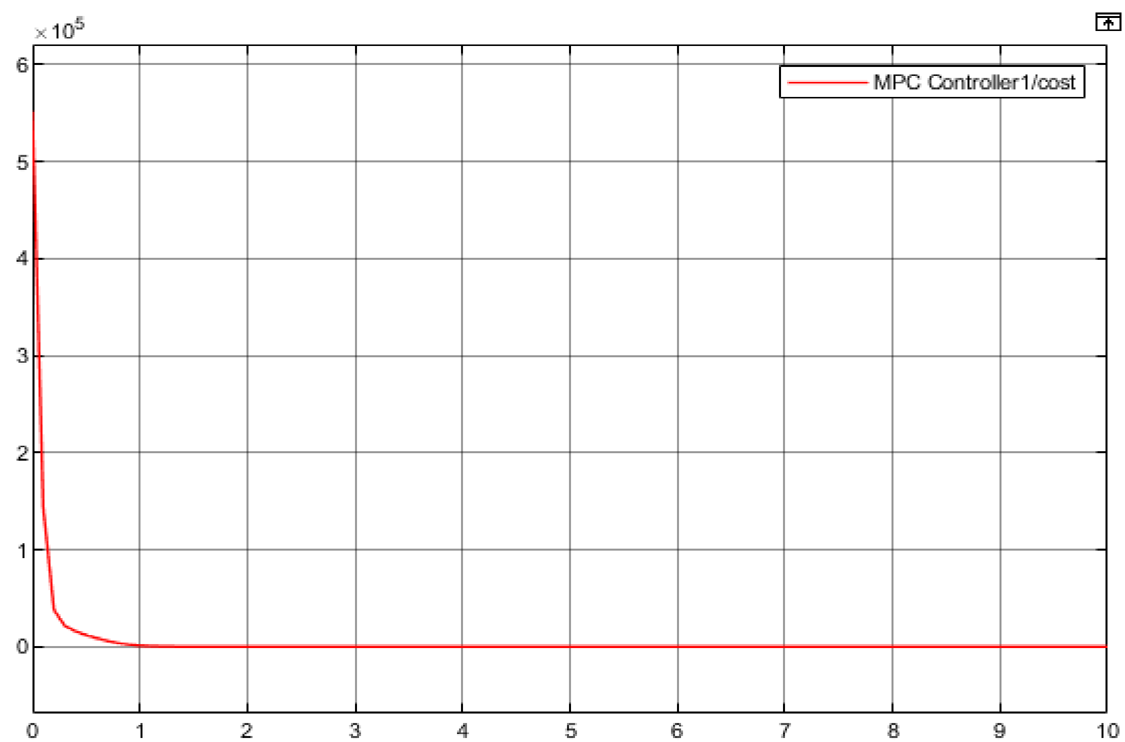


Figure 5.14: Optimal cost function of MPC

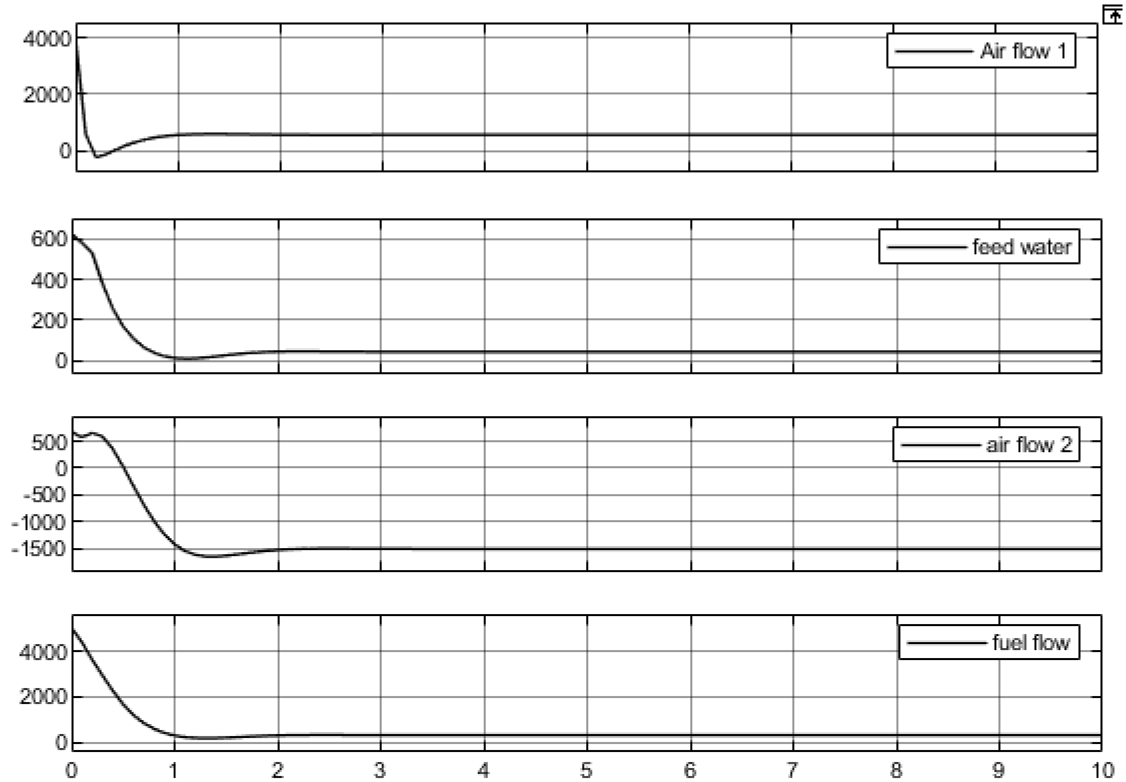


Figure 5.15: Response of Manipulated variable from MPC

The controllers are assessed based on performance criteria like rising time, settling time, steady-state error, peak value and overshoot. MPC controller with RBFNN model outperforms MPC controller with conventional state space model in all performance criteria. The closed-loop response of the system is illustrated in Figure (5.16 - 5.18). The response of MPC controllers with RBFNN and state space model performance characteristics are presented in Table 5.3.

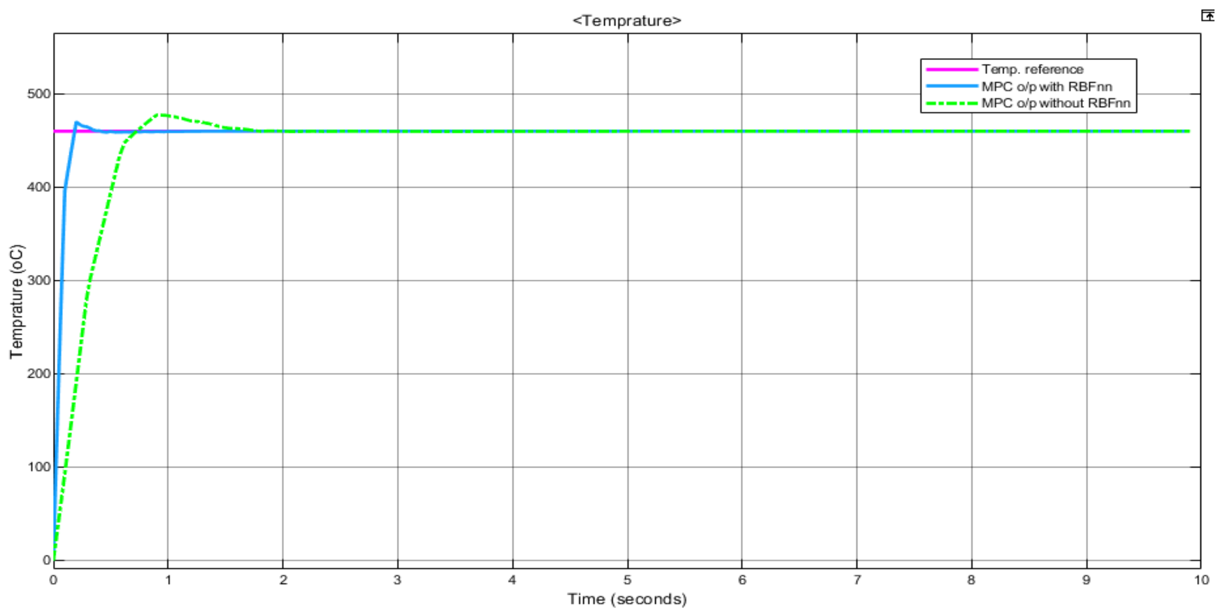


Figure 5.16: Temperature response of MPC with and without RBF neural network model

Figure 5.16 shows the temperature response of MPC controlled RBFNN and state space modelled biomass boiler. As shown in Table 5.3 the MPC with the conventional state space model has higher overshoot, rise time and settling time compared to MPC with RBFNN model. However, the steady-state error for both models is zero. The RBFNN model controlled by MPC exhibits faster performance. As a result; it can be concluding MPC with RBFNN model has better performance than MPC with conventional state space model in rise time, settling time and maximum overshoot performance criteria for a measured temperature output.

Table 5.3: Comparison of controller performance

Performance criteria	**Model with RBF**			**Model without RBF**			**Model with Fuzzy [27]**		
	Temperature in °C	Pressure in PSI	Level in %	Temperature in °C	Pressure in PSI	Level in %	Temperature in °C	Pressure in PSI	Level in %
Rise Time(sec)	0.094	0.368	0.0422	0.4927	1.254	0.129	0.8	2.349	-
Settling time(sec)	0.2072	0.6841	0.673	1.3231	2.038	3.203	4	5	7
Overshoot(%)	2.1086	1.19	15.698	3.616	1.607	25.67	1.53	0.214	-

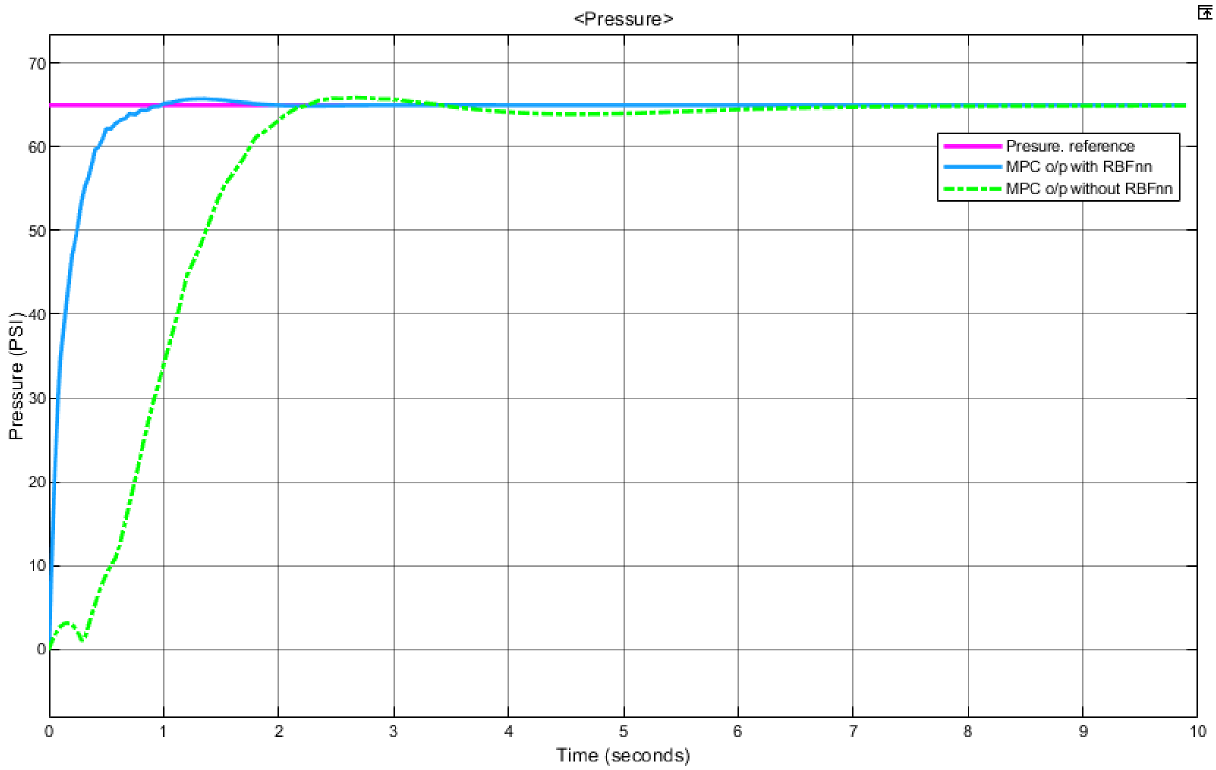


Figure 5.17: Pressure response of MPC with and without RBF neural network model

Figure 5.17 shows the pressure response of MPC-controlled RBFNN and state space modeled biomass boiler system. As shown in Table 5.3, MPC with the conventional state space model has higher overshoot, rising time, and settling time than MPC with RBFNN model. The steady-state error is 0.01PSI for MPC with state space model. The RBFNN model controlled by MPC exhibits faster performance. As a result, it can be concluding MPC with RBFNN model has better performance than MPC with the conventional state space model in rise time, settling time and maximum overshoot performance criteria for a measured pressure output.

Figure 5.18 shows the drum water level response of MPC-controlled RBFNN and state space modeled biomass boiler which is MIMO system. As shown in Table 5.3, MPC with the conventional state space model has higher overshoot, rising time, and settling time than MPC with RBFNN model. However, the steady-state error for both models is zero. The RBFNN model controlled by MPC exhibits faster performance. As a result, it can be concluding MPC with RBFNN model has better performance than MPC with conventional state space model in rise time, settling time and maximum overshoot performance criteria for a measured level output.

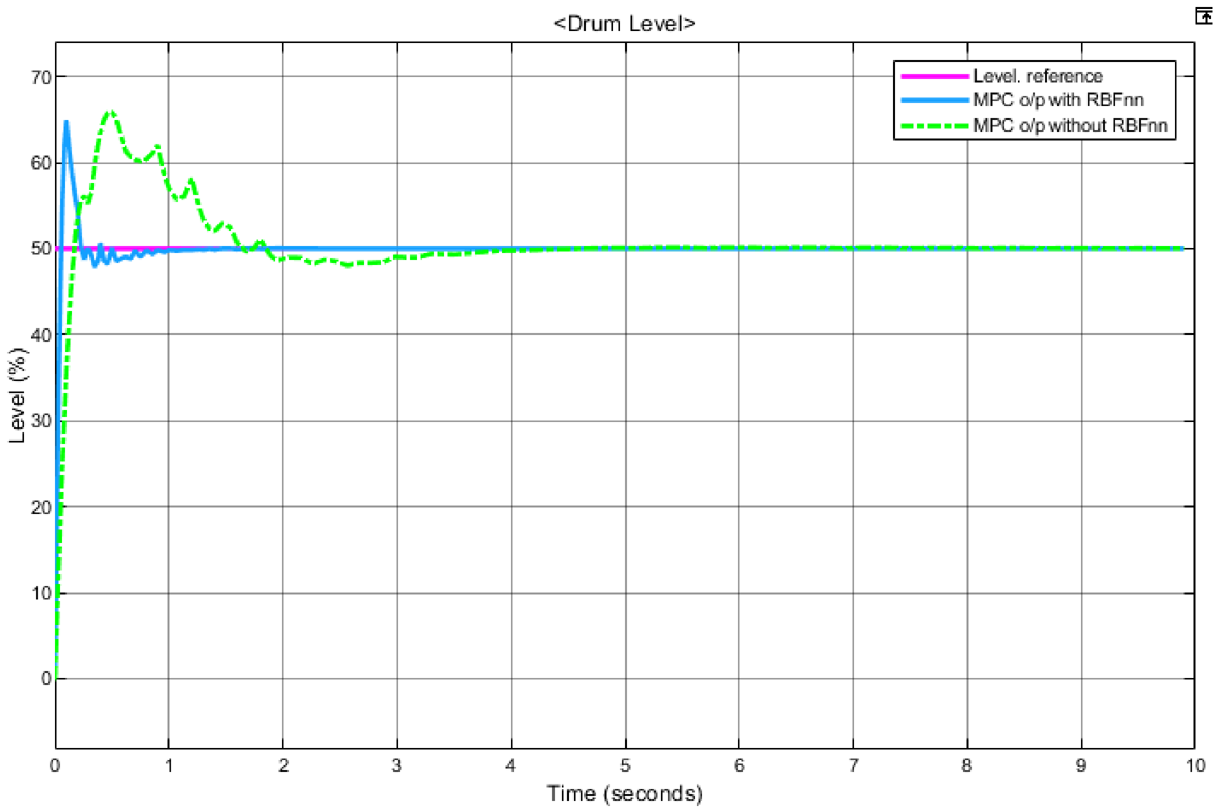


Figure 5.18: Drum level response of MPC with and without RBF neural network model

5.5 Controller reference variation tracking capabilities

Results from the simulation are performed for temperature, pressure and water level references. The considered references are below and above the references to find both MPC controllers to examine system performance at low and high references. The Temperature references of 460°C and 500 °C are utilised in the simulation with 7 sec intervals. Pressure references that are taken for simulation are 60PSI and 65PSI applied sequentially at 7 sec time intervals. Drum level references that are taken for simulation are 40%, and 50% applied successively at 7 sec time interval. Figure 5.19 illustrates that the MPC with RBFNN model can track the biomass boiler temprture references efficiently compared to MPC without RBFNN model. The result shows that the temperature using MPC with RBFNN model is achives better results in overshoot, settling time, steady-state error and rise time as above temperature analysis.

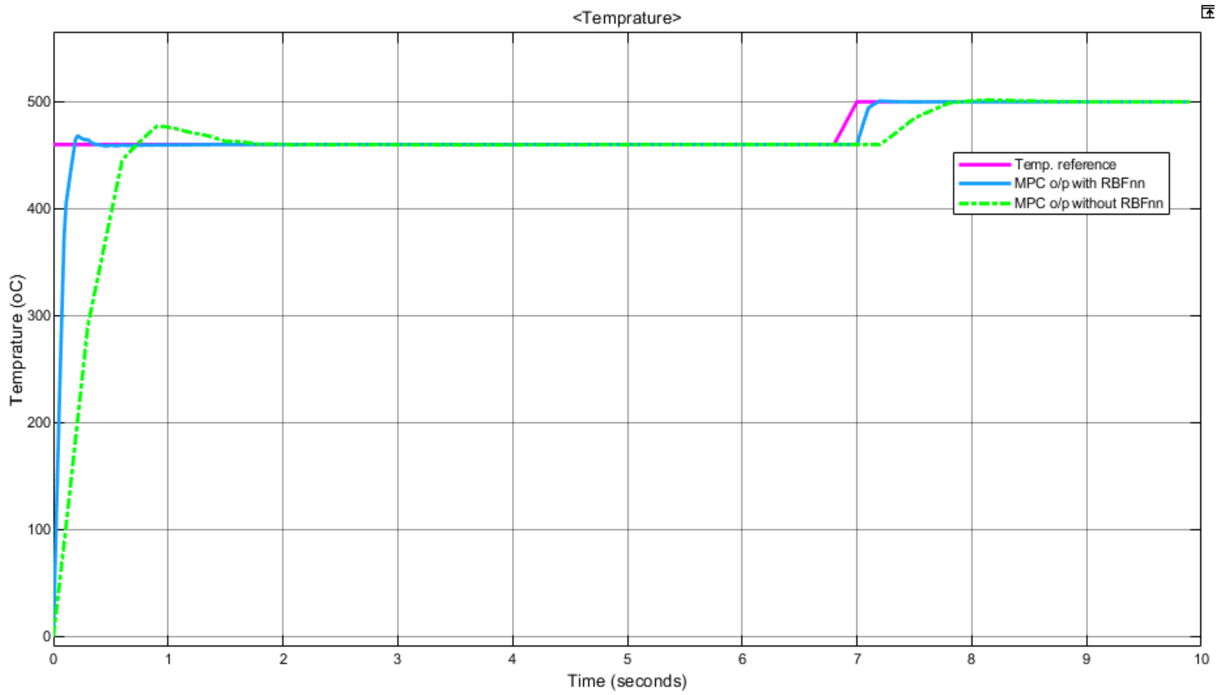


Figure 5.19: Tracking capability for different temperature references

Figure 5.20 shows that the MPC with the RBFNN model can track the biomass boiler pressure references efficiently compared to MPC without RBFNN model. The result shows that the pressure using MPC with RBFNN model is achives better result in overshoot, settling time, rise time and peack value.

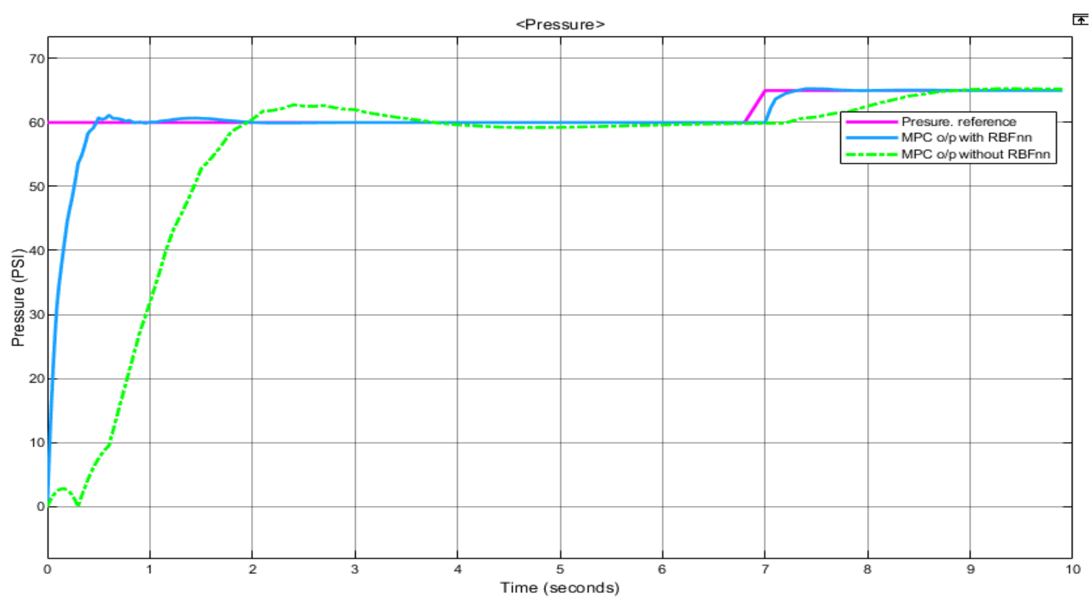


Figure 5.20: Tracking capability for different pressure references

As shown in Figure 5.21 the MPC controller with RBFNN model can track the biomass boiler drum level references efficiently compared to MPC without RBFNN model/convectional state space model. The result shows that the drum level using MPC with RBFNN model achieves better results in overshoot, settling time, and rise time as other controlled variables.

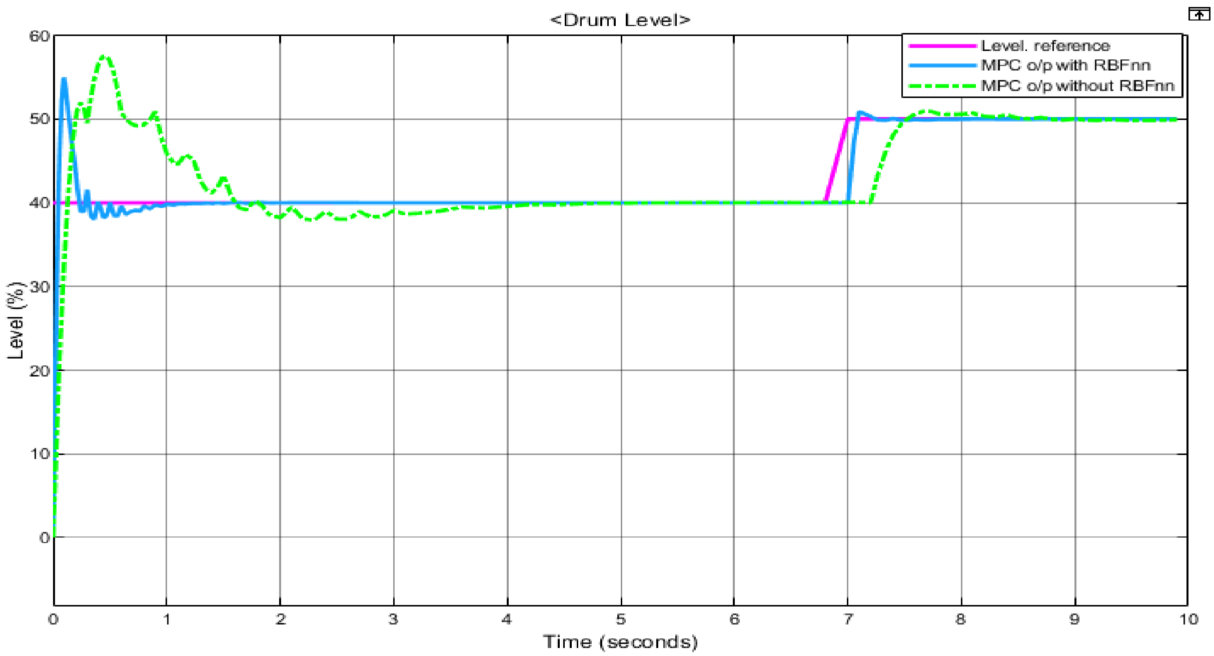


Figure 5.21: Tracking capability for different drum level references

CHAPTER SIX
CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

Throughout the entire study, four significant tasks were carried out. All those are analysis of the Radial Basis Function Neural Network based Biomass boiler model, design of Model predictive controllers for both RBFNN and ordinary state space model and then, a comparison of the previous two controllers' performance based on findings from MATLAB/Simulink. For two different models have been performed. This was done by finding the RBF based nonlinear neural network model for the biomass boiler, and the global instantaneous linearization approach was used to linearise. The controlled variables chosen are Pressure, Temperature, and water level of the system. These variables are nonlinear as well as time-varying inside the biomass boiler operation. There is a lot of interaction between both inputs and outputs in the MIMO biomass boiler process. Because of this, the system design is controlled effectively using the model predictive controller.

Based on the collected data, the biomass boiler model was developed using RBFNN. Using the MATLAB MPC designer toolbox the model predictive controller is automatically designed after the linearisation process. The simulation was run to follow the reference values for Temperature, Pressure, and water level, which were 480°C, 65 PSI and 50%, respectively. With a model predictive controller suggested control performance is accomplished. The results of the boiler model simulation are examined with and without RBFNN. RBFNN based boiler models generate great result because they are more accurate than models without RBFNN. Taking into account each parameter specifications and the responses of each controlled variable. The controller's parameters were manually adjusted. Prediction horizon (P) = 30, control horizon (M) = 7, and 0.1 second sampling time were the tunning settings for the Model Predictive Controller that demonstrated an excellent response. These simulation results show that when compared to the MPC controller using the state space model, the RBF neural network model based MPC achieved faster rising times for temperature and pressure of 0.398 sec and 0.88 sec, respectively, as well as faster settling times for temperature, pressure, and water level of 1.296 sec, 1.345 sec, and 2.53 sec.

6.2 Recommendations

As demonstrated in the results and discussion section, the Radial basis function neural network-based model predictive control performs better than the standard state space based model predictive control for temperature, pressure, and water level of biomass boiler process. Since the modeling in the identification phase focuses only on simulation to confirm the steady state data, anyone may use it and put it into practice. In this study, a linearised RBF nonlinear neural network model based MPC controller is designed. Nonlinear model predictive control and adaptive model predictive control can be used to improve the control of the biomass boiler. In future work, considering that time varying, multi input multi output and non linear system systems like a biomass boiler, a nonlinear model predictive controller is more powerful than a linear model predictive controller. By applying the genetic algorithm, local search optimisation (LSO) and particle swarm optimisation (PSO) the tuning approach may also be advanced to automated tuning, which may enhance the effectiveness of controllers. Finally, the research may further be expanded for digital circuits by using digital signal processing (DSP) and field programmable gate arrays (FPGA).

REFERENCES

[1] T. Panklib, “Potential of Agricultural Residues for Small Biomass Power Generation in Thailand,” *Int. J. Adv. Cult. Technol.*, vol. 4, no. 1, pp. 1–9, 2016, doi: 10.17703/ijact.2016.4.1.1.

[2] N. E. Benti *et al.*, “The current status, challenges and prospects of using biomass energy in Ethiopia,” *Biotechnol. Biofuels*, vol. 14, no. 1, pp. 1–24, 2021, doi: 10.1186/s13068-021-02060-3.

[3] R. L. Bain and R. P. Overend, “Biomass for heat and power,” *For. Prod. J.*, vol. 52, no. 2, pp. 12–19, 2015.

[4] H. Moradi, F. Bakhtiari-Nejad, and M. Saffar-Avval, “Robust control of an industrial boiler system; a comparison between two approaches: Sliding mode control & H∞ technique,” *Energy Convers. Manag.*, vol. 50, no. 6, pp. 1401–1410, 2009, doi: 10.1016/j.enconman.2009.03.002.

[5] H. Yu, T. Xie, S. Paszczyñski, and B. M. Wilamowski, “Advantages of radial basis function networks for dynamic system design,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 12, pp. 5438–5450, 2011, doi: 10.1109/TIE.2011.2164773.

[6] Ke-Lin Du · M. N. S. Swamy, *Neural Networks and Statical Learning*. London: Springer-Verlag, 2014.

[7] M. M. D. James B. Rawlings, David Q. Mayne, *Model predictive control*, 2nd ed. Santa Barbara, California: Nob Hill publishing, 2019.

[8] Jerry Gilman, *Boiler control systems engineering*, 2nd ed., vol. 58, no. 12. United State of America: International Society of Automation, 2010.

[9] J. Zhang and X. Wu, “Predictive functional control simulation of boiler combustion control system,” *2011 2nd Int. Conf. Mech. Autom. Control Eng. MACE 2011 - Proc.*, pp. 529–532, 2011, doi: 10.1109/MACE.2011.5986977.

[10] Z. Li, X. Wang, X. Gao, and X. Zhang, “Utility boiler’s combustion performance modeling based on modular RBF network,” in *Proceedings - 2011 7th International Conference on Natural Computation, ICNC 2011*, 2011, vol. 2, pp. 873–877, doi: 10.1109/ICNC.2011.6022166.

[11] F. M. de Mello, A. J. G. da Cruz, and R. de Sousa, *Fuzzy Control Applied to Combustion in Sugarcane Bagasse Boilers*, vol. 46. Elsevier Masson SAS, 2019.

[12] P. Manke and S. Tembhurne, “Application of Back Propagation Neural Network to Drum Level Control in Thermal Power Plants,” *Int. J. Comput. Sci. Issues*, vol. 9, no. 2, 2012.

[13] K. Xiangsong, C. Xurui, and G. Jiansheng, “PID controller design based on radial basis function neural networks for the steam generator level control,” *Cybern. Inf. Technol.*, vol. 16, no. 5, pp. 15–26, 2016, doi: 10.1515/cait-2016-0048.

[14] L. Li and W. Ding, “Optimization control strategy of boiler water level based on fuzzy PID,” *Proc. 28th Chinese Control Decis. Conf. CCDC 2016*, pp. 5893–5896, 2016, doi: 10.1109/CCDC.2016.7532052.

[15] H. Li, Y. Zhang, and D. Li, “Internal model control using GA-NN for boiler drum,” in *Proceedings - 2011 7th International Conference on Natural Computation, ICNC 2011*, 2011, vol. 2, pp. 658–662, doi: 10.1109/ICNC.2011.6022240.

[16] F. Mohammadhassani, A. Ramezani, and M. Razzazan, “Drum Boiler Control with Output Constraints using Model Predictive Control Method,” *Modares J. Electr. Eng.*, vol. 14, no. 1, 2014.

[17] D. Li, Q. Wang, and L. Zhao, “Design of Biomass Boiler Intelligent Heating System Using Fuzzy PID,” in *International Conference on Electromechanical Control Technology andTransportation (ICECTT2018)*, 2018, no. Icectt, pp. 19–22, doi: 10.5220/0006964200190022.

[18] V. Plaček and C. Oswald, “Fuzzy Controller for Medium-Scale Biomass Boiler,” *Holist. approach to Environ.*, vol. 6, no. 4, pp. 181–187, 2016.

[19] J. Tavoosi and A. Mohammadzadeh, “A new recurrent radial basis function network-based model predictive control for a power plant boiler temperature control,” *Int. J. Eng. Trans. C Asp.*, vol. 34, no. 3, pp. 667–675, 2021, doi: 10.5829/ije.2021.34.03c.11.

[20] C. Pornsing and A. Watanasungsuit, “Steam generating prediction of a biomass boiler using artificial neural network,” *Proc. - 2016 2nd Int. Conf. Control. Autom. Robot. ICCAR 2016*, vol. 1, no. 1, pp. 281–284, 2016, doi: 10.1109/ICCAR.2016.7486741.

[21] P. Ganesan, S. J. Rathna, and R. Saidur, “Application of artificial neural network to map the performance characteristics of boiler using different algorithms,” *Int. J. Green Energy*, vol. 18, no. 11, 2021, doi: 10.1080/15435075.2021.1891908.

[22] H. Peng, “Multivariable RBF-ARX model-based predictive control for nonlinear systems,” *IFAC Proc. Vol.*, vol. 7, no. PART 1, pp. 882–887, 2007, doi: 10.3182/20070822-3-za-2920.00146.

[23] H. Peng, G. Kitagawa, J. Wu, and K. Ohtsu, “Multivariable RBF-ARX model-based robust MPC approach and application to thermal power plant,” *Appl. Math. Model.*, vol. 35, no. 7, pp. 3541–3551, 2011, doi: 10.1016/j.apm.2011.01.002.

[24] J. Tavoosi, Y. Azarakhsh, A. Mohammadzadeh, S. Mobayen, J. H. Asad, and R. Safdar, “Multivariable Model Reference Adaptive Control of an Industrial Power Boiler Using Recurrent RBFN,” *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/9754368.

[25] A. Mohamed, H. Elrasoul, A. Supervised, A. Taifour, and A. Ismail, “Boiler Control Design Using Fuzzy Logic,” Sudan University of Science and Technology, 2017.

[26] S. K. Sunori, P. K. Juneja, and A. B. Jain, “Model Predictive Control System Design for Boiler Turbine Process,” *Int. J. Electr. Comput. Eng.*, vol. 5, no. 5, pp. 1054–1061, 2015.

[27] A. Getnet, “Fuzzy Model Predictive Control for Biomass boiler,” Addis Ababa Science and Technology University, 2019.

[28] W. Tan, H. J. Marquez, and T. Chen, “Multivariable robust controller design for a boiler system,” *IEEE Trans. Control Syst. Technol.*, vol. 10, no. 5, pp. 735–742, 2002, doi: 10.1109/TCST.2002.801787.

[29] L. K. H. M. NØrgaard, O. Ravn, and N. K. Poulsen, *Neural Networks for Modeling and Control of Dynamic Systems*. London, UK: Springer, 2003.

[30] Haviluddin and R. Alfred, “Performance of modeling time series using nonlinear autoregressive with eXogenous input (NARX) in the network traffic forecasting,” *Proc. - 2015 Int. Conf. Sci. Inf. Technol. Big Data Spectr. Futur. Inf. Econ. ICSITech 2015*, vol. 2013, no. June 2013, pp. 164–168, 2016, doi: 10.1109/ICSITech.2015.7407797.

[31] N. Ismail, I. M. Ramli, and M. H. F. Rahiman, “Modeling induction-based steam distillation system by using nonlinear auto-regressive with exogenous input (NLARX) structure,” *Proc. - 2015 6th IEEE Control Syst. Grad. Res. Colloquium, ICSGRC 2015*, pp. 125–129, 2016, doi: 10.1109/ICSGRC.2015.7412478.

[32] B. Prasad, I. E., A. Budiyono, D. Min, and E. Choi, “System Identification of NN-based Model Reference Control of RUAV during Hover,” *Artif. Neural Networks - Ind. Control Eng. Appl.*, 2011, doi: 10.5772/15414.

[33] O. Davydov and D. T. Oanh, “On the optimal shape parameter for Gaussian radial basis function finite difference approximation of the Poisson equation,” *Comput. Math. with Appl.*, vol. 62, no. 5, pp. 2143–2161, 2011, doi: 10.1016/j.camwa.2011.06.037.

[34] H. Faris, I. Aljarah, and S. Mirjalili, “Evolving Radial Basis Function Networks Using Moth-Flame Optimizer,” in *Handbook of Neural Computation*, 1st ed., Australia: Elsevier Inc., 2017, pp. 537–550.

[35] J. Liu, *Radial basis function (RBF) neural network control for mechanical systems: Design, analysis and matlab simulation*. Beijing, China: Tsinghua University Press, 2013.

[36] Q. Xin, "RBF neural network based generalized predictive control for nonlinear stochastic systems," Lakehead University, 2013.

[37] H. Peng, T. Ozaki, V. Haggan-Ozaki, and Y. Toyoda, "A parameter optimization method for radial basis function type models," *IEEE Trans. Neural Networks*, vol. 14, no. 2, pp. 432–438, 2003, doi: 10.1109/TNN.2003.809395.

[38] C. N. Ko, "Identification of non-linear systems using radial basis function neural networks with time-varying learning algorithm," *IET Signal Process.*, vol. 6, no. 2, pp. 91–98, 2012, doi: 10.1049/iet-spr.2011.0025.

[39] P. E. Orukpe, "Model-predictive control fundamentals," *Niger. J. Technol.*, vol. 31, no. 2, pp. 139–148, 2017, doi: 10.1007/978-3-319-49347-3_26.

[40] S. H. Zak, "An Introduction to Model-Based Predictive Control (MPC)," in *lecture notes on ECE680, Purdue University*, 2017.

[41] T. Report, S. Ciannella, U. Federal, and C. Grande, "Applied Model Predictive Control - a brief guide do MATLAB / Simulink MPC toolbox APPLIED MODEL PREDICTIVE CONTROL by," no. August 2014, 2016, doi: 10.13140/RG.2.1.2334.7369.

[42] M. Lawryńczuk, *Computationally Efficient Model Predictive Control Algorithms*, vol. 3. Switzerland: Springer International Publishing, 2014.

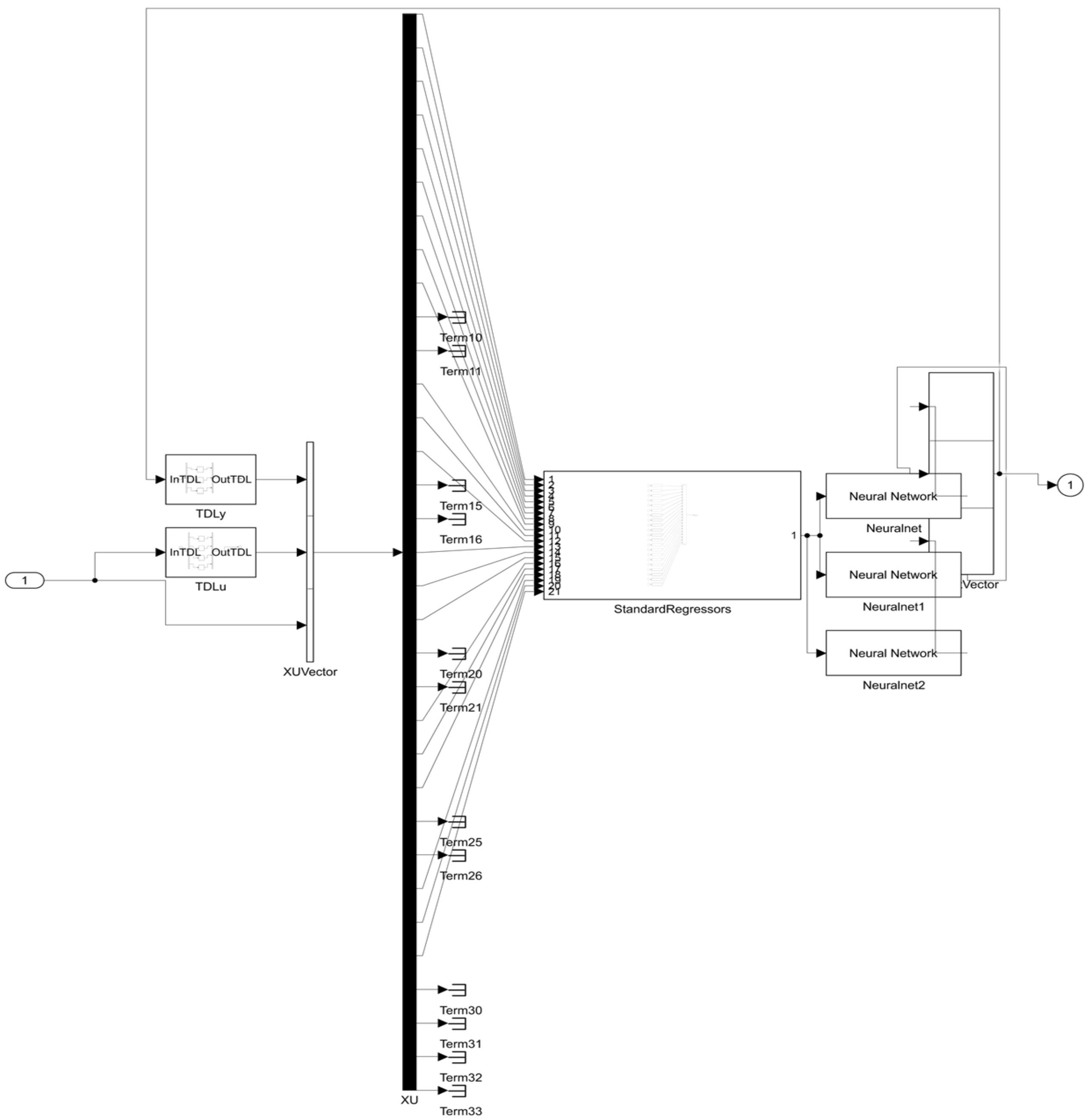
[43] T. Kang, H. Peng, F. Zhou, X. Tian, and X. Peng, "Robust predictive control of coupled water tank plant," *Appl. Intell.*, vol. 51, no. 8, pp. 5726–5744, 2021, doi: 10.1007/s10489-020-02083-7.

[44] M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: an engineering perspective," *Int. J. Adv. Manuf. Technol.*, vol. 117, no. 5–6, pp. 1327–1349, 2021, doi: 10.1007/s00170-021-07682-3.

[45] S. Li, P. Jiang, and K. Han, “RBF neural network based model predictive control algorithm and its application to a CSTR process,” *Chinese Control Conf. CCC*, vol. 2019-July, pp. 2948–2952, 2019, doi: 10.23919/ChiCC.2019.8865797.

APPENDICES

Appendix A. Expanded Simulink model of RBFNN model



Appendix B. MATLAB Codes of with and with out RBFNN model

B.1. Radial Basis Function Neural Network MatLab programs for running the Simulink model

```
clear all
clc
mydata=xlsread(' measureddata.xlsx','Sheet1','A1:G200');
in1=mydata(:,1);
in2=mydata(:,2);
in3=mydata(:,3);
in4=mydata(:,4);
out1=mydata(:,5);
out2=mydata(:,6);
out3=mydata(:,7);
inputs=[in1 in2 in3 in4];
outputs=[out1 out2 out3];
data = iddata(outputs,inputs,0.1);
data.InputName={'Air  Flow1';'Air  Flow2';'Water  Flow';'stoker
speed'};
data.OutputName={'Temperature';'Pressure';'Drum Level'};
data.InputUnit={'TPH','TPH','Kg/s','RPM'};
data.OutputUnit={'oC','PSI','%'};
data.TimeUnit = 'sec';
net = cascadeforwardnet([30]);
net.layers{1}.transferFcn = 'radbas';% 'radbas' stands for Ra-
dial basis function
net.trainFcn = 'trainbr';
net.divideParam.trainRatio = 90/100;
net.divideParam.valRatio = 5/100;
net.divideParam.testRatio = 5/100;
net.trainParam.min_grad=1e-12;
```

```
net.trainParam.mu_max=1e100;
net.trainParam.epochs=1000;
net.performFcn = 'mse';
net_estimator = neuralnet(net);
RBFNNmodel = nlarx(data,[3 3 3 3 3 3 3 3 3 3 3;3 3 3 3 3 3 3 3
3 3 3;3 3 3 3 3 3 3 3 3 3 3 ],net_estimator)
```

B.2. MatLab programs execute the Simulink model without using a Radial Basis Function Neural network (Estimation of state space)

```
clear all
clc
mydata=xlsread('measureddata.xlsx','Sheet1','A1:G200');
in1=mydata(:,1);
in2=mydata(:,2);
in3=mydata(:,3);
in4=mydata(:,4);
out1=mydata(:,5);
out2=mydata(:,6);
out3=mydata(:,7);
inputs=[in1 in2 in3 in4];
outputs=[out1 out2 out3];
data = iddata(outputs,inputs,0.1);
data.InputName={'Air Flow1';'Air Flow2';'Water Flow';'stoker
speed'};
data.OutputName={'Temperature';'Pressure';'Water Level'};
data.InputUnit={'TPH','TPH','Kg/s','RPM'};
data.OutputUnit={'oC','PSI','%'};
data.TimeUnit = 'sec';
ssModel=ssest(data)
```