Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants

Mehret Getahun Agonafer

A Thesis Submitted to

Department of Electrical Power and Control Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Master of Science Degree in Electrical Power and Control Engineering (Control Engineering)

Office of Graduate Studies

Adama Science and Technology University

October 2023.

Adama, Ethiopia.

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DECLARATION

I hereby declare that this Master Thesis entitled **“Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants”** is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Mehret Getahun	________________	________________
Name of student	Signature	Date

RECOMMENDATION

I the major advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled **"Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants"** prepared under my guidance by **Mehret Getahun** Submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Electrical Power and Control Engineering, postgraduate in Control Engineering. Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Dr. Tefera Terefe	______________	______________
Major Advisor/Supervisor	Signature	Date

APPROVAL SHEET

I, the advisor of the thesis entitled **"Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants**" developed by **Mehret Getahun,** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Tefera Terefe ____________________ ________________

Major Advisor/Supervisor Signature Date

We, the undersigned, members of the Board of Examiners of the thesis by **Mehret Getahun** have read and evaluated the thesis entitled "**Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants**" and examined the candidate during the open defence. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Electrical Power and Control Engineering, postgraduate in Control Engineering.

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Finally, approval and acceptance of the thesis are contingent upon the submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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ABSTRACT

Electrical energy is a necessary requirement in our common daily life as a way of reconstructing human development to financial productivity. Renewable energy beginnings are substitutes to increase energetic strength and productivity, but they need a direct control structure to receive optimum power product. It is new-era science used to produce electricity from household waste, that is used to decrease the need for landfills for waste and preserve the use of more priceless fuels, thereby protecting raw materials. A boiler turbine generator is an energy conversion device that is commonly used in thermal power plants. The boiler unit is one of the major components in a power plant which is used to store water and collect the steam by heating the water of tubes in the tuber. The control mechanism of steam boiler in Reppie waste-to-energy (WtE) power plant, which is found in Ethiopia, currently uses Programmable Logic Controller (PLC). However PLC is logic based control and it is based on the current measurement of the system which cannot predict the future condition of the system and it cannot handle the constraints inaddition PLCs have limitations in their ability to capture the nonlinear behavior of the system. This thesis considers controlling the Drum leve, Temperature and pressure of waste-to-energy thermal power plant boilers based on the measured input-output data gather from Reppie waste-to-energy plant. The model is obtained using system identification techniques such as Radial Basis Function Autoregressive with Exogenous input (RBF-ARX) model then apply Model predictive controller, in which the performance is compaired with (Linear Quadratic Regulator) LQR. From the result the LQR has around 5.99 second but MPC has small settling 0.3955 time for temperature also for pressure the MPC has around 0.6678 second and LQR has 12.507 second settling time lastly MPC has 0.0195 rise time but LQR has very large rise time time to regulate the drum level MPC has 0.5223settling time and LQR has 8.302 settling time. Due to the analysis the proposed controller MPC has better performance for setpoint tracking than LQR. The system was implemented using MATLAB/Simulink.

Keywords: *Thermal power plant, MPC, PID, ARX, RBF, MATLAB, System Identification.*

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AGA	Adaptive Genetic Agorithm
ARX	Autoregressive with Exogenous Input
FIS	Fuzy Inference System
GUI	Graphical User Interface
LQR	Linear Quadratic Regulator
MATLAB	Matrix Laboratory
PID	Proportional Derivative Integral
MPC	Model Predictive Controller
PI	Proportional Integral
DCS	Distributed Control System
PLC	Programmable Logic Controller
LTI	Linear Time Invariant
ID	Induced Draft
FD	Forced Draft
NARX	Nonlinear Autoregressive with Exogenous Input
MSW	Municipal Solid Waste
RBF	Radial basis function
SMC	Sliding Mode Control
UK	United Kingdom
WtE	Waste-to-Energy

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Thermal power plants are facilities that produce electricity by transforming heat energy into electrical energy. These plants typically use fossil fuels, like coal, oil, or natural gas, as the primary source of heat. However, there is growing interest in using waste materials as a fuel source in thermal power plants, particularly in the form of waste-to-energy (WtE) steam boilers (Kumar Gaurav et al., 2019).

Thermal power plants' WtE steam boilers are made to burn a range of waste materials, including biomass, industrial waste, and municipal solid waste.A WtE steam boiler operates on a similar concept as other types of boilers do. High-temperature burning of the MSW in a furnace heats the water in the boiler to the point that steam is produced, which is then passed through a turbine. A generator spins by the turbine to produces electricity. (Abbas et al., 2017).

The trash will be burned in a combustion chamber at the waste-to-energy incineration facility. Water will be heated with the generated heat until it converts to steam, which powers a turbine generator to generate energy. Handling trashed items is known as solid waste management. In one type of waste management, unwanted waste items are eliminated through techniques like landfilling and incineration (Abbas et al., 2017).

WtE is a well-established option for municipal solid waste (MSW) treatment, driven by the need to reduce the environmental stresses of landfilling as a result of reducing the volume of the original waste by 90% and the desire to increase the proportion of energy generated by renewable sources in the form of electricity or heat that can easily be used for power generation. (Fraol Alemu, 2019).

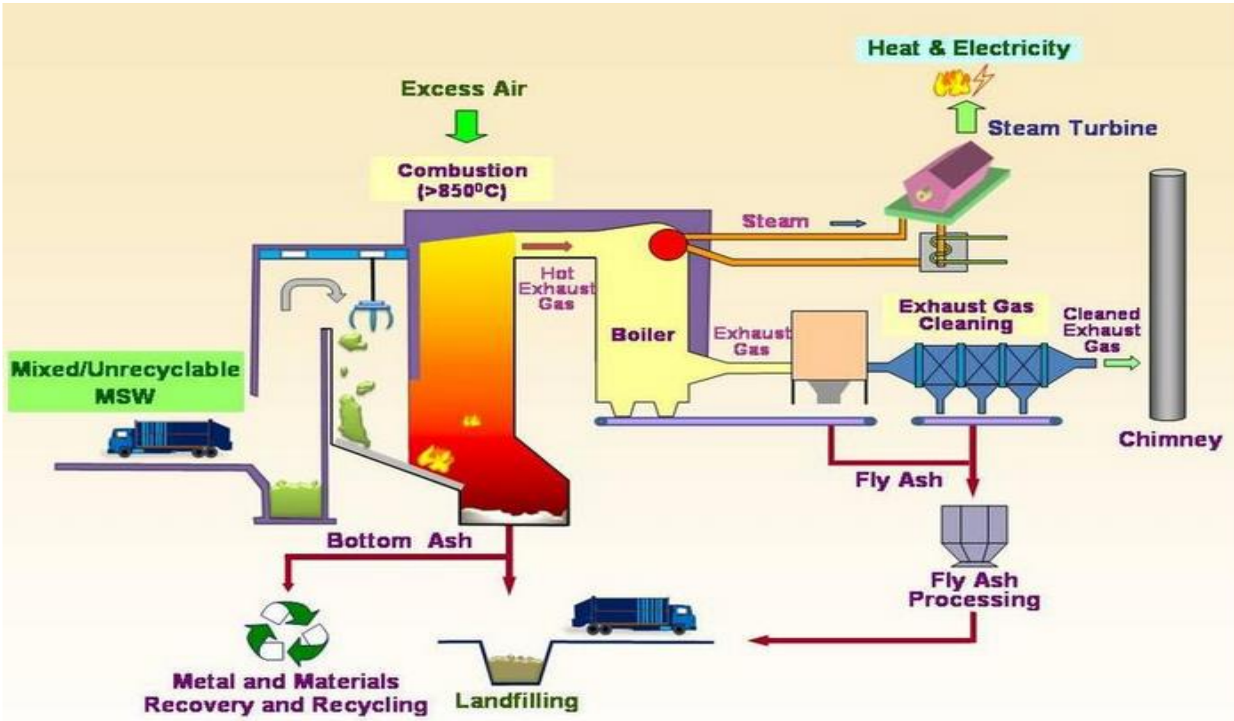


Figure 1.1 Process in waste to energy plant (Abbas et al., 2017).

The construction of Koshe-Reppie Waste to Energy plant began in 2014 under an agreement signed between UK based Cambridge industries and the Ethiopian government. Cambridge Industries Ltd. collaborated on the project's development, design, and construction. The Reppie waste to energy plant project is one of the projects in Ethiopia's capital Addis Abeba. It is situated in the kolefe keranio sub-city, the location of kosha, the continent's largest garbage dump. The project is the first of its kind in Ethiopia and East Africa because it uses municipal solid waste to generate energy inside the city limits. Additionally, it will be the first bracelet power in the nation to offer electricity continuously and providing electricity 24 hours per day. The facility is considered the modern waste disposal system and it eliminates over 1,400 tons of waste per day which covers about 80% of refuse generated by Addis Ababa (Abebe, 2018). the production of energy from municipal solid waste Waste to energy plant established by Ethiopia Electric Power and Addis Abeba City Administration to produce 25-MW to 50MW of electricity daily. (Assnakew, 2018).

To guarantee the secure and proficient operation of WtE steam boilers, it is essential to control vital parameters such as steam pressure, steam temperature, and drum level. Steam pressure and temperature control are critical to ensure that sufficient steam is produced to meet the energy demands of the system, while drum level control is necessary to prevent damage to the boiler and ensure the safety of the system (Kumar* et al., 2020).

Model predictive control (MPC), a control technique that uses a mathematical model of the system to predict its behavior and generate optimal control inputs to achieve the desired performance objectives, is one way to control these parameters. MPC can be used to control steam pressure, steam temperature, and drum level in WtE steam boilers, and can perform better than conventional control strategies.

The system identification method known as radial basis function-autoregressive exogenous (RBF-ARX) modeling can be used to implement MPC in this study of WtE steam boilers. can be applied to record the intricate dynamics of the system. By using radial basis functions to represent the system's nonlinear behavior, these models are able to accurately capture the complex dynamics of the system. The system may be identified and described using the data collected from the boiler.

1.2 Statement of the Problem

The waste-to-energy (WtE) steam boiler is a critical component of the thermal power plant, as it provides a sustainable and efficient way to generate energy from waste materials that would otherwise be disposed of in landfills. Developing an effective control strategy for the WtE steam boiler can help maximize the environmental benefits of the process by reducing waste and optimizing energy production. The control of steam temperature, steam pressure, and drum level is critical to ensuring the safe and efficient operation of the steam boiler system. The control mechanism of steam boiler in Reppie waste-to-energy (WtE) power plant, which is found in Ethiopia, currently uses Programmable Logic Controller (PLC). However PLC, is a control system that operates on logic-based principles. It relies on real-time measurements of the system's current state and lacks the capability to predict future conditions. Moreover, PLCs are unable to effectively handle constraints that may arise within the system. Additionally, they have limitations when it comes to accurately capturing and representing the nonlinear behavior exhibited by the system.Therefore, there is a need for advanced control strategies that can handle the complex dynamics of WtE steam boilers and provide improved control performance. To overcome these limitations need to improve the control performance. This study aims to develop a model predictive control (MPC) strategy for waste-to-energy (WtE) steam boilers using a radial basis function-autoregressive exogenous (RBF-ARX) model, which is used to accurately represent the nonlinear dynamics of the WtE steam boilers. After completing mathematical model MPC is used to predict its behavior and generate optimal control inputs to achieve desired performance objectives, then the performance of MPC is compaierd with Linear quadratic Regulator controller.

1.3 Objectives

1.3.1 General objective

The main objective of this study is to develop Radial Basis Function Autoregressive with Exogenous based Model Predictive Controller for Waste to Energy Steam Boiler in Thermal Power Plants.

1.3.2 Specific objectives:

The specific objectives of this study are to:

- Collecting of steam boiler data from Reppie wast to energy power plant.
- Develop an RBF-ARX model by using system identification techniques.
- Design MPC to control the steam temperature, steam pressure, and drum level of the boiler.
- Compare the performance of the MPC controller with a linear quadratic regulator (LQR) controller.

1.4 Scope of the Study

The scope of this study is to design a Model Predictive Control (MPC) technique for controlling a waste-to-energy (WtE) steam boiler using a Radial Basis Function-Autoregressive Exogenous (RBF-ARX) model. The control of the steam temperature, steam pressure, and drum level of the WtE steam boiler are the only variables covered by this study. The development of the system's mathematical model using system identification and data received from Reppie's waste-to-energy plant's input-output system. The design or implementation of any hardware modifications to the plant is not covered by this study.

1.5 The motivation for the study

With the growing need for sustainable and efficient energy systems, the use of environmentally friendly and economically viable alternative energy sources is essential. WtE boilers are a promising solution because they can generate energy from waste that would otherwise go to landfill. Waste-to-energy systems are one of the technologies currently used to convert various combinations of hazardous waste into useful electrical energy. The effective design of control algorithms plays a key role in the development of this advanced technology by taking into account the appropriate physical dynamics and nonlinearities of the system. For this study, a dynamic physical model of the boiler system was obtained using system identification based on data obtained from the Reppie waste-to-energy plant. Using advanced control strategies, such as MPC with the RBF-ARX model, can improve control performance and contribute to the development of more efficient and sustainable energy systems.

1.6 Significance of the Study

Waste-to-Energy plants, which convert waste into energy, can contribute to the circular economy by utilizing different types of waste that cannot be recycled. Steam boilers in thermal power plant operate under high pressure and temperature conditions, which can pose significant safety risks if not properly controlled. Implementing effective control strategies for pressure, temperature and drum level helps prevent potential hazards, such as overpressure, overheating and water level fluctuations, which can lead to equipment damage, accidents or even explosions. Efficient control of steam boiler is crucial for optimizing energy usage and maximizing efficiency. designinig and implementing control algorithms used for stable and consistent process conditions ensuring reliable and uninterrupted operation.

1.7 Thesis organization

This study is organized as follows.

Chapter two: explains the theoretical foundation and related research on controlling thermal power plant systems for waste-to-energy conversion.

Chapter three: deals with the methodology followed and the mathematical model of the system.

Chapter Four: develop model predictive controller and linear quadratic control techniques for the nonlinear dynamic model of the system.

Chapter Five: presented the simulation's results along with a thorough analysis, and then came the broad conclusions. This chapter also suggests some recommendations for future work.

Chapter six: provides a conclusion and a suggestion for upcoming works.

CHAPTER TWO

LITERATURE REVIEW

2.1. Chapter Overview

This chapter considers an overview of the boiler system, system identification techniques and related works on the control of the proposed system using various controllers, along with their benefits and drawbacks.

2.2. Introduction

Currently, a significant portion of the world's energy production comes from steam power plants. It is crucial that these plants operate efficiently to ensure continuous power generation. The primary principle of thermal power plants is to produce superheated steam from boilers, which is then used to power high-pressure turbines. The turbines drive a generator that produces electricity (Kumar* et al., 2020).

The boiler is a critical component of a thermal power plant. It is responsible for generating the steam that drives the turbine, which in turn generates electricity. The boiler must be designed and operated carefully to ensure that it operates safely and efficiently (Chen et al., 2020).

2.3. Steam Boiler system

A steam boiler is a closed vessel designed to convert the heat energy produced by the combustion of fuels into steam, which can be used for various industrial processes, heating applications, or power generation (CED Engineering, 2021).

2.3.1. Types of Steam Boiler

Different researchers agreed that based on the tubes' contents, boilers can be divided into two categories. (CED Engineering, 2021), (Parvez, 2017):

- **Fire tube boilers:** Hot combustion gases go through tubes that are encircled by water in fire tube boilers. The water is warmed by the hot gasses and turns into steam. Fire tube boilers are generally basic and cheap to construct. In any case, they are not as productive as water tube boilers.
- **Water tube boilers:** The water flows through the tubes in water tube boilers, which are encompassed by hot combustion gasses. The water is warmed by the hot gasses and turns into steam. Water tube boilers are more proficient than fire tube boilers, but they are moreover more complex and costly to construct.

2.3.2. Working principle of steam boiler

The working principle of a boiler system involves converting heat energy from fuel combustion into steam, which is then used for a variety of applications. It is composed of the water-steam system and the fuel/air-flue gas system:

- **Fuel/air-flue gas system:** It is additionally referred to as a factory heater. In this waste-to-energy system, solid waste is burned in a furnace to produce high-temperature fuel gas. The forced-draft fan provides the air required for combustion, while the air preheater increases combustion efficiency by warming the incoming air using waste heat from the exhaust gas (Flanagan, 2013; Sumalatha & Rao, 2020). The process involves transforming the chemical energy of the fuel into the thermal energy present in the fuel gas. The heat from the combustion gas is then transferred through the superheater's several phases and radiation to the furnace's water wall. Superheater absorbs extremely high temperatures and transforms them into steam in the pipes while suspended above the furnace. The heater, economizer, and air preheater all come after the superheater in the combustion gas pipeline. To reheat steam or to pre-heat the supply water and supply air, these units make the most of the remaining heat. Burning air is drawn into the precipitator and out of the boiler through the chimney by forced draft and induced draft fans, respectively. The plant's ash and slag system receives the ash and slag from the combustion process after being collected in the ash hopper.
- **Water-steam system:** is another name for water edge or plant's waterside. A feed pump pulls feed water from the condenser and feeds the boiler with it. The feed water is heated

using economizers, low-pressure and high-pressure feed heaters, and residual heat from turbine gas in order to increase plant efficiency. The removal of dissolved gases from supply water is another purpose for deaerators. (Wu et al., 2015). The drum sends feed water into the furnace water wall, where it absorbs radiant heat and separates into saturated steam and feed water. The steam passes through several stages of the superheater to reach higher temperatures and pressures. Finally, the steam expands in the turbines, causing them to rotate at high speeds, which in turn drives generators to produce electricity.

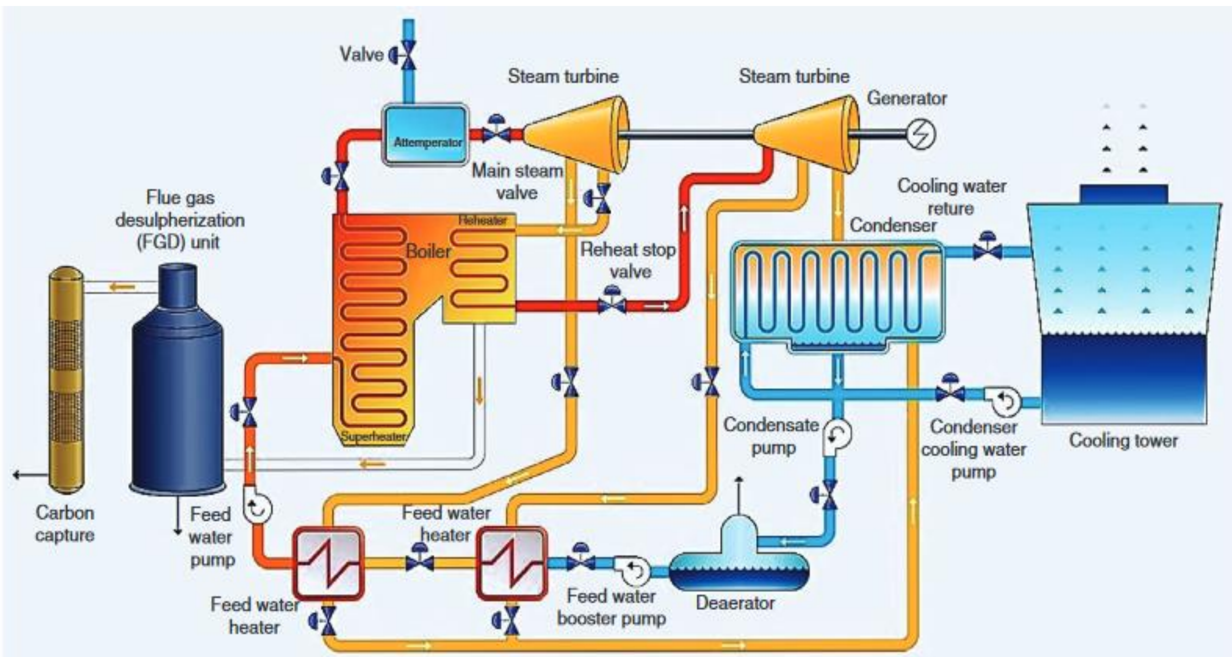


Figure 2.1 Simplified supercritical power plant (Wu et al., 2015).

The boiler used in the Reppie waste-to-energy plant is a water-tube drum boiler. These boilers are sealed pressure vessels that convert water into steam using heat generated from the combustion of municipal solid waste (MSW). This boiler is a one-cylinder natural circulation water tube boiler located in the upper part of the furnace. Boiler feed water, at a temperature of 120℃, is pumped by a feed water pump and passes through a deaerator to remove dissolved gases. After preheating in the economizer, feed water is introduced into the drum. The water is then heated by the water wall, creating a mixture of steam and water that returns to the drum. The saturated steam is separated in the drum and further heated through the superheater, resulting in the superheated steam being sent to the turbine (Fraol Alemu, 2019).

2.3.3. Steam Boiler components

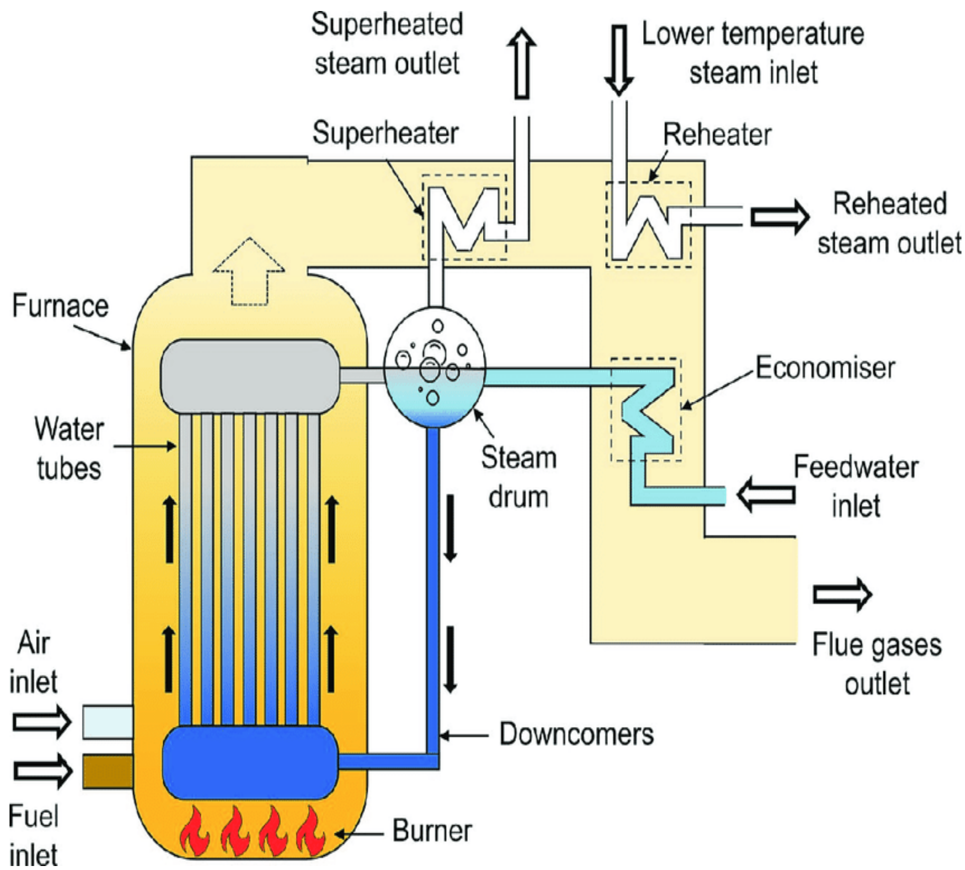


Figure 2.2 General configuration of a steam boiler (Cheng et al., 2016).

- **Furnace:** furnace is an important part of the boiler, responsible for burning waste to create heat. The furnace is usually located at the bottom of the boiler and is designed to burn various wastes(Grant, 2009). The furnace may include other components, such as a flue gas treatment system to reduce emissions, a heat exchanger to recover heat from the flue gas, and an ash handling system to remove ash generated during the process. combustion process. Water flows through vertical pipes arranged in the middle of the exhaust stream(Wu et al., 2015).
- **Steam drum:** The steam drum, which is typically found at the top of the boiler, is a crucial component. A big cylindrical container called a steam drum is used to store and separate steam and water. Its primary purpose is to create space where water and steam can separate, leaving dry steam to depart the boiler. A network of tubes connects the

steam drum to the remainder of the boiler, allowing water to move from the steam drum to the rest of the boiler (Grant, 2009).

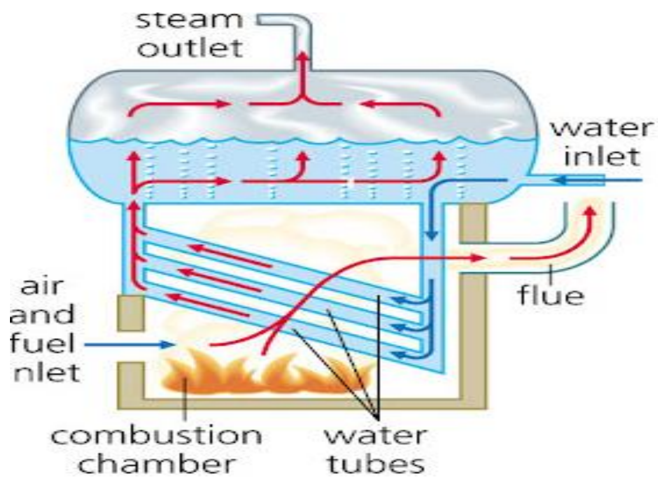


Figure 2.3 Schematic picture of an industrial drum boiler(Bendib & Batout, 2018).

- **Superheater:** A superheater is a component of a boiler that increases the temperature and energy content of the steam the boiler produces. Superheaters are used in waste-to-energy boilers to take the saturated steam produced by the boiler and raise its temperature. They are typically found near the top of the boiler. The superheater normally consists of a number of tubes that come into contact with the hot combustion process exhaust gases (Grant, 2009).
- **Economizer:** By collecting heat from the flue gases before they are released into the atmosphere, an economizer is intended to increase the boiler's overall efficiency. The steam boiler's feedwater is heated in the economizer before being fed to the steam generator. When the feedwater enters the economizer, it passes through a number of tubes that are in contact with the boiling hot flue gases produced by the combustion process. In order to improve the boiler's efficiency, the economizer in a waste-to-energy steam boiler recovers part of the heat that would otherwise be lost through the flue gas stack (Grant, 2009).
- **Air preheater:** By warming the combustion air before it enters the furnace, a preheater is intended to increase the boiler's efficiency. By raising the temperature of the combustion air, the preheater's main purpose is to increase the efficiency of the combustion process.

This helps in raising the furnace's temperature and enhances waste material burning (Grant, 2009).

- **Rreheater:** A reheater is a heat exchanger that reheats steam in a waste-to-energy steam boiler after it has gone through the turbine. This raises the temperature of the steam, which can enhance the boiler's overall efficiency and the turbine's performance. Steam is still hot after it has gone through the turbine, but it is not hot enough to be used again. The reheater raises the temperature of the steam so that it can be utilized to power the turbine once more (Grant, 2009).
- **Water tube boiler:** A number of tubes are stacked vertically or horizontally inside the furnace to make up the water tube boiler. The tubes are normally filled with water and made of steel. The water inside the tubes is heated as the combustion gases flow over them. The steam is collected in a steam drum that is situated above the boiler as the water heats up and starts to boil (Grant, 2009).
- **Feed water system:** The boiler receives water through the feed water system. The following elements make up the feed water system most frequently: (Grant, 2009)
    - **Makeup water:** Makeup water is the water that is pumped into the boiler in order to make up the water lost to evaporation and blowdown.
    - **Feedwater pumps:** Feedwater pumps are used to move the makeup water from the storage tank to the boiler.
    - **Deaerator:** The deaerator is a device that removes dissolved gases from the makeup water.
    - **Boiler feedwater treatment system:** The boiler feedwater treatment system is used to treat the makeup water to prevent scaling, corrosion, and foaming.
    - **Feedwater control system:** The feedwater control system makes sure that the boiler receives the appropriate volume of makeup water.
- **Combustion air system:** Air is a critical component in the combustion process, as it provides oxygen for the combustion of the waste material and ensures that the garbage is fully burned. The air supply needs to be adjusted based on the type and amount of waste being processed to maintain normal incineration operation, ensure sufficient mixing of

flue gases, and cool the grate and furnace wall. The air system of an incinerator typically consists of two main parts: primary air and secondary air.

- **primary air** is responsible for supplying the necessary oxygen to initiate and sustain the combustion process in the furnace.
- **Secondary air** is introduced into the flue gas stream to provide additional oxygen and to ensure that the flue gases are well mixed.

To maintain safe and efficient operation of the incinerator, furnace wall cooling air and sealing air are also used.

- **The furnace wall** cooling air helps to reduce the temperature of the furnace wall and prevent damage from the high temperatures generated during the combustion process.
- **The sealing air** is used to seal the incinerator, preventing leaks of flue gases and ensuring that the combustion process is contained within the furnace.

- **Condensate system:** The condensate system is an important component that is responsible for collecting and returning the condensed steam (condensate) from the steam system back to the boiler. After being used to generate power in the turbine, the steam is exhausted and sent to the condenser, where it is cooled and condensed back into water. The resulting hot water is then pumped to a cooling tower.

2.4. System Modeling

System modeling is the process of generating a mathematical representation of a system that illustrates its dynamics and behavior. System modeling is used in the context of steam boilers to simulate the behavior of the boiler system under various operating situations. As listed below, there are various methods of system modeling.

- **White-box models:** They are predicated on the mathematical description of a system's physical law. These models presuppose that all relevant system dynamics information is available, including the functional form of the system's describing equations. According to (Karimshoushtari & Novara, 2020)., this indicates that the model's structure and its parameters are known .

- **Black-box models** depend solely on input and output data. The underlying system dynamics are assumed to be unknown in these simulations. Input-output data are the only source used to estimate the model's parameters since the model's structure and details are unknown (Arendt et al., 2018).
- **Grey-box models** are a combination of white-box and black-box models. These models presuppose that some but not all of the system dynamics knowledge is known. Part of the model structure is known from fundamental principles, and the remainder is inferred from data (Yusof et al., 2015).

First-principles modeling is a traditional approach to modeling systems that relies on the physical laws that govern the system's behavior. This approach can be very accurate, but it can also be very difficult and time-consuming to develop, especially for complex systems (S. Rao, 2018).

System identification modeling, on the other hand, is a more recent method of modeling systems that uses historical data to create a mathematical representation of the behavior of the system. This approach is often easier and faster to develop than first-principles modeling, and it can be used to model systems that are too complex to be modeled accurately using traditional analytical techniques (K. Kang et al., 2023). The system identification approach requires substantially less time to estimate a model than the first principle method, and it is a better option for predicting time and a complicated system's mathematical model.

System Identification

System identification refers to a methodology used to construct a mathematical representation of a system's dynamics by analyzing measured data of its input and output (Tsai et al., 2021). Typically, this procedure entails collecting experimental data from a physical system and using that data to estimate the parameters of a mathematical model that accurately describes the behavior of the system. The resulting mathematical model can then be employed to study how the system responds to various conditions and inputs, as well as to design controllers that can regulate its behavior (Kim et al., 2017). A visual depiction of the system identification procedure is presented in Figure 2.4.

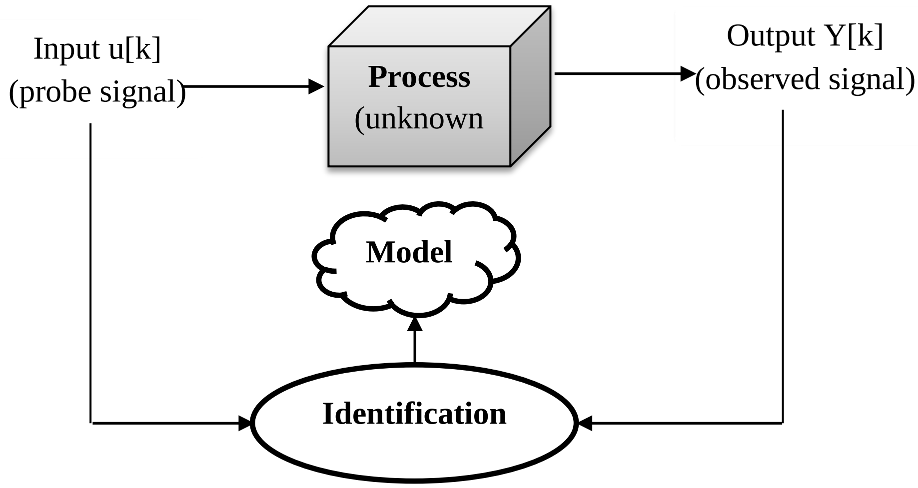


Figure 2.4 cheme of system identification (Rao, 2018).

Some steps are necessary for the System identification procedure, including (Ljung, 2011).

i. The system's input and output data are measured,
ii. Selection of a candidate model structure,
iii. Choosing and utilizing a technique to calculate the values of the parameters ,
iv. The estimated model should be validated and evaluated to see if it is suitable for the application's requirements.

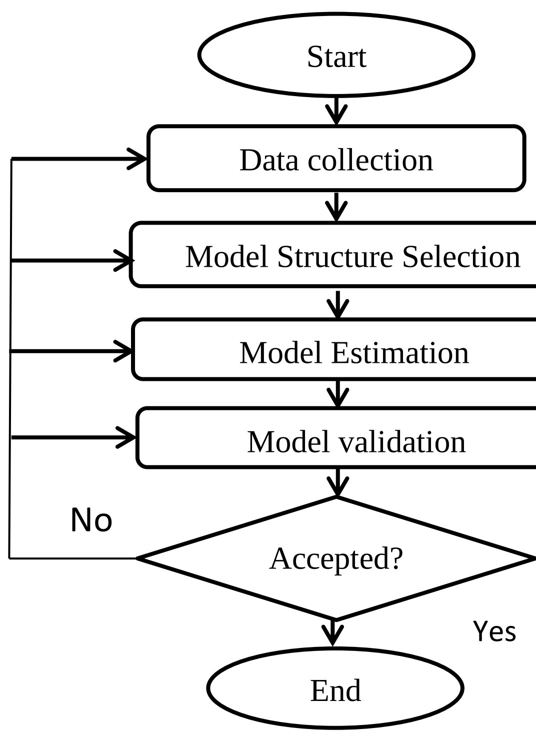


Figure 2.5 System identification procedure (Yusof et al., 2015).

2.5. Related Works

Numerous scholars and researchers have proposed various control strategies for power plant steam boiler control. This section aims to provide a comprehensive review of different related works, highlighting their contributions and limitations. The following are some notable studies in this field:

(Keadtipod & Banjerdpongchai, 2017) provides an industrial boiler supervisory cascade model predictive control design. Applying cascade model predictive control to several control loops, such as water level, drum pressure, and steam temperature, is the goal of this work, which intends to enhance the boiler's performance. The performance of the boiler is also improved by the MPC because proportional-integral (PI) controls don't offer sufficient results. The expected response, however, is not well addressed by MPC.

The idea of controlling and regulating the boiler drum's level using MATLAB is put up by (Kayalvizhi, 2018). Systems that use closed-loop control employ the conventional PID and hybrid fuzzy-PID controller approaches. Investigating settling time, rising time, dead time, and steady state error along with simulation data helps to assess the performance of the controllers. The parameters of the Hybrid Fuzzy-PID are automatically changed to meet the intended response and provide a superior performance based on the outcomes of the simulation. It is significant to highlight that the study's primary focus was the boiler drum's control level, and the effects of other parameters were not taken into account. It is also important to note that in order to determine the performance rules, the fuzzy PID controller relies on expert knowledge. Due to the potential difficulty in acquiring and efficiently incorporating this specialized knowledge, this requirement places restrictions on the overall control system.

In (Sholapur et al., 2016), The authors take into account fuzzy sliding mode control (SMC)-based control. Analysis compared the suggested controller's performance to that of the adaptive genetic algorithm (AGA) sliding mode controller and the traditional PID controller. According to the results, a sliding mode controller using fuzzy logic performs better in steady-state situations and exhibits time rise, a tiny overshoot, and time rise. The problem with this is that because the control system has become more sophisticated, it is difficult to empirically validate this type of control strategy and it also requires a lot of computation.

(Yu et al., 2017) The research describes fuzzy neural network- and PID-based boiler water level management using Matlab. The performance of the neural network and the classic PID are compared in order to determine the best PID parameter values.According to the investigation, the neural network fuzzy PID has greater oscillation attenuation, less overshoot, and a very strong ability to adapt to environmental changes. These controllers are neural network based, which normally requires a lot of training data and may be sensitive to changes in operating conditions.

The sliding mode controller for controlling drum level is suggested by (Deshmukh, 2018). Integral action is used by the author to lessen the influence of the sliding mode controller's chattering. With the aid of simulations done in MATLAB/Simulink, the performance analysis is done utilizing step and ramp input to confirm the steady state characteristics. The author came to the conclusion that the proposed controller performs better than the traditional one during the discussion of the results of the performance comparison of the sliding mode controller with conventional PID. The problem with this is that, because the control system has become more sophisticated, this kind of control strategy is difficult to empirically test and also requires a lot of calculation.

To regulate boiler water level control systems with interval parameters, (Gayvoronskiy, 2020) suggested a method based on a vertex D-partition for synthesizing linear P-controllers. The authors' objective was to evaluate the synthesized system's robust control quality. To do this, he used a multiparametric interval root locus to show the stability of the system's extreme operating modes while also analyzing the step reactions of the system. It is important to note that this kind of control system has difficulty being experimentally verified and performs best within a certain range of tasks.

According to (Bharathi et al., 2020), Using variable steam flow and intake water flow as their foundation, the authors create a dynamic model and control of boiler drum level. When there are fluctuations in steam flow or water supply, the major goal is to maintain the level. Following modeling, the authors use PID, fuzzy logic in the Mamdani framework, and the Sugeno fuzzy inference system (FIS) with Matlab's graphical user interface to improve the system performance. Sugeno FIS is more adaptable than other control techniques, according to their analysis. However, since the sugeno FIS output has a long settling time, it affects the performance of real-time systems. Additionally, sugeno FIS is challenging to express because it requires expertise and is best suited for multiple input, single output systems, leading the authors to believe that only the drum level accurately depicts the impact of steam flow.

(Meng et al., 2020) In the study, fuzzy logic controllers are used to control the level of boiler drums. The performance of the suggested controller was analyzed and contrasted with traditional PID. According to the analysis, fuzzy logic can lessen overshoot, although it responds more slowly than standard PID. To find the performance rules, fuzzy controllers mostly rely on expert knowledge. This requirement places restrictions on the entire control system because it may be difficult to efficiently acquire and incorporate this specialized knowledge.

The authors of this paper (Gowthaman et al., 2017) discuss controlling the level of the boiler drum using a hybrid fuzzy logic PID controller. Analysis was done using Labview to compare the suggested controller's performance to that of a traditional PID. In terms of settling time, rising time, dead time, and steady state error, the two were compared for performance. The hybrid fuzzy PID controller, according to simulation results, provides superior dynamic responsiveness, a faster settling and response time, and zero steady state error. In this situation, the controller's performance is dependent on experience in order to determine the controller's best value and produce an efficient response.

Fuzzy PID and PID controllers are used frequently in research however they are ineffective and inaccurate for nonlinear and multivariable systems like steam boilers. because these controllers call for the separation of MIMO and SISO systems. Decoupling, on the other hand, may not be able to handle the right dynamic behavior of the system because it loses the interactions between variables and is developed using large mathematical modeling. In order to improve the regulation of these parameters, this study investigates and develops advanced control strategies, such as MPC controllers using RBF-ARX models. The Reepie waste-to-energy facility provided the real input-output data used in the system dynamic model. System identification enables the construction of efficient control techniques to adjust temperature, pressure, and drum level variables by precisely describing the system's behavior.

CHAPTER THREE

METHODOLOGY AND SYSTEM MODELING

3.1. Chapter Overview

An overview of the used materials and methodologies is provided in this chapter. The primary objective is to develop a mathematical model of the system using black box modeling methods. and also dig more into the methods for finding nonlinear systems that are accessible. The goal is to give readers an understanding of the research methodology employed in this study by describing the approach and going over these procedures.

3.2. Materials

To make various activities easier, this study uses several of software applications. For creating and modifying the thesis material, Microsoft Office 2016 is used, which offers a full array of tools like Microsoft Word and PowerPoint. Math Type 6.0 is used to easily incorporate equations and formulas into Microsoft Office applications, improving the presentation of mathematical material. Mendeley Desktop 1.19.8 is employed as a reference management tool to organize and manage bibliographic information. Additionally, the MATLAB/SIMULINK software package is utilized, offering computational capabilities and technical toolboxes for data analysis, modeling, and simulation. MATLAB provides a versatile environment for implementing algorithms and conducting numerical computations, while SIMULINK supports the development and simulation of dynamic systems through block diagrams. These software tools collectively contribute to the efficiency and effectiveness of the thesis work, enabling tasks such as documentation, visualization, mathematical representation, reference management, and technical analysis.

3.3. Methods

The following methodologies were used to accomplish this study.

1. Literature review

The first step is to conduct a literature review of boiler controls. This involves reading articles, conference papers, user manuals, and other relevant sources. The purpose of the literature review is to get a thorough grasp of the present state of knowledge about boiler controls, as well as related challenges and opportunities.

2. Data collection

The next phase is to gather information about everything from the Reppie waste to how much energy the boiler system uses. To construct system models and assess the efficacy of control laws, this data can be employed. Measurements of boiler status variables, such as steam temperature, pressure, and drum level, must be included in the data. Additionally, measurements of control inputs like fuel flow and air flow rate should be included.

3. System identification

Once the information has been gathered, the system model can be established. Black-box system identification methods, like the RBF-ARX model, are useful for accomplishing this. The RBF-ARX model combines a Gaussian radial basis function neural network with a linear ARX model structure to create a hybrid time-varying pseudolinear model.

4. Controller design

Once the system model is determined, the control laws of the model predictive controller (MPC) and linear quadratic regulator (LQR) can be designed. MPC is a control technique that uses optimization algorithms andLQR is a control technique that minimizes the quadratic cost function of the system.

5. Simulation

To model the system, the designed control laws were put into practice in MATLAB/SIMULINK. The simulations can be used to assess and compare the effectiveness of the control laws. The entire thesis project is finally completed, and recommendations are offered for more research in the field. The methods employed for this thesis study is summarized in Figure 3.1.

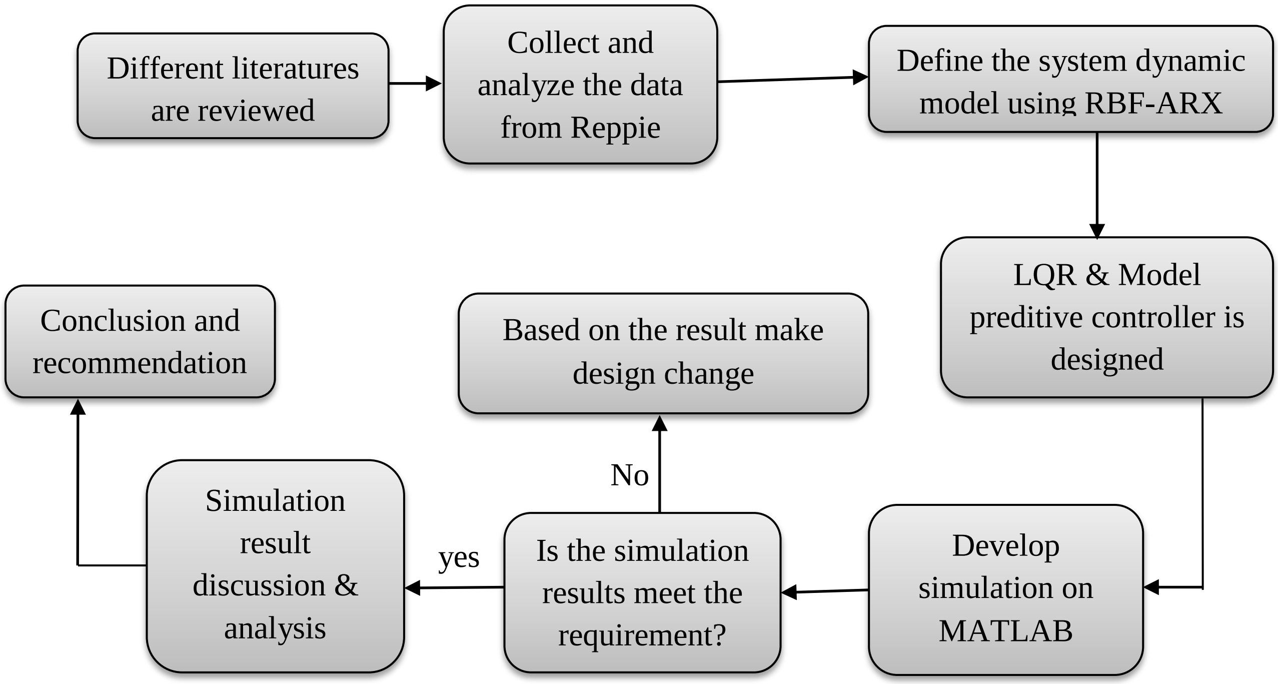


Figure 3.1 summarizes the methodology used for this thesis work.

3.4. System Block Diagram

A block diagram for a model predictive control system is shown in Figure 3.2. In order to forecast the future values of the output variables, the system uses a model. These predictions are then contrasted with the actual outputs, producing residuals that act as feedback signals to a Prediction block. Set-point calculations and control calculations are two different forms of model predictive control computations that are carried out at each sampling instant. Inequality constraints, including upper and lower bounds, can be applied to the input and output variables in both types of calculations.

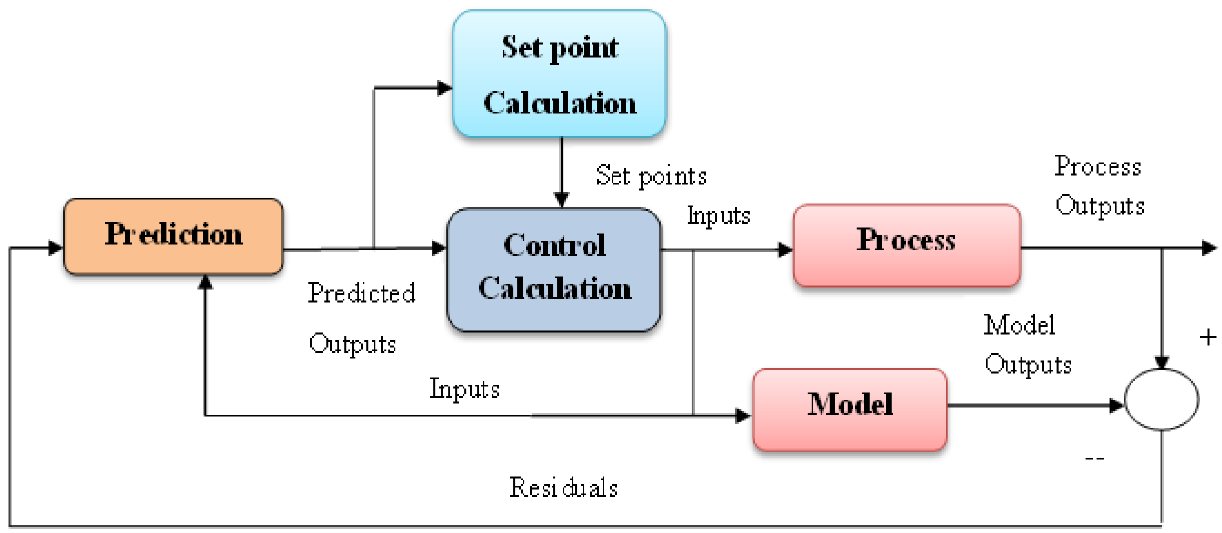


Figure 3.2 Block diagram of the proposed control system.

3.5. Modeling and identification of steam boiler

A model is a good (mathematically) substitute for a process. Models are very useful: simulation using models is a very economical, safe and powerful alternative to experiments.

A simulation of steam boilers is an essential tool for enhancing the efficiency, dependability, and safety of such systems. In order to understand potential problems and implement new control strategies, models can be used for predicting the behavior of steam boilers under a variety of operating conditions. (Nikula et al., 2016).

The mathematical model of a steam boiler system is created in this thesis using the system identification approach. Using historical data, this approach creates a model of the relationship between the system's input and output variables. The system's behavior under different conditions can then be predicted using the model.

Table 1.1 The technical specification and basic parameter of the main equipments (China National Electric Engineering, 2018)(China National Electric Engineering, 2018).

No	Items	Parameter
1	Garbage disposal capacity	640T/D
2	Rate Evaporation	54.1T/H
3	Rate steam outlet pressure	6.0MPa
4	Rate steam outlet temperature	420^{o}C
5	Boiler design pressure	6.0MPa
6	Boiler design water temperature	120^{o}C

The identification procedure will go through these steps (Sulaiman et al., 2016)

i. Data collection through observation (input and output data from a real-time experiment)

ii. Selection and estimation of the model structure

iii. a model's validation

3.5.1. Data Collection

Collecting input-output data from the system under study is the first step in the system identification process. In this study, data was collected from the Reppie waste-to-energy plant. The collected dataset comprises seven variables, wherein four variables correspond to the inputs witch is used to excite the boiler system, and the remaining three variables represent the outputs of interest.

Figure 3.3 visually presents the collected input data, illustrating the various input variables used to stimulate the system. But on the other side, Figure 3.4 displays the collected output data, highlighting the recorded values of the output variables. These figures serve as visual representations of the acquired data, facilitating further analysis and modeling of the system.

Data from the input and output are recorded between the time intervals: $1 \leq K \leq N$.

$$z^N = \{u(1), y(1), \ldots u(N), y(N)\} \tag{3.1}$$

where N=1762.

Where: u(k) - input data, y(k) - output data, N - number of the data set, k – discrete time step of the data set.

$$Y(k) = \begin{bmatrix} y_1(k): \text{main steam temperature} \\ y_2(k): \text{main steam pressure} \\ y_3(k): \text{drum level} \end{bmatrix}, \qquad U(k) = \begin{bmatrix} u_1(k): \text{water flow} \\ u_2(k): \text{ airflow1} \\ u_3(k): \text{ airflow2} \\ u_4(k): \text{ fuel input} \end{bmatrix} \tag{3.2}$$

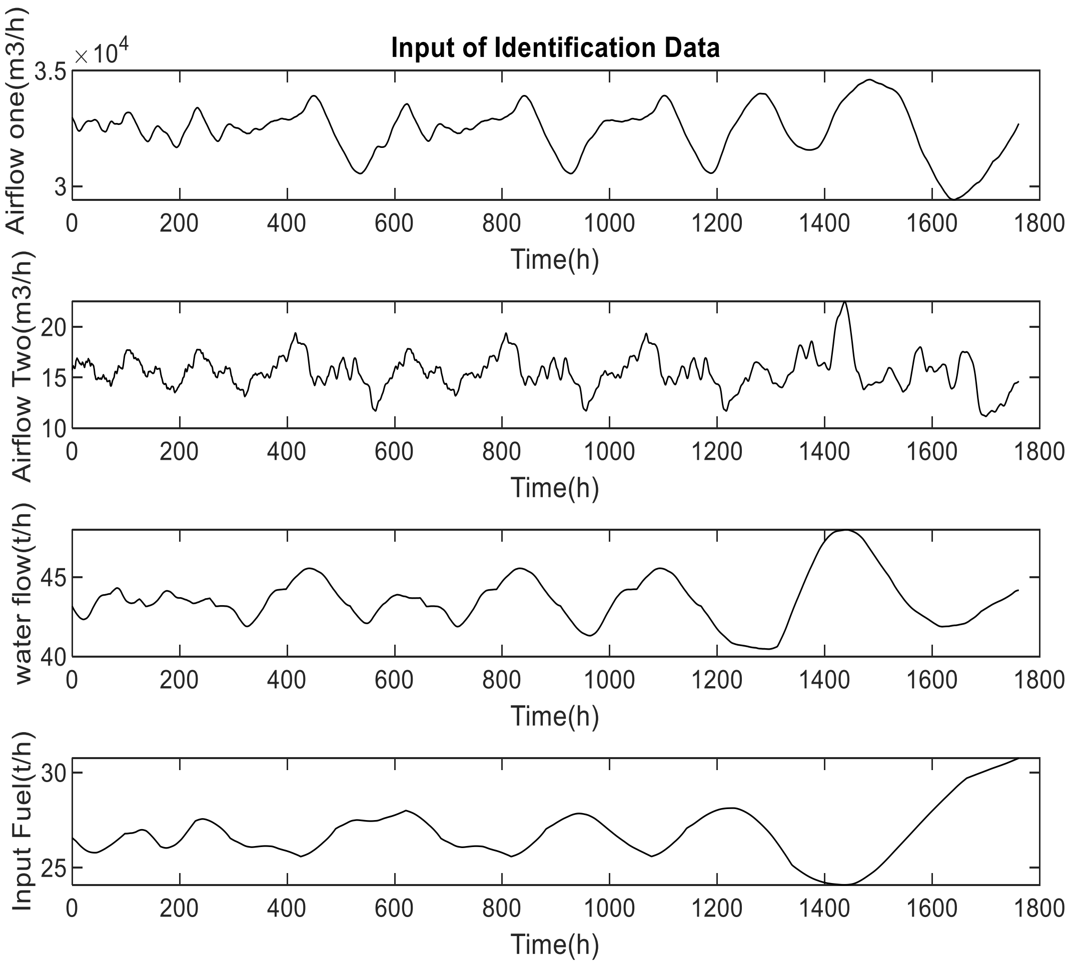


Figure 3.3 MATLAB Data plot for steam boiler inputs.

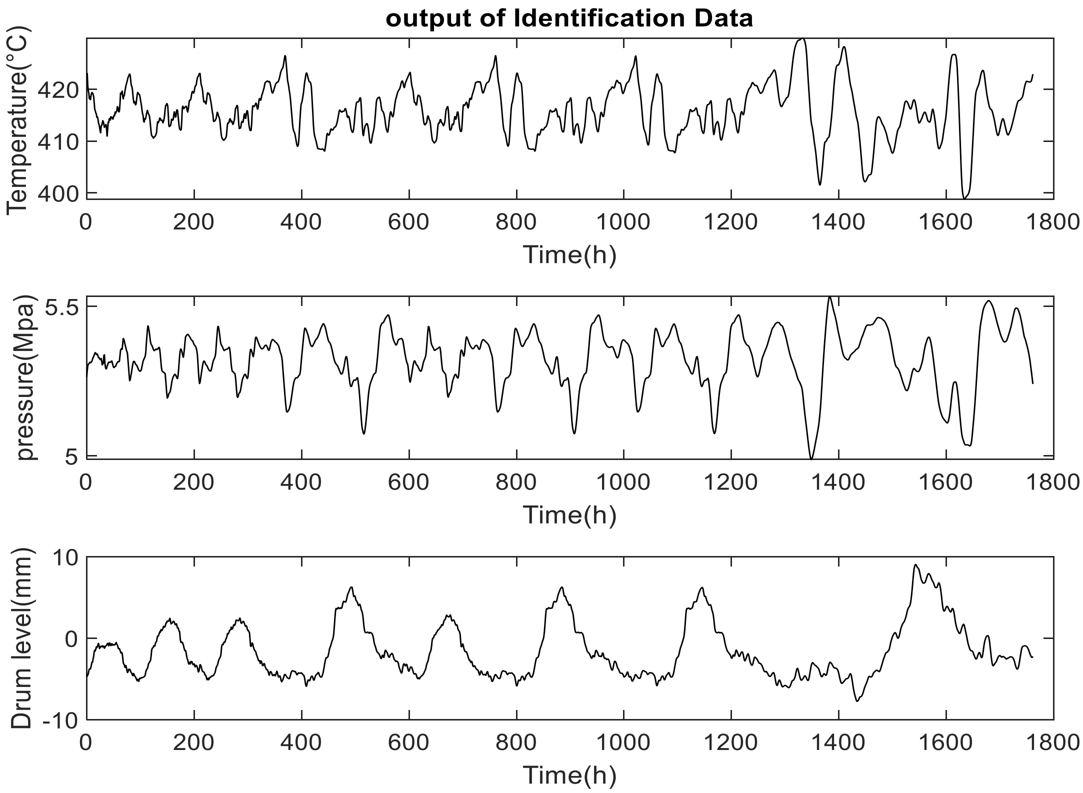


Figure 3.4 MATLAB Data plot for boiler output.

It is usual practice to divide the recorded data into training and validation sets during the system identification procedure. The system identification model can be developed and evaluated according to this classification (Wang et al., 2017).

The dataset consists of 1762 pairs of data {U(k), Y(k)}, as shown in Figures 3.3 and 3.4. To effectively utilize this data, it has been divided into two equal portions. The first 881 samples are allocated as the training data, as illustrated in Figure 3.5. This training data is utilized to develop the system identification model. The remaining samples are designated as the validation (or test) data, as shown in Figure 3.6. To assess the effectiveness and correctness of the simulated model, the validation data will be used.

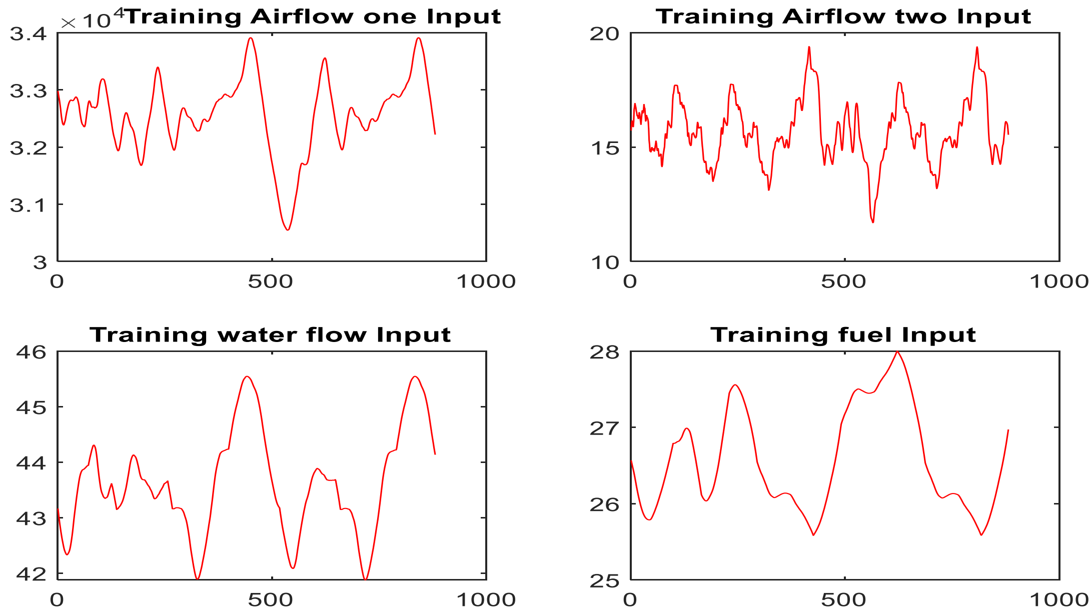


Figure 3.5 Input Data plot for training.

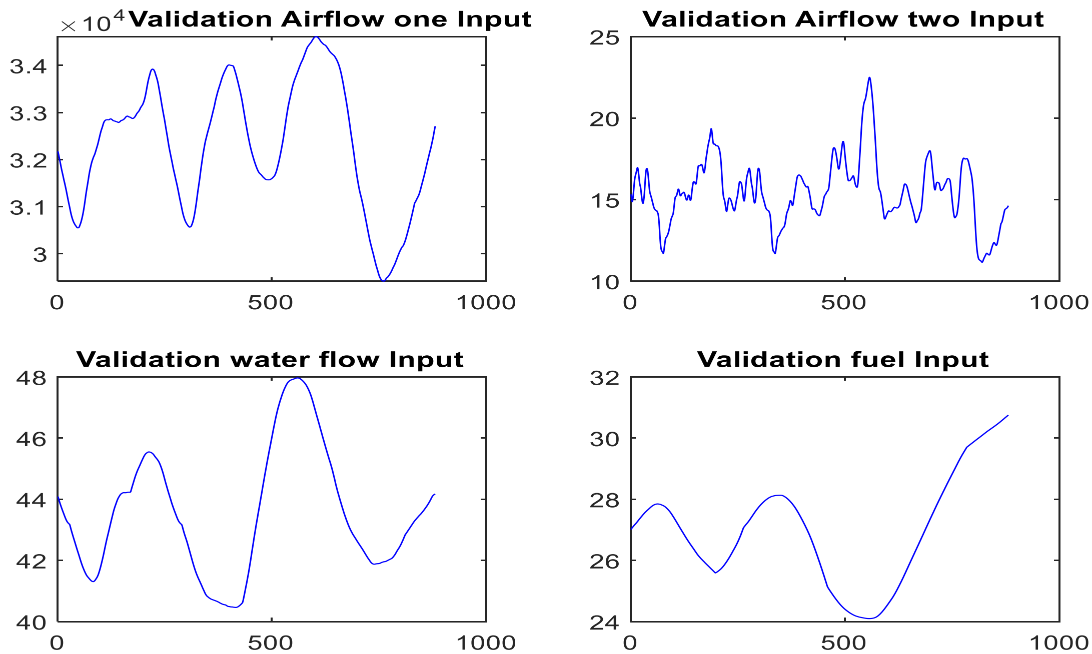


Figure 3.6 Input Data plot for Validation.

3.5.2. Model Structure Selection and Parameter Estimation

Selecting the model structure comes next in the system identification process after gathering and analyzing the input-output data.

Real-world systems frequently have inherent nonlinearities. Given the prevailing circumstances, it is necessary to develop a controller utilizing a nonlinear model that accurately represents the behavior of the system (Ohtsu et al., 2015). This paper introduces a statistical modeling approach for nonlinear systems based on the Radial Basis Function network-style coefficients AutoRegressive model with eXogenous variable (RBF-ARX) model. Specifically, the proposed approach utilizes the state-dependent autoregressive with exogenous (ARX) model with functional coefficients controller, which is a widely employed modeling technique for capturing the intricate dynamics of complex nonlinear systems.

State-dependent ARX models

A class of autoregressive with exogenous (ARX) models called state-dependent ARX (SD-ARX) models can depict a system's nonlinear dynamic features. Utilizing state-dependent coefficients, which allow the model's coefficients to change in response to the system's state, they do this. This makes it possible for the SD-ARX model to represent the system's local nonlinearities (Xu et al., 2020). A discrete-time nonlinear system has dynamic properties that are dependent on time-varying working points and are locally linearizable at each working point. A nonlinear autoregressive exogenous (ARX) model is able to adequately represent this system (A. B. Rao, 2018).

Nonlinear ARX (NARX) Model

The NARX (Nonlinear Auto Regressive with Exogenous Input) model, which is frequently used to identify nonlinear systems and to describe their dynamics. It extends the ARX model by incorporating non-linear relationships between the system's outputs, past outputs, and inputs (Y. Zhou, 2020).

The relationship between a system's current output and its previous outputs, as well as its current and previous inputs, is expressed mathematically by the ARX model. It is based on the idea that the current behavior of a system can be described by its previous outputs and inputs (Peng et al., 2003).

The discrete-time nonlinear ARX model can be used to explain nonlinear systems with time-varying operating points (Ramachandran et al., 2018)

$$\mathrm{y(k) = f(w(k-1)) + e(k)} \tag{3.3}$$

$$\mathrm{w(k-1) = [y(k-1)^T, ..., y(k-n_y)^T, u(k)^T, u(k-1)^T, ..., u(k-n_u)^T]} \tag{3.4}$$

Where: F(.) denotes a nonlinear function, y(k) is the output, u(k) is the input, e(k) is the Gaussian white noise with zero means, and n_y and n_u are the corresponding output and input order.

If the function n f(•) in equation (3.3) exhibits continuous differentiability at any equilibrium point, it becomes possible to approximate f(•) using a Taylor series expansion(T. Kang et al., 2023).

$$\begin{aligned} &\mathrm{f(w(k-1)) = f(w_0) + f^{'}(w_0)^T(w(k-1) - w_0) +} \\ &\mathrm{\frac{1}{2}(w(k-1) - w_0)^T f^{"}(w_0)(w(k-1) - w_0) + ... + r_n(w(k-1))} \end{aligned} \tag{3.5}$$

$$\begin{cases} y(k) = \phi_0(w(k-1)) + \sum_{i=1}^{n_y} \phi_{y,i}(w(k-1))y(k-i) + \sum_{i=1}^{n_u} \phi_{u,i}(w(k-1))u(k-i) + e(k) \\ \eta_0 = f(w_0) - f^{'}(w_0)^T w_0 + \frac{1}{2} w_0{}^T f^{"}(w_0)w_0 + ... \\ \eta_1(w(k-1)) = r_n(w(k-1)) \\ v_0 = f^{'}(w_0)^T - \frac{1}{2} w_0{}^T f^{"}(w_0) - \frac{1}{2} w_0{}^T f^{"}(w_0)^T + ... \\ v_1(w(k-1)) = \frac{1}{2} w(k-1)^T f^{"}(w_0) + ... \\ \eta_0 + \eta_1(w(k-1)) = \phi_0(w(k-1)) \\ v_0 + v_1(w(k-1)) = [\phi_{y,1}(w(k-1)), ..., \phi_{y,n_y}(w(k-1)), \phi_{u,1}(w(k-1)), ..., \phi_{u,n_u}(w(k-1))] \end{cases} \tag{3.6}$$

Where: $\phi_0(w(k-1)), \left\{\phi_{y,i}(w(k-1)), i = 1, 2...n_y\right\}, \left\{\phi_{u,i}(w(k-1)), i = 1, 2...n_u\right\}$ are

State-dependent function coefficients at each regression variable after Taylor expansion, which change with state working point $w(k-1)$, is the state variable that cause the non linear change of the system. It can be the system output signal, control input signal or a combination of these signal. At time k, and it could be the output or the input signal, or both, or any other appropriate signal in the system to be considered. Model in equation (3.6) has an autoregressive structure that is analogous to a linear ARX model, and its state-dependent coefficients matrices make the model's behavior change with $w(k-1)$, so it may be regarded as a state-dependent ARX model (F. Zhou et al., 2015).

Radial basis function network

Radial basis function neural networks (RBFNN) can be used to approximating the SD-ARX model coefficients. Given its superior accuracy in simulating nonlinear functions, RBF networks are utilized to roughly represent the state-dependent components of coefficient matrices. RBF networks are also ideal for learning local variations because the basis functions are local (Y. Zhou, 2020).

An artificial neural network that is employed for function approximation is known as an RBF neural network. Input, hidden, and output layers make up RBF networks. Data input is handled by the input layer. Radial basis functions (RBFs) make up the hidden layer. The output is produced by the output layer. One of the most well-liked neural network types, RBF has lately developed into a potent function or tool used for approximation, modeling, and forecasting (Faruq et al., 2019). The RBF design, shown in Figure 3.7, consists of an input layer, a hidden layer with Gaussian activation functions, and an output layer.

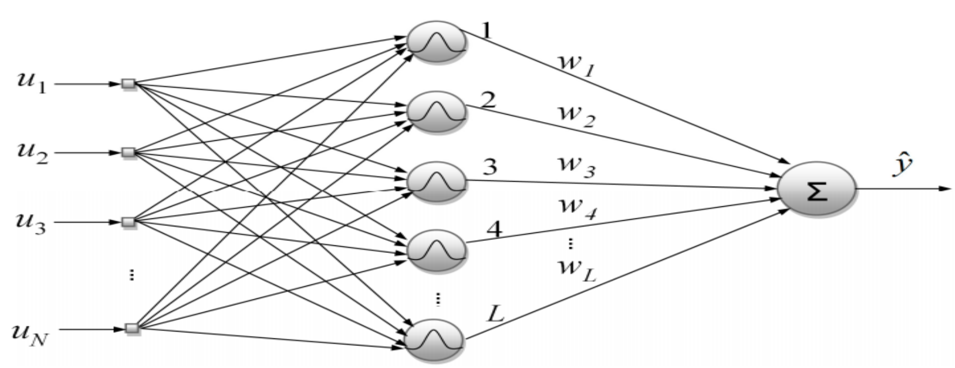


Figure 3.7 Typical Gaussian basis function RBF network structure (Alexandridis et al., 2018).

In the RBF, the input layer transforms the data into hidden neurons that incorporate radial basis activation functions. These activation functions typically involve calculating the distance between the network inputs and the centers of the hidden layer. The resulting outputs from the hidden layer are then weighted to form the output assembly of the RBF.

The mathematical description of RBF output is as follows (Yang et al., 2022)

$$y(k) = \sum_{i=1}^{m} w_i(k)\phi_i(k) \tag{3.8}$$

Where: m is the number of hidden neurons, $w_i(k)$ is the weight between the i^{th} hidden layer and the output layer at time t, and $\phi_i(k)$ is the output of the i^{th} hidden layer neuron, described as:

$$\phi_i(k) = \exp(-\frac{\| x(k) - z_i(k) \|^2}{2\sigma_i(k)^2}) \tag{3.9}$$

Where: $x(k) = [x_1(k), x_2(k), ..., x_n(k)]^T$ is the input vector, $z_i(k) = [z_{1,i}(k), z_{2,i}(k), ..., z_{n,i}(k)]^T$ is the ceter vector of i^{th} hidden neuron at time t, and ; $\| x(k) - z_i(k) \|$ is the Euclidean distance between $x(k)$ and $z_i(k)$, $\sigma_i(k)$ is the width of the i^{th} hidden neuron at time t.

Radial-basis function networks (RBF networks) stand out from other neural networks because of their ability to provide global approximation and fast learning speed. Gaussian RBF networks are specifically chosen to approximate the elements of the coefficient matrices in equation (3.6), the resulting model is referred to as the RBF-ARX model.

RBF-ARX Models

The RBF-ARX model, introduced by Peng in the late twentieth century, is a hybrid model that combines the RBF network and ARX modeling approach (Zeng et al., 2017). By integrating the strengths of state-dependent ARX models for capturing nonlinear dynamics and RBF networks for function approximation, the RBF-ARX model offers a powerful (T. Kang et al., 2021). Mathematically, the expression of the RBF-ARX model can be formulated as follows:

$$
\begin{cases}
y(k) = \phi_0(w(k-1)) + \sum_{i=1}^{n_y} \phi_{y,i}(w(k-1))y(k-i) + \sum_{i=1}^{n_u} \phi_{u,i}(w(k-1))u(k-i) + e(k) \\
\phi_0(w(k-1)) = c_0^0 + \sum_{j=1}^{m} c_j^0 \exp\{-\lambda_j^y \left\| w(k-1) - z_j^y \right\|_2^2\} \\
\phi_{y,i}(w(k-1)) = c_{i,0}^y + \sum_{j=1}^{m} c_{i,j}^y \exp\{-\lambda_j^y \left\| w(k-1) - z_j^y \right\|_2^2\} \\
\phi_{u,i}(w(k-1)) = c_{i,0}^u + \sum_{j=1}^{m} c_{i,j}^u \exp\{-\lambda_j^u \left\| w(k-1) - z_j^u \right\|_2^2\} \\
z_j = \{z_{j,1}, z_{j,2}, \ldots., z_{j,n_x}\}
\end{cases}
\tag{3.10}
$$

Where: n_y, n_U, m and $n_x = \dim\{w(k-1)\}$ are the order of the model; $z_j \,(j = 1, 2, \ldots.m)$ are the center of RBF network; $\lambda_j \,(j = 1, 2, \ldots.m)$ are the scaling parameter. $c_j^0 \,(j = 1, 2, \ldots.m), c_{i,j}^y \,(i = 1, 2, \ldots.n_y,\, j = 0, 1, 2, \ldots.m)$ & $c_{i,j}^u \,(i = 1, 2, \ldots.n_u,\, j = 0, 1, 2, \ldots.m)$, are the weight coefficients of RBF nets and $\left\| \bullet \right\|_2$ denote vector 2 norms.

The parameter optimization algorithm presented in this research study provides a notable benefit for parameter estimation in the RBF-ARX model. The model's parameters are estimated offline through the utilization of a structured nonlinear parameter optimization method (SNPOM). The SNPOM approach involves partitioning the parameter search space into two distinct subspaces: the linear weight subspace and the nonlinear parameter subspace. This division allows for efficient and effective exploration of the parameter space.

The structured nonlinear parameter optimization method (SNPOM) employed in this study combines the Levenberg-Marquardt method (LMM) for estimating the nonlinear parameters and the least-squares method (LSM) for estimating the linear parameters of the RBF-ARX model during each iteration of the search process (Tian et al., 2019). Compared to alternative approaches, SNPOM offers enhanced flexibility, faster convergence, and improved computational efficiency (F. Zhou et al., 2015). The implementation of SNPOM for the RBF-ARX model is outlined as follows:

A) Parameter Classification

For the RBF-ARX model the linear parameters are geven by:

$$\theta_L \overset{\Delta}{=} \{c_i^0, c_{j,i}^y, c_{k,i}^u | i=0,1,...,m;\ j=1,2,...,n_y;\ k=1,2,...,n_u\} \tag{3.11}$$

The nonlinear parameters are given by:

$$\theta_N \overset{\Delta}{=} \{\lambda_i; z_i^j | i=1,2,...,m;\ j=y,u\} \tag{3.12}$$

The mathematical representation of the RBF-ARX model it can be rewritten as follows:

$$y_i(k) = f(\theta_L, \theta_N, \Omega(k-1)) + e(k) \tag{3.13}$$

$$y_i(k) = \varphi(\theta_N^i, \Omega(k-1))^T \theta_L^i + e(k) \tag{3.14}$$

Where: y(k) is the output at time k, φ(.) is the RBF network input, θ is the parameter vector, θ_N^i is the vector including all nonlinear parameters and θ_L^i is the vector including all linear weight e(k) is the model error and $\Omega(k-1) = [y(k-1)^T, u(k-1)^T, w(k-1)^T]$.

Equation (3.14) is the regression form of model (3.15) which is linear with respect to the linear parameter vector.

B) Initialization

First, the order must be chosen, to determining the order of the RBF-ARX model for a steam boiler through trial and error involves an iterative process to find the optimal order that provides a good fit to the data. the following steps can be taken (Zhang et al., 2016):

1. Start with an initial guess for the order of the RBF-ARX model.
2. Fit the RBF-ARX model to the available data using the initial order. This involves estimating the model parameters and evaluating the model's performance.
3. Assess the goodness of fit and model performance metrics, such as the mean squared error (MSE). If the model does not provide a satisfactory fit, proceed to step 4.
4. Adjust the order of the RBF-ARX model by increasing or decreasing the number of basis functions, autoregressive terms, or exogenous inputs.
5. Repeat steps 2 to 4 by fitting the revised RBF-ARX model to the data and evaluating its performance.

6. Compare the performance metrics between different model orders and select the order that achieves the best balance between model complexity and accuracy.

Then the intial value are chosen. The intiaial values of the scaling factors in the model are given by:

$$\lambda_j^0\text{=-log } \in_k \text{/max}\{\|\text{w(k-1)-Z}\|_2^2\}, \varepsilon_k\text{=[0.1-0.0001]} \tag{3.15}$$

These factors will ensure that the linear weights are bounded when the signal w(k-1) Moves far away from the centers. After selecting an initial nonlinear parameter vector and keeping it fixed, use the LSM to compute initial linear weights as follows:

$$\theta_L^0 = R(\theta_N^0 + \bar{Y}) \tag{3.16}$$

$$R(\theta_N^0)^+ = [R(\theta_N^0)^T R(\theta_N^0)]^{-1} R(\theta_N^0)^T$$

$$R(\theta_N^0) = [\phi(\theta_N^0, \bar{\Omega}_\tau), \phi(\theta_N^0, \bar{\Omega}_{\tau+1}, ..., \phi(\theta_N^0, \bar{\theta}_{M-1})] \tag{3.17}$$

$$\bar{Y} = (\bar{y}_{\tau+1}, \bar{y}_{\tau+2}, ..., \bar{y}_M)^T$$

$$\{\bar{y}_i, \bar{\Omega}_{\tau+1} \mid i = 1, 2, ..., M\}$$

Where,

$\{\bar{y}_i, \bar{\Omega}_{\tau+1} \mid i = 1, 2, ..., M\}$ is the measured dataset, τ is the largest time lag of the variables, M is the data length and $R(\theta_N^0)^+$ is the pseudo inverse of $R(\theta_N^0)$ calculated using singular value decomposition (SVD).

C) Estimation of linear and non linear parameters

The quadratic objective function is:

$$V(\theta_N, \theta_L) \equiv \frac{1}{2} \| F(\theta_N, \theta_L) \|_2^2, \tag{3.18}$$

Where

$$F(\theta_N,\theta_L)\equiv\begin{bmatrix}\hat{y}_{\tau+1|\tau}-\hat{y}_{\tau}\\ \hat{y}_{\tau+2|\tau+1}-\hat{y}_{\tau+2}\\ \vdots\\ \hat{y}_{M|M-1}-\hat{y}_{M}\end{bmatrix} \tag{3.19}$$

$$\hat{y}_{n+1|n}=f(\theta_N,\theta_L,\bar{\Omega}_n),\ \text{n=}\tau,\tau+1,...,M-1 \tag{3.20}$$

Then the linear and non linear parameters are obtained as the minimizer of the optimization problem

$$(\hat{\theta}_N,\hat{\theta}_L)=\arg\min_{\theta_N,\theta_L}\ \mathrm{V}(\theta_N,\theta_L) \tag{3.21}$$

The iteration step is denoted by $\mathrm{j}=(0,1,2...\mathrm{j}_{\max})$ and the Jacobin matrix of $F(\theta_N^j,\theta_L^j)$ with respect to θ_N^j is denoted by

$$J(\theta_N^j)=(\partial F(\theta_N^j,\theta_L^j)/\partial\theta_N^j)^T \tag{3.22}$$

The innovation strategy for the nonlinear parameters θ_N^j is

$$\theta_N^{j+1}=\theta_N^j+\beta_k d_k \tag{3.23}$$

Where d_j is the search direction, and β_j is a scalar step length parameter that gives the distance to the minimum. In order to increase the robustness of the search process, which is based on the LMM, and d_j is obtain from the set of linear equation

$$[J(\theta_N^j)^T(\theta_N^j)+\gamma_j\mathrm{I}]d_j=-J(\theta_N^j)^T F(\theta_N^j,\theta_L^j) \tag{3.24}$$

Where the scalar γ_j controls both the magnitude and the direction of d_j. When γ_j tends to zero, the d_j will tend toward the Gauss-Newton direction. As γ_j tends to infinity, d_j tends toward the steepest descent direction. The size of γ_j is determined at each iteration by using a method similar to that of the function “lsqnonlin” in the matlab optimization toolbox (Yuan & Wang, 2009).

A structured nonlinear parameter optimization method (SNPOM) can be quickly used to optimize the RBF-ARX model. The model parameters are estimated using the SNPOM approach, which offers a very good fit to the real data (Nawaz et al., 2016).

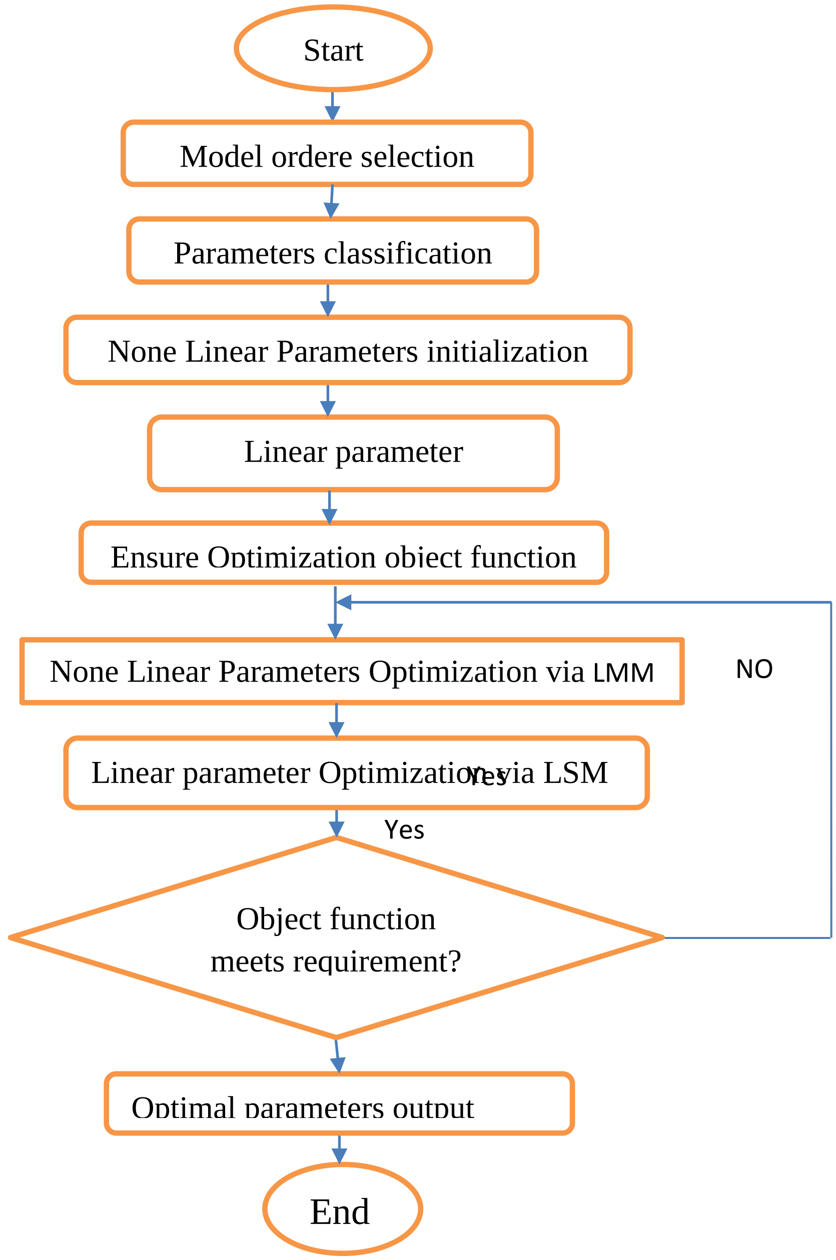
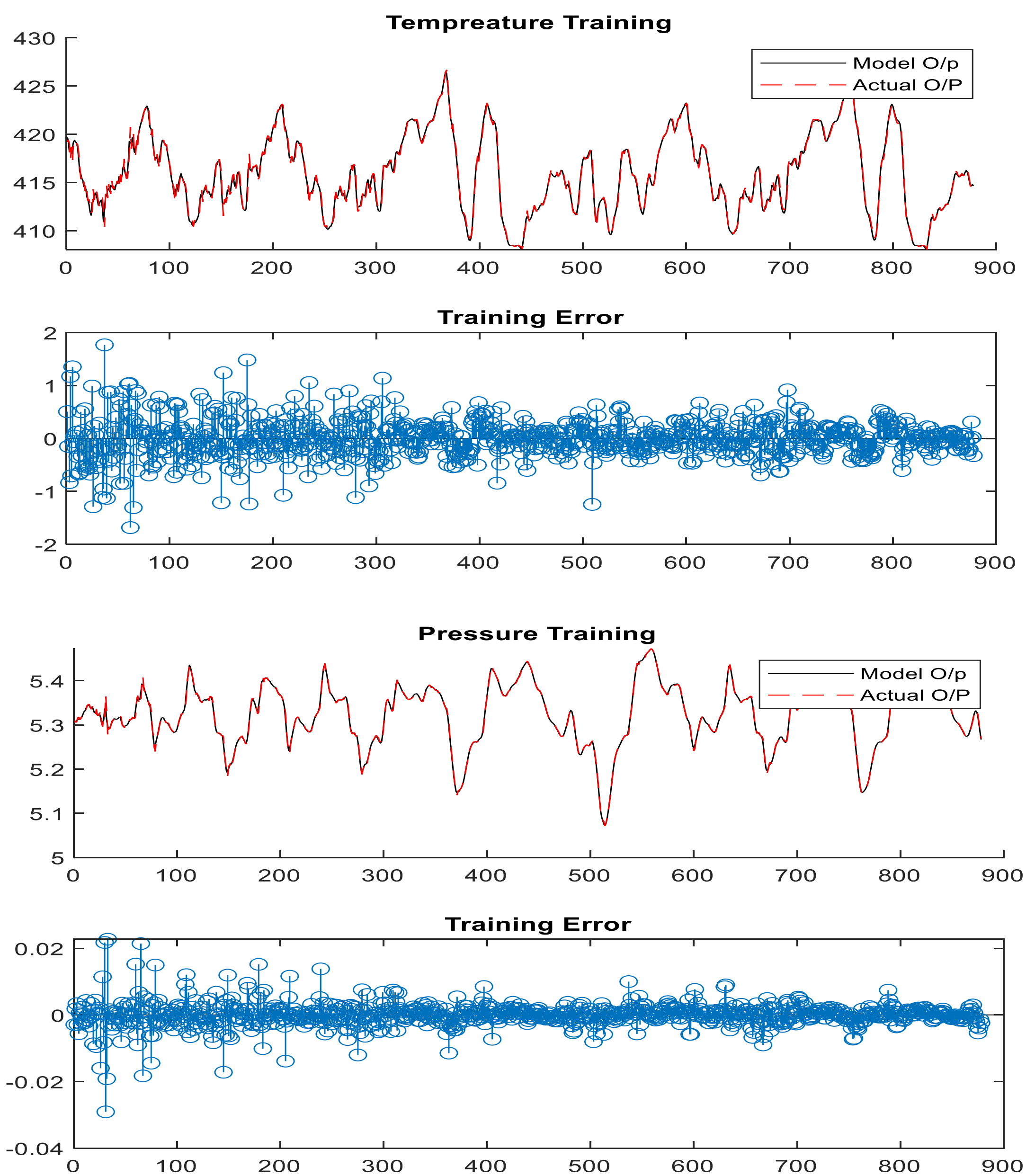


Figure 3.8 Flow chart of structured nonlinear parameters optimization method. LMM, Leven beg–Marquardt method; LSM, least square method.

After repetitively training and comparison, the orders of RBF-ARX model steam boiler system are finally determined as $n_y = 3$, $n_u = 3$, m=1 and $n_x = 2$.

The following graph shows the training data for temperature, pressure, and drum level, along with the residual error for each variable. The residual error is the difference between the actual value and the predicted value. As shown in the figure below, the residual error is relatively small for all three variables, indicating that the RBF-ARX model is able to accurately predict the values of these variables.

Figure 3.9 illustrates the modeling residuals and presents a comparison between the actual data and the data generated by the MIMO-RBF-ARX model for the training dataset.



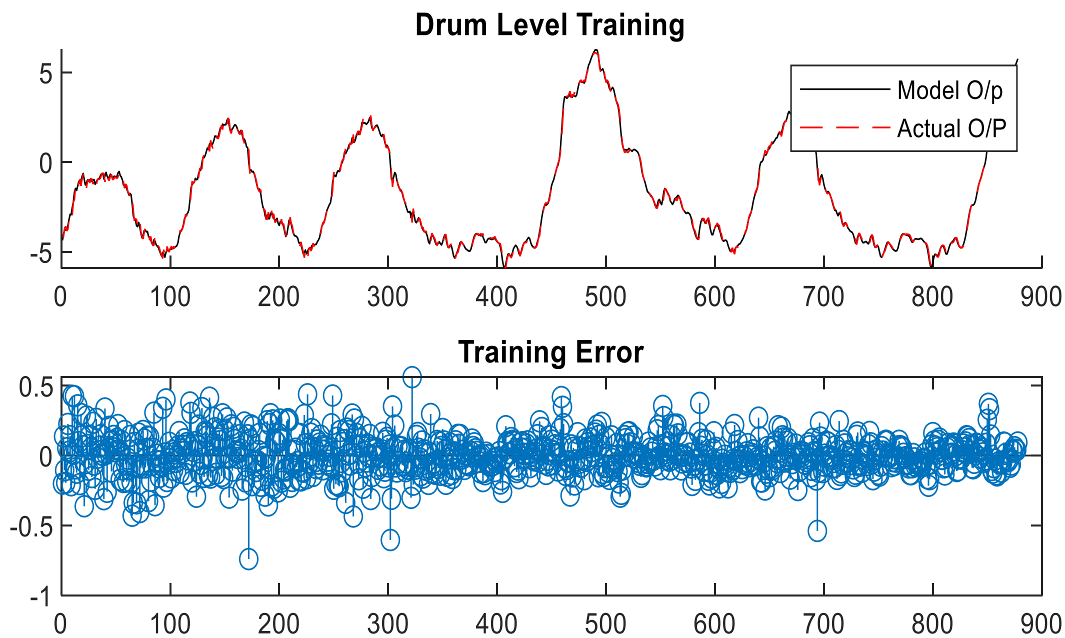


Figure 3.9 Outputs of the identified model and actual system for training data and Modeling error for training data.

The graph shows the training data curve based on curve fit and minimum mean square error, which has residual error evaluated by mean square error and has the minimum error. The mean squared error (MSE) values for Temperature, Pressure, and Drum level are 0.1307, 1.3702*10^-5, and 0.020, respectively. The lower the MSE value, the better the model's predictive accuracy and the better the regression model is. The curve fit is obtained by minimizing the sum of squared errors (SSE) using the least-squares fitting method. The residual error is evaluated by the MSE, which is calculated by taking the mean of the squared differences between the predicted and actual values. The minimum error indicates the best fit of the model to the data.

3.5.3. Model Validation

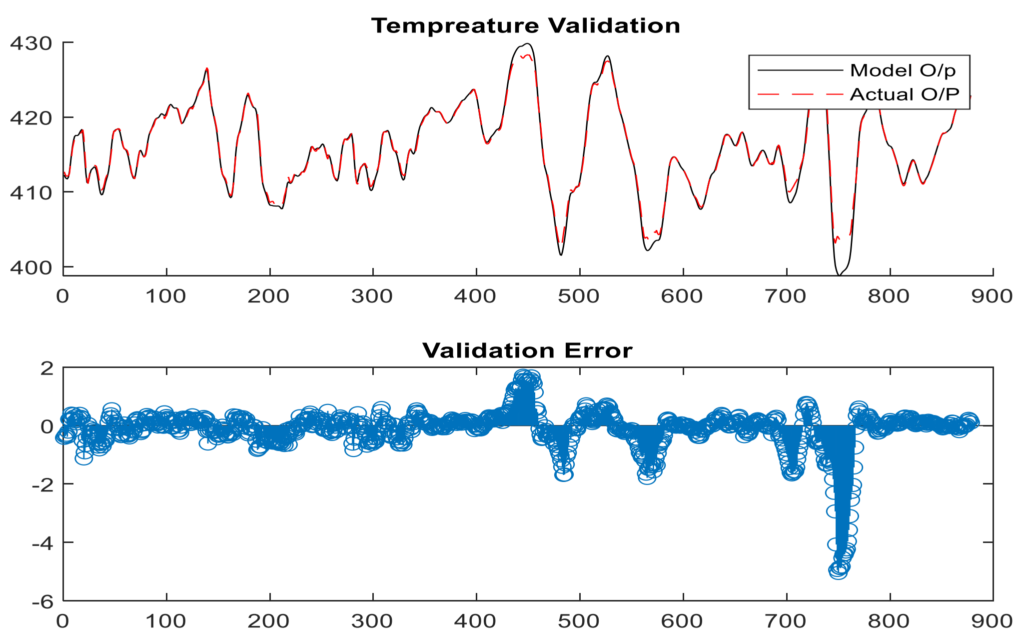
In this step, the validation data used as input data for the model to generate predictions , the real values (from the data set) and predicted values (from the model). Then compare the values predicted by the model with the values in the validation data set.

Model validation is the process of evaluating the accuracy and reliability of a model and indicates high confidence in the estimation. In system identification, it is the process of determining whether a model accurately represents the behavior of the system it is intended to represent (Merwe et al., 2018).

There are a number of different criteria that can be used to evaluate a model. One of the most common is the mean square error (MSE). The MSE is the average squared difference between the model's output and the actual system output. A lower MSE indicates that the model is more accurate. The formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.25}$$

Where: n is the number of observations, y_i is the actual value, and $\hat{y}_i$ is the estimated value. Figure 3.9 show the model validation of the RBF-ARX model, as well as modeling residuals for the validation data.



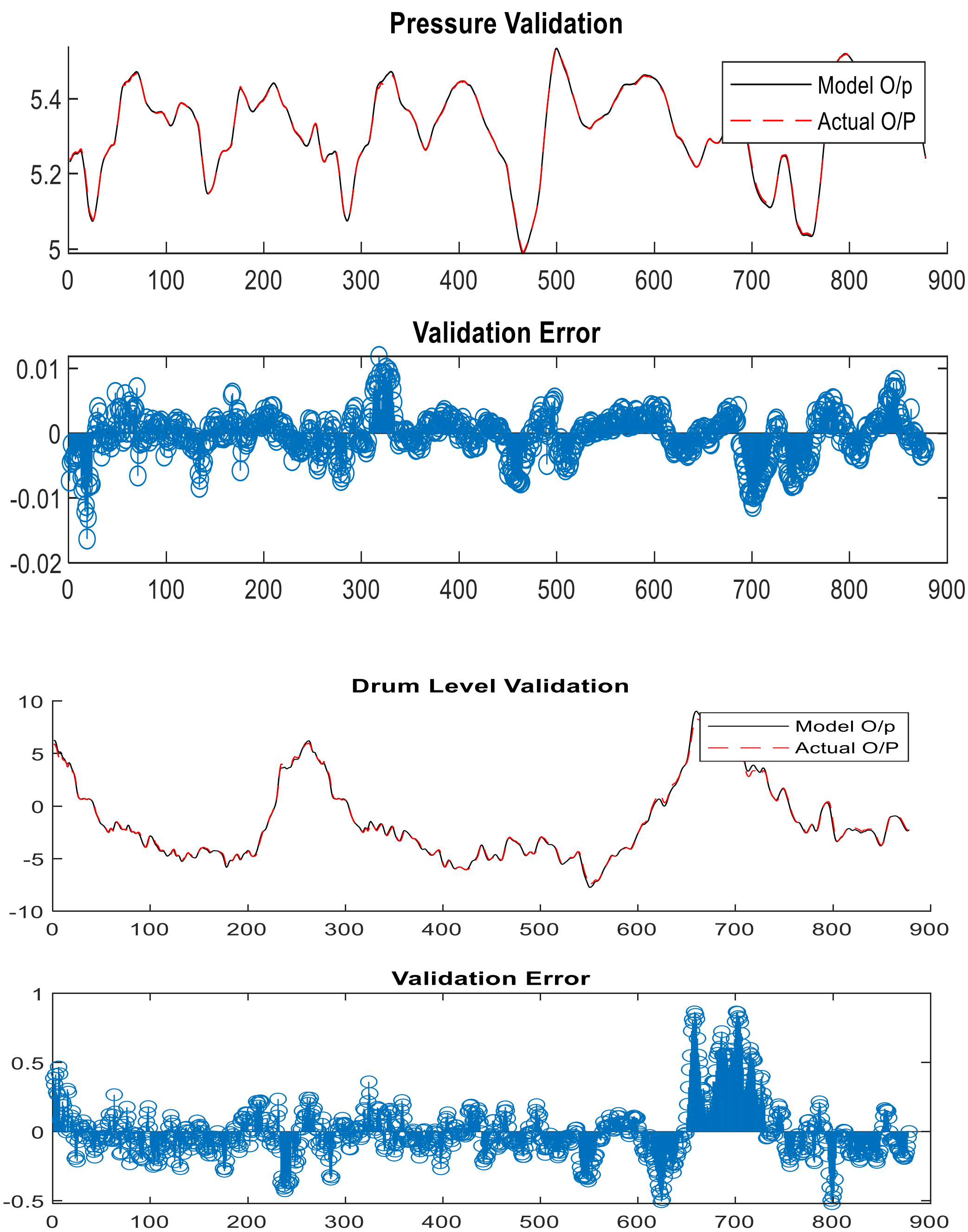


Figure 3.10 Result of MIMO RBF-ARX model validation.

The model validation graph for the steam boiler system shows a good curve fit and mean square error for the parameters Temperature, Pressure, and Drum level. The mean square error (MSE) values for Temperature, Pressure, and Drum level are 0.322, 3.22*10^-5, and 0.0219, respectively. The lower the MSE value, the better the model's predictive accuracy and the better the regression model is. The curve fit is obtained by minimizing the sum of squared errors (SSE) using the least-squares fitting method. The residual error is evaluated by the MSE. The minimum error indicates the best fit of the model to the data. The good curve fit and low MSE values suggest that the model is accurate and can be used for predicting the behavior of the steam boiler system. The model validation graph for the steam boiler system shows that the model is accurate and can be used for predicting the behavior of the system. The low MSE values indicate that the model has good predictive accuracy, and the curve fit suggests that the model fits the data well.

MIMO RBF-ARX model

The RBF-ARX model in equation (3.10) can be rewritten as the following matrix polynomial form:

$$\mathrm{y(k)} = \mathrm{C(w(k-1))} + \sum_{i=1}^{n_y} A_i(w(k-1))\mathrm{y(k-i)} + \sum_{i=1}^{u_n} B_i(w(k-1))\mathrm{u(k-i)} + \mathrm{E(k)} \tag{3.26}$$

$$\mathrm{C(w(k-1))} = [\phi_0^1(\mathrm{w(k-1)}) \quad \phi_0^2(\mathrm{w(k-1)}) \quad \phi_0^3(\mathrm{w(k-1)})] \tag{3.27}$$

$$\phi_0^i(\mathrm{w(k-1)}) = c_0^i + \sum_{j=1}^{m} c_j^i \exp\left\{-\lambda_j^y \left\| w(k-1) - z_j^y \right\|_2^2\right\} \tag{3.28}$$

$$A_i(\mathrm{w(k\text{-}1)}) = \begin{bmatrix} a_{11,i}(w(k-1)) & \cdots & a_{13,i}(w(k-1)) \\ \vdots & \ddots & \vdots \\ a_{31,i}(w(k-1)) & \cdots & a_{33,i}(w(k-1)) \end{bmatrix} \tag{3.29}$$

$$B_i(\mathrm{w(k\text{-}1)}) = \begin{bmatrix} b_{11,i}(w(k-1)) & \cdots & b_{14,i}(w(k-1)) \\ \vdots & \cdots & \vdots \\ b_{31,i}(w(k-1)) & \cdots & b_{34,i}(w(k-1)) \end{bmatrix} \tag{3.30}$$

Where,

$$a_{n,i}(w(k-1)) = \begin{cases} c_{i,0}^{ny} + \sum_{j=1}^{m} c_{i,j}^{ny} \exp\left\{-\lambda_j^y \left\| w(k-1) - z_j^y \right\|_2^2\right\}, & \mathrm{i} \le \mathrm{n}_y \\ 0, & \mathrm{i} > \mathrm{n}_y \end{cases} \tag{3.31}$$

$$b_{n,i}(w(k-1)) = \begin{cases} c_{i,0}^{nu} + \sum_{j=1}^{m} c_{i,j}^{nu} \exp\left\{-\lambda_j^u \left\| w(k-1) - z_j^u \right\|_2^2\right\}, & \mathrm{i} \le \mathrm{n_u} \\ 0, & \mathrm{i} > \mathrm{n}_u \end{cases} \tag{3.32}$$

$y(k)=[y_1(k)\ \ y_2(k)\ \ y_3(k)]^T$ are the output which are the steam Temperature, steam pressure and drum level respectively. $u(k)=[u_1(k)\ \ \mathrm{u}_2(k)\ \ \mathrm{u}_3(k)\ \ \mathrm{u}_4(k)]^T$ denotes the primary air, second air, feed water and fuel input.

Assuming that, at a steady state $u_{s,}y_s$ and w_s are the values of the related variables, then from the MIMO RBF-ARX model yields.

$$\mathrm{y}_s = \mathrm{C}(\mathrm{w}_s) + \sum_{i=1}^{n_y} A_i(w_s)\mathrm{y}_s + \sum_{i=1}^{u_n} B_i(w_s)\mathrm{u}_s \tag{3.33}$$

The increment equation around the steady state from equation (3.26) and (3.35)

$$\Delta\mathrm{y(k)} - \Delta\mathrm{C(w(k-1))} = \sum_{i=1}^{n_y} A_i(w_s)\Delta\mathrm{y(k-i)} + \sum_{i=1}^{u_n} B_i(w_s)\Delta\mathrm{u(k-i)} + \mathrm{E(k)} \tag{3.34}$$

Where

$$\begin{cases} \Delta y(k) = y(k) - \mathrm{y}_s \\ \Delta u(k) = u(k) - u_s \\ \Delta c(w(k-1)) = c(w(k-1)) - c(w_s) \end{cases} \tag{3.35}$$

The increment MIMO RBF-ARX model can be transformed into a state space equation model by defining state vector as follows:

$$\begin{cases} x(k) = [x_{1,k}^1 \quad x_{2,k}^1 \quad \cdots \quad x_{p_n,k}^1, \\ \qquad\quad x_{1,k}^2 \quad x_{2,k}^2 \quad \cdots \quad x_{p_n,k}^3, \\ \qquad\quad x_{1,k}^3 \quad x_{2,k}^3 \quad \cdots \quad x_{p_n,k}^3,] \\ x_{1,k}^1 = y_1(k) - y_{1s} - \phi_0^1(w(k-1) + \phi_0^1(w_s) \\ x_{1,k}^2 = y_2(k) - y_{2s} - \phi_0^2(w(k-1) + \phi_0^2(w_s) \\ x_{1,k}^3 = y_3(k) - y_{3s} - \phi_0^3(w(k-1) + \phi_0^3(w_s) \\ p_n = \max(n_y, n_u) \end{cases} \tag{3.36}$$

A state-space model corresponding to the model given by

$$\begin{cases} x(k+1) = Ax(k) + B\Delta u(k) \\ \Delta y(k) = cx(k) \end{cases} \tag{3.37}$$

Where the system matrix (A), input marix (B) and output (C) are generated by using the output and input data of waste to energy steam boiler of Rappi Thermal Power Plant. These data are depicted Appendex III. The numerical values of these matrices are generated and portrayed below by using (3.29) to (3.32) and matlab code as seen in Appendex II.

$$A = \begin{bmatrix} 0 & 0 & 0.9445 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.500 & 0 & -1.4409 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2.00 & 2.9100 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1.0043 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5000 & 0 & -1.5207 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2.000 & 2.9905 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9902 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.5000 & 0 & -1.5161 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2.0000 & 2.8092 \end{bmatrix} \tag{3.38}$$

$$B = \begin{bmatrix} 0.0026 & -0.0070 & 0.5441 & -0.8268 \\ -0.0026 & -0.0053 & -0.5506 & 0.8210 \\ 0.0026 & 0.0147 & 0.5581 & -0.8153 \\ 0.0001 & -0.1179 & -0.1814 & 0.0680 \\ -0.0001 & 0.1177 & 0.1784 & -0.0678 \\ 0.0001 & -0.1176 & -0.1756 & 0.0676 \\ 0.0042 & -2.5185 & 1.2584 & -2.0244 \\ -0.0042 & 2.5136 & -1.2818 & 1.9756 \\ 0.0042 & -2.5179 & 1.3074 & -1.9233 \end{bmatrix} \tag{3.39}$$

$$C = \begin{bmatrix} 0 & 0 & 2.000 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.2500 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4.000 \end{bmatrix} \tag{3.40}$$

CHAPTER FOUR

CONTROLLER DESIGN

4.1. Introduction

The control of steam boiler systems in thermal power plants is a critical task that requires accurate and reliable control strategies. Two popular control strategies for steam boiler systems are Linear Quadratic Regulator (LQR) and Model Predictive Control (MPC). In this chapter, discuss the design of these two control strategies for steam boiler systems in thermal power plants. The focus will be on the controller design, and explore the various approaches and techniques used to develop accurate and reliable control strategies. The chapter will cover the following topics.

4.2. LQR Controller Design

The Linear Quadratic Regulator (LQR) is a well-established control strategy that is commonly employed to optimize the performance of dynamic systems. It leverages a quadratic cost function and a linear mathematical model of the system to determine the optimal control inputs. The LQR controller seeks to minimize the cost function by adjusting the control inputs in a way that balances the system's deviations from the desired state and the control effort required(Lublin & Athans, 2010).

The problem is determining control law u that minimize cost function on equation subjected to (Lewis et al., 2013)

$$x(k+1) = Ax(k) + Bu(k) \tag{4.1}$$

We must locate u such that it minimizes the subsequent cost function.

$$J = \sum_{k=0}^{\infty}\left(x(k)^T Qx(k) + u(k)^T Ru(k) + \lambda^T (Ax(k) + Bu(k) - x(k+1))\right) \tag{4.2}$$

Matrix Q is a weighing matrix for state error and R is a weighing matrix for input. The Choice depended on the optimization problem and design specifications. If state error is required to be minimized matrix Q should be high and if input to the system is required to be minimized more than the state tracking error matrix R should be high. In state feedback controller design penalizing input is same as penalizing state, since the control signal is linear combination of the state of the system.

The possible starting of guessing the values of the matrices can be one of the following

- Simplest choice: $Q = I$, $R = \rho I \Rightarrow L = x^2 + \rho u^2$ then vary ρ to get something that has good response.
- Diagonal weights

$$Q = \begin{bmatrix} q_1 & 0 & 0 & 0 \\ 0 & q_2 & 0 & 0 \\ 0 & 0 & q_3 & 0 \\ 0 & 0 & 0 & q_4 \end{bmatrix} \tag{4.3}$$

Choose each $q_i = \frac{1}{\tilde{x}_i^2}$, where $\tilde{x}_i$ is the tolerable error of each state of the system.

- Output weighting

Let $z = Hx$ be the output need to keep small. Assume (A, H) observable. Use

$Q = x^T x$, $R = \rho I \Rightarrow$ trade off z^2 vs ρu^2.

Where $H = x^T Qx + u^T Ru + \lambda^T$ and $\lambda(t) = P(t)x(t)$

- Trial and error (on weights)

Most of the time $Q = C^T C$ and the weight of the matrix is adjusted based on the performance requirement of the system. In this study uses trial and error weight adjustment by considering the initial weight to be $Q = \gamma C^T C$ and $R = \rho I$, where $\gamma = 5000$ and $\rho = 5$. Using these parameters, matrix A, B and C of the identified system to determine the state feedback gain matrix va1ue using MATLAB command, K_{lqr} =lqrd(A,B,Q,R,Ts) where T_s is system sampling time. The value of the matrix is

$$K_{lqr} = \begin{bmatrix} -99328.44 & -167646.67 & -68027.16 & 46478.48 & 89116.10 & 42492.98 & 4931.06 & 7817.23 & 2410.61 \\ -13287.01 & -20646.43 & -7408.41 & 1520.76 & 16045.23 & 13997.26 & 280.29 & 223.76 & -241.80 \\ 77033.91 & 125227.80 & 48185.66 & -32444.04 & -60780.01 & -27746.31 & 7630.74 & 11.07 & -6978.84 \\ -12232.33 & -15275.37 & -3009.76 & 18356.02 & 32798.64 & 13907.55 & 8759.32 & 3125.10 & -5677.85 \end{bmatrix} \quad (4.4)$$

Since the states of the system are not fully accessible, it is mandatory to design state observer for the system. In this study uses Luenberger full state observer to estimate the states of the system(Estimation, 2018).

The identified state space representation of boiler system for thermal power plant is completely observable dynamic system, hence it is possible to design a state observer. Assume the state vector x is given by its estimate $\hat{x}$

$$\hat{x}(k+1) = \hat{A}\hat{x}(k) + \hat{B}u(k) + L_c y(k) \quad (4.5)$$

The matrices $\hat{A}, \hat{B}$ are unknown

In full state observer design problem x and $\hat{x}$ has equal dimension. The deviation (estimation error) $\tilde{x} = x - \hat{x}$, will be

$$\tilde{x}(k+1) = Ax(k) + Bu(k) - \hat{A}\hat{x}(k) - \hat{B}u(k) - L_c y(k) \quad (4.6)$$

replacing $\hat{x}$ by $x - \tilde{x}$, which leads to

$$\tilde{x}(k+1) = [A - \hat{A} - L_c C]x(k) + \hat{A}\tilde{x}(k) + [B - \hat{B}]u(k) \quad (4.7)$$

If we need $\tilde{x}$ to become zero independent of x and u, is only possible if and only if $\hat{B} = B$, $\hat{A} = [A - L_c C]$ and $\hat{A}$ is stable. If this condition is fulfilled, the error dynamics $\tilde{x}$ becomes

$$\tilde{x}(k+1) = \hat{A}\tilde{x}(k) = [A - L_c C]\tilde{x}(k) \quad (4.8)$$

Thus the design problem is finding suitable L_c such that the estimation error dynamics goes to zero as $t \to \infty$, or determining suitable L_c that place the closed loop eigenvalues of estimation error dynamics $\tilde{x}(k+1) = (A - L_c C)x(k)$ at the desired location.

The problem of state feedback controller gain matrix design and state estimator gain matrix design obeys duality property. This implies that if estimation error dynamics is expressed in an observable canonical form, the feedback matrix L_c can be determined from full state feedback matrix K_f for the corresponding controllable canonical form representation of estimation error dynamics just by transposing K_f and vise-versa. Hence, the same MATLAB command is used to determine LQR controller state feedback gain matrix, $\mathrm{L_c} = \mathrm{lqrd}(\mathrm{A}^T, \mathrm{C}^T, \mathrm{Q}, \mathrm{R}_y, \mathrm{T_s})^T$, where $R_y = \lambda I$ and $\lambda = 50$. The value of the matrix is

$$L_c = \begin{bmatrix} 0.99 & -5.56^{-12} & 2.23^{-13} \\ 1.46 & -1.43^{-11} & 2.00^{-12} \\ 20.78 & 1.19^{-12} & 8.86^{-14} \\ 3.70^{-12} & 7.93 & 1.99^{-11} \\ -6.87^{-12} & 0.02 & 1.29^{-12} \\ 9.82^{-12} & 24.03 & 1.92^{-11} \\ 4.90^{-13} & -6.0^{-13} & 0.98 \\ 3.61^{-12} & -8.44^{-13} & 1.44 \\ 9.05^{-14} & 2.43^{-12} & 20.77 \end{bmatrix} \tag{4.9}$$

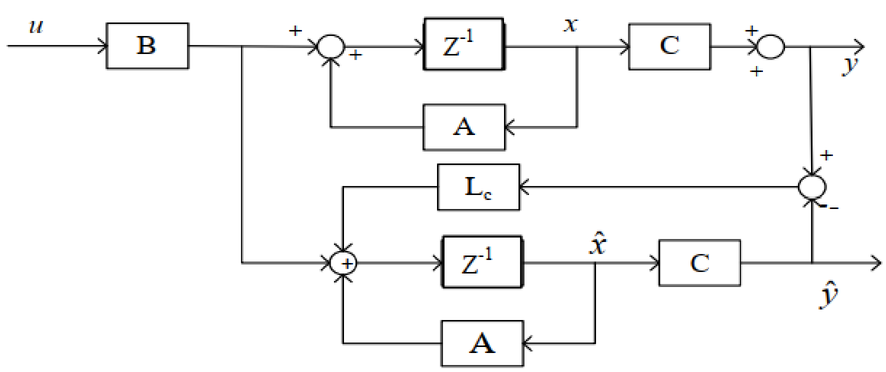


Figure 4.1 Full State observer block diagram representation.

To achieve fast convergence of the controlled output y to a specific nonzero constant set-point value r. This set-point values (x_d, u_d), represents an equilibrium point of the system, where the output is expected to stabilize. For a reference tracking steady state

$$u(k) = -Kx(k) + K_o r(k) \tag{4.10}$$

Replacing for $u(k)$ in the state space equation;

$$x(k+1) = Ax(k) + Bu(k) \Rightarrow \dot{x} = (A - BK)x(k) + BK_o r \tag{4.11}$$

As time goes to infinity the state x, goes to the desired state x_d and the input u, tends toward desired input u_d, having dynamic equation:

$$x_d(k) = Ax_d(k) + Bu_d(k) \Rightarrow x_d(k+1) = (A - BK)x_d(k) + BK_o r \tag{4.12}$$

$$u_d(k) = -Kx_d(k) + K_o r(k) \tag{4.13}$$

The tracking error $\tilde{x} = x - x_d$ is then

Since $\dot{x}_d$ is zero at $k \to \infty$

$$x_d(k) = -(A - BK)^{-1} BK_o r(k) \tag{4.15}$$

Replacing for x_d in equation, the desired control law is

$$u_d = K(A - BK)^{-1} BK_o + K_o)r \tag{4.16}$$

And the output of the dynamic system y, goes to r,

$$y = Cx_d + Du_d = r \tag{4.17}$$

Replacing for u_d and x_d, the value of matrix K_o is:

$$K_o = -(C(A - BK)^{-1} B - D((K(A - BK)^{-1} B + I))^{-1} \tag{4.18}$$

Using MATLAB, the value of the matrix K_o is:

$$K_o = \begin{bmatrix} -26.79 & -0.62 & 4.69 \\ 2.29 & -51.19 & -0.12 \\ -5.41 & -4.56 & 24.26 \\ 14.92 & 8.08 & 15.80 \end{bmatrix} \tag{4.19}$$

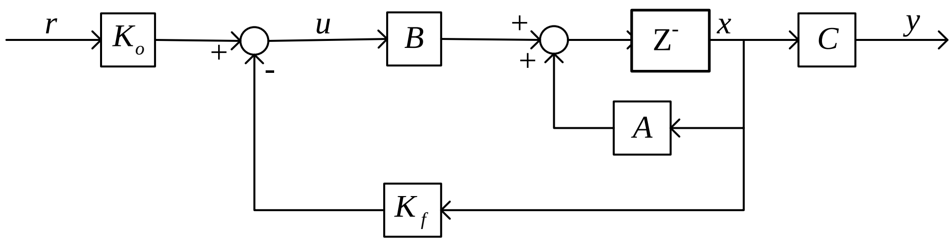


Figure 4.2 Reference output Tracking with full state feedback.

4.3. Model Predictive Controller Design

Model-based predictive control is a type of control system that utilizes a model of the process being controlled to predict future values of the process outputs and states. The term can be broken down into two distinct parts: "model-based" and "predictive control."

As the name suggests, model-based control requires the use of a model of the process being controlled. This model can take many forms, but it is typically a mathematical representation that describes the behavior of the process. The model can be developed using various techniques, such as first-principles modeling or data-driven modeling.

Predictive control, on the other hand, involves predicting the future values of the process outputs and states from the current time. This is done by using the model of the process to simulate its behavior over time. By simulating the process, the controller can predict how it will behave in the future and adjust its inputs accordingly to achieve a desired outcome.

One key advantage of model-based predictive control is that it can handle complex systems with multiple inputs and outputs. By utilizing a model of the process, the controller can take into account the interactions between different variables and make more informed decisions about how to adjust its inputs.

Another advantage is that predictive control can handle constraints on the system. For example, if there are limits on certain inputs or outputs, the controller can take these constraints into account when making predictions and adjusting its inputs.

4.3.1. Models Types used in designing MPC

Computers, microcontrollers, and other digital devices with microprocessors frequently employ the Model Predictive Control (MPC) algorithm. In order to control a process, a discrete representation of the process model is required.

Using a mathematical model of the steam boiler system, MPC is a model-based control technique that aims to predict future behavior and optimize control actions. MPC chooses the best control inputs to minimize a predetermined cost function while taking into account the system's current state and anticipated evolution. As a result of its predictive abilities, MPC is better equipped to anticipate problems before they arise, adjust to changing operating circumstances, and enhance system performance (Fiedler et al., 2023).

4.3.2. Model based Predictive Control

MPC can be used to regulate the steam boiler in a thermal power plant by anticipating how the system will behave in the future and adjusting the control inputs, like the fuel flow rate and the air flow rate, to get the performance you want. The steam pressure, steam temperature, and drum level can all be controlled in the steam boiler using MPC.

Let consider the system (Orukpe, 2012)

$$x(k+1) = Ax(k) + Bu(k), x_0 = x(kh) \tag{4.20}$$

$$y(k+1) = Cx(k) \tag{4.21}$$

The solution to the above state equation by considering the state input has constant between some intervals i.e. [kh,(k+1)h] become:

$$x(k+1) = e^{A_h} x(k) + \int_{kh}^{(k+1)h} e^{A_{(kh+h-\tau)}} Bd\tau u(k) \tag{4.22}$$

$$x(k+1) = e^{A_h} x(k) + \int_0^h e^{A_\eta} Bd\eta u(k) \tag{4.23}$$

Where $\eta = kh + h - \tau$

$$x(k+1) = \Phi x(k) + \Gamma u(k) \tag{4.24}$$

Where $\Phi = e^{A_h}$ and $\Gamma = e^{A_\eta} Bd\eta$

$$y(k) = Cx(k) \tag{4.25}$$

Where $\Phi \in R^{n\times n}, \Gamma \in R^{n\times m}, andC \in R^{p\times n}$

By applying the backward difference operator, $\Delta x(k+1) = x(k+1) - x(k)$

Therefore the value of $\Delta x(k+1)$ become:

$$\Delta x(k+1) = \Phi \Delta x(k) + \Gamma \Delta u(k) \tag{4.26}$$

Also by applying the backward difference operator in output the equation become:

$$\Delta y(k+1) = y(k+1) - y(k) \tag{4.27}$$

By substituting the above equation on the $y(k)$

$$\Delta y(k+1) = Cx(k+1) - Cx(k) \tag{4.28}$$

$$\Delta y(k+1) = C\Delta x(k+1) \tag{4.29}$$

By substituting the equation of $\Delta x(k+1)$

The output equation become

$$\Delta y(k+1) = C\Phi \Delta x(k) + C\Gamma \Delta u(k) \tag{4.30}$$

Hence,

$$y(k+1) = y(k) + C\Phi \Delta x(k) + C\Gamma \Delta u(k) \tag{4.31}$$

By combining the equation of $\Delta x(k+1)$ and $y(k+1)$ in to one equation

$$\begin{bmatrix} \Delta x(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} \Phi & O \\ C\Phi & I_p \end{bmatrix} \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} \Gamma \\ C\Gamma \end{bmatrix} \Delta u(k) \tag{4.32}$$

$$y(k) = \begin{bmatrix} O & I_p \end{bmatrix} \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix} \tag{4.33}$$

Based on the above equation define the augmented matrices

$$x_a(k) = \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix}, \Phi_a(k) = \begin{bmatrix} \Phi & O \\ C\Phi & I_p \end{bmatrix}, \Gamma_a = \begin{bmatrix} \Gamma \\ C\Gamma \end{bmatrix}, and\ C_a = \begin{bmatrix} O & I_p \end{bmatrix} \tag{4.34}$$

Therefore the augmented matrices become:

$$x_a(k+1) = \Phi_a x_a(k) + \Gamma_a \Delta u(k) \tag{4.35}$$

$$y(k) = C_a x_a(k) \tag{4.36}$$

Where $\Phi_a \in R^{(n+p)\times(n+p)}, \Gamma_a \in R^{(n+p)\times m}, and C_a \in R^{p\times(n+p)}$

The augmented state vector obtained at each sampling time, the control objective is the control input sequence at each sampling time. The control sequence at each sampling time can be expressed as

$$\Delta u(k), \Delta u(k+1), ..., \Delta u(k+N_p-1), Where\ N_p \text{ is the predection horizon} \tag{4.37}$$

The above control input sequence will give the predicted sequence of the state vector

$$x_a(k+1|k), x_a(k+2|k), ..., x_a(k+N_p|k) \tag{4.38}$$

It used to compute the predicted sequence of the pants output

$$y(k+1|k), y(k+2|k), ..., y(k+N_p|k) \tag{4.39}$$

Based on the above information compute the control sequence and apply $u(k)$ to the plant and to get $x(k+1)$. Then repeat the process again, using $x(k+1)$ as an initial condition and compute $u(k+1)$.

Based on the plant model parameters and the measurement of the augmented matrices $x_a(k)$, evaluate the augmented states over the prediction horizon successively by applying the following recursion formula

$$x_a(k+1|k) = \Phi_a x_a(k) + \Gamma_a \Delta u(k) \tag{4.40}$$

$$x_a(k+2|k) = \Phi_a x_a(k+1|k) + \Gamma_a \Delta u(k+1) \tag{4.41}$$

$$x_a(k+2|k) = \Phi_a{}^2 x_a(k) + \Phi_a \Gamma_a \Delta u(k) + \Gamma_a \Delta u(k+1) \tag{4.42}$$

$$x_a(k+N_p|k) = \Phi_a{}^{N_p} x_a(k) + \Phi_a{}^{N_p-1} \Gamma_a \Delta u(k) + \cdots + \Gamma_a \Delta u(k+N_p-1) \tag{4.43}$$

The above equation can be represent in matrices form

$$\begin{bmatrix} x_a(k+1|k) \\ x_a(k+2|k) \\ \vdots \\ x_a(k+N_p|k) \end{bmatrix} = \begin{bmatrix} \Phi_a \\ \Phi_a{}^2 \\ \vdots \\ \Phi_a{}^{N_p} \end{bmatrix} x_a + \begin{bmatrix} \Gamma_a & & \\ \Phi_a \Gamma_a & \Gamma_a & \\ \vdots & \ddots & \\ \Phi_a{}^{N_p-1} \Gamma_a & \cdots & \Gamma_a \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_p-1) \end{bmatrix} \tag{4.44}$$

To design the controller that would force the plant output y to track the given reference signal, the sequence of predicted outputs become

$$\begin{bmatrix} y(k+1|k) \\ y(k+2|k) \\ \vdots \\ y(k+N_p|k) \end{bmatrix} = \begin{bmatrix} C_a x_a(k+1|k) \\ C_a x_a(k+2|k) \\ \vdots \\ C_a x_a(k+N_p|k) \end{bmatrix} \tag{4.45}$$

$$\begin{bmatrix} y(k+1|k) \\ y(k+2|k) \\ \vdots \\ y(k+N_p|k) \end{bmatrix} = \begin{bmatrix} C_a \Phi_a \\ C_a \Phi_a{}^2 \\ \vdots \\ C_a \Phi_a{}^{N_p} \end{bmatrix} x_a(k) + \begin{bmatrix} C_a \Gamma_a & & \\ C_a \Phi_a \Gamma_a & C_a \Gamma_a & \\ \vdots & \ddots & \\ C_a \Phi_a{}^{N_p-1} \Gamma_a & \cdots & C_a \Gamma_a \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_p-1) \end{bmatrix} \tag{4.46}$$

To reduce the above complicity let consider

$$Y=\begin{bmatrix} y(k+1|k) \\ y(k+2|k) \\ \vdots \\ y(k+N_p|k) \end{bmatrix}, \Delta U=\begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_p-1) \end{bmatrix}, W=\begin{bmatrix} C_a\Phi_a \\ C_a\Phi_a{}^2 \\ \vdots \\ C_a\Phi_a{}^{N_p} \end{bmatrix},$$

$$and\ Z=\begin{bmatrix} C_a\Gamma_a & & \\ C_a\Phi_a\Gamma_a & C_a\Gamma_a & \\ \vdots & \ddots & \\ C_a\Phi_a{}^{N_p-1}\Gamma_a \cdots & C_a\Gamma_a & \end{bmatrix} \tag{4.47}$$

The output equation become

$$Y(t)=Wx_a+Z\Delta U \tag{4.48}$$

Now consider to construct the control sequence, $\Delta u(k), \Delta u(k+1), ..., \Delta u(k+N_p-1)$ that would minimize the cost function

$$J(\Delta U)=\frac{1}{2}(r_p-Y)^T Q(r_p-Y)+\frac{1}{2}\Delta U^T R\Delta U \tag{4.49}$$

Where $Q=Q^T>0$ and $R=R^T>0$ are real symmetric positive semi-definite and positive definite weight matrices, respectively. The multiplying scalar, ½ is just to make subsequent manipulations cleaner. Finally the vector r_p consists of the values of the command signal at sampling times, $k+1, k+2, \ldots, k+N_p$. The selection of the weight matrices Q and R reflects our control objective to keep the tracking error $\|r_p-Y\|$ "small" using the control actions that are "not too large".

CHAPTER FIVE

RESULT AND DISCUSSION

5.1. Introduction

In this chapter, a steam boiler's Simulink building components are discussed. Additionally, simulation results are shown, along with a brief analysis and discussion. Results from the simulation show how the steam boiler operates when a controller is present. Furthermore, a linear quadratic controller and the closed-loop model predictive controller for steam boilers are contrasted. Utilizing the MATLAB software, the complete simulation is performed.

5.2. Simulink model of (LQR) controller for steam boiler

Using a discrete-time state-space model, a Linear Quadratic Regulator (LQR) controller for a steam boiler may be designed in Simulink while taking into account steam temperature, steam pressure, and drum water level. By using system identification techniques, the state-space model of the system can be derived from the input-output real data of the system. The states of the system can also be estimated using a Luenberger complete state observer. A explanation of the Simulink design of a LQR controller for a steam boiler taking into account the provided parameters and a state observer is given below:

- Figure 5.1 shows the Simulink block diagram for the LQR controller design.
- The LQR controller design involves the following steps:
  - Obtain the discrete-time state-space model of the system using system identification methods.
  - Define the cost function that needs to be minimized. The cost function is a quadratic function of the state variables and control inputs.
  - Use the `dlqr` function in MATLAB to calculate the optimal gain matrix K, the solution S of the associated algebraic Riccati equation, and the closed-loop poles P for the state-space model.
  - Implement the LQR controller in Simulink using the gain matrix K.

- The Luenberger full state observer can be designed to estimate the states of the system. Since the system is completely observable, it is possible to design a state observer.
- The state observer design involves the following steps:
  - Define the observer dynamics that describe how the observer estimates the states of the system.
  - Use the `place` function in MATLAB to calculate the observer gain matrix Lc that places the observer poles at desired locations.
  - Implement the state observer in Simulink using the observer gain matrix Lc.
- The LQR controller and state observer can be combined to form a closed-loop control system that regulates the steam temperature, steam pressure, and drum water level to their desired setpoints.
- The closed-loop control system can be evaluated by simulating it in Simulink and analyzing the simulation results. The simulation results should show that the control system can regulate the system states to their desired setpoints.

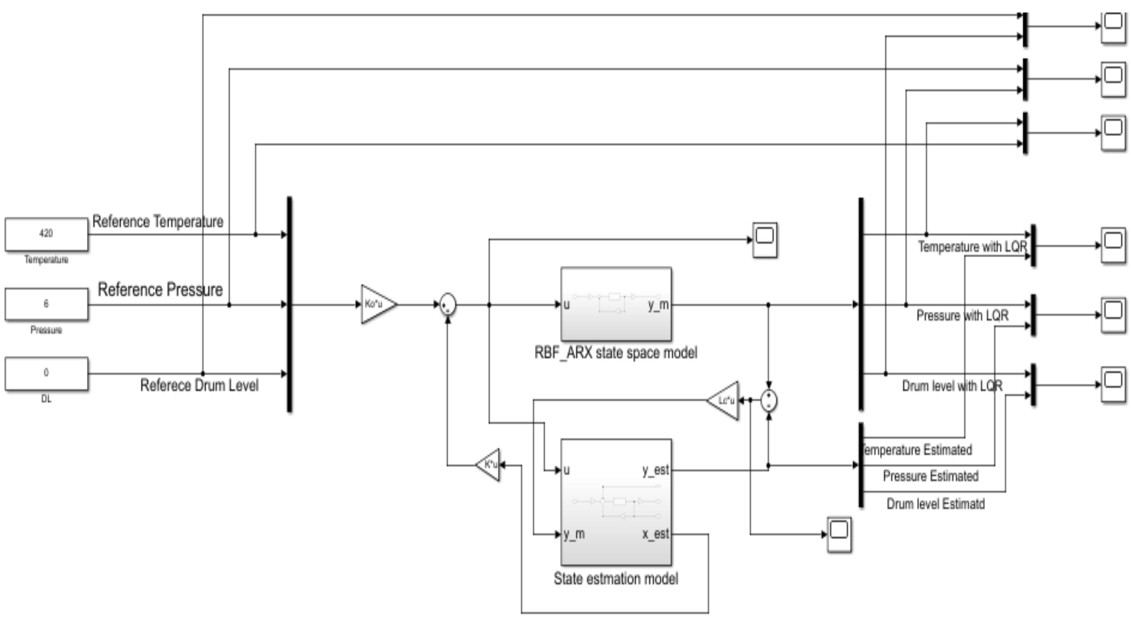


Figure 5.1 Matlab Simulink for steam boiler system with LQR.

The simulation results show that the LQR controller can regulate the steam temperature, steam pressure, and drum water level to their desired setpoints. The closed-loop control system is evaluated by simulating it in Simulink and analyzing the simulation results. The simulation results can be further analyzed to evaluate the performance of the LQR controller.

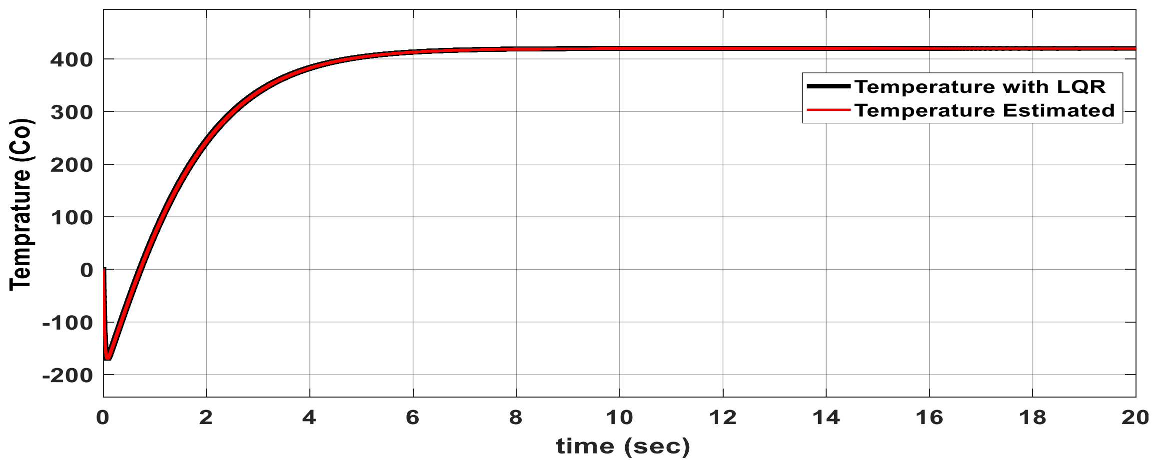


Figure 5.2 Simulation of Steam Temperature with LQR and Compare with State Estimator.

In Figure 5.2, the system response with the LQR controller is displayed, along with the simulated estimated states of the system. The graph specifically focuses on the temperature parameter, with a reference value of 420 degrees Celsius.

The graph shows the response of the system over time, illustrating how the LQR controller adjusts the control inputs to regulate the temperature and maintain it close to the desired reference value. The estimated states, obtained through the Luenberger observer, provide an estimation of the actual temperature state of the system.

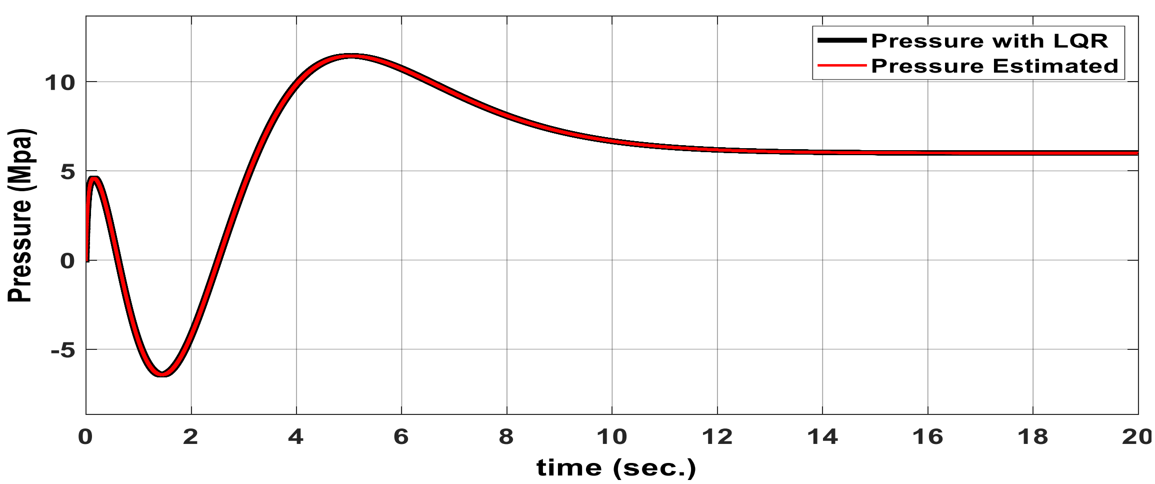


Figure 5.3 Simulation of Steam Steam with LQR and Compare with State Estimator.

Figure 5.3, it shows the system response with the LQR controller, but this time the focus is on the pressure parameter. The reference pressure value is set at 6 mega pascals. The graph demonstrates how the LQR controller manipulates the control inputs to regulate the pressure, ensuring it tracks the reference value effectively. The estimated states of the pressure obtained from the Luenberger observer are also depicted.

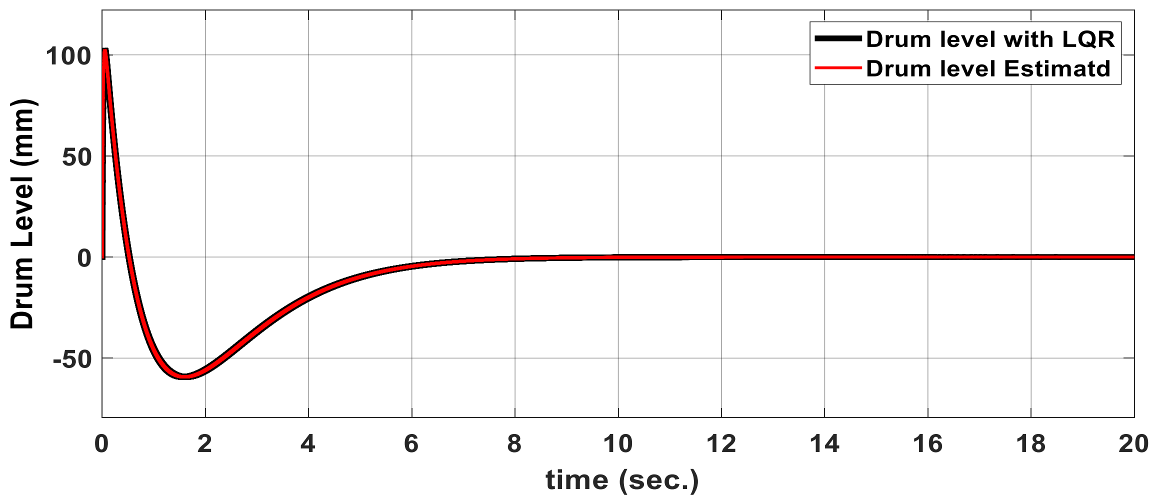


Figure 5.4 Simulation of Drum Level with LQR and Compare with State Estimator.

Figure 5.4 pertains to the system response with the LQR controller, with the graph specifically targeting the drum water level parameter. The reference value for the drum water level is set at zero millimeters. The graph exhibits how the LQR controller adjusts the control inputs to maintain the drum water level close to the reference value. The estimated states of the drum water level obtained through the Luenberger observer are included in the graph as well.

Through the analysis of these figures, the performance of the LQR controller can be thoroughly evaluated. Key performance metrics such as rise time, settling time and overshoot can be examined for each parameter. By comparing these metrics against predefined specifications or control objectives, the effectiveness of the LQR controller in regulating the steam temperature, pressure, and drum water level can be assessed.

5.3. Simulink model of (MPC) controller for steam boiler

The Simulink design of a Model Predictive Controller (MPC) for a steam boiler considering steam temperature, steam pressure, and drum water level can be done using a discrete-time state-space model. The MPC MATLAB toolbox can be used to tune the parameters of the MPC. In this case, the prediction horizon is set to 15 time steps, while the control horizon is set to 5 time steps.

The Simulink block diagram for the MPC controller design is shown in Figure 5.5. This depicts the integration of the MPC controller, the state-space model, and the measured inputs and outputs of the steam boiler system. The MPC controller utilizes the current and predicted future states of the system to compute the optimal control actions.

- The MPC controller design involves the following steps:
  - Obtain the discrete-time state-space model of the system using system identification methods.
  - Define the cost function that needs to be minimized. The cost function is a quadratic function of the state variables and control inputs.
  - Use the MPC MATLAB toolbox to tune the parameters of the MPC, such as the prediction horizon and control horizon.

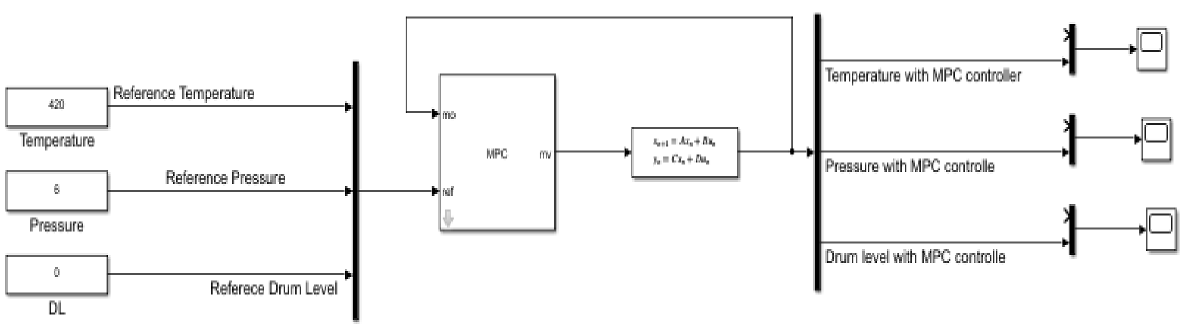


Figure 5.5 Implement the MPC controller in Simulink using the MPC block.

The MPC controller, based on the provided system dynamics and the prediction horizon, optimizes the control inputs over a finite time horizon to minimize a specified cost function. The predicted future behavior of the system is taken into account to determine the optimal control actions at each time step. This predictive capability enables the MPC controller to handle constraints and system dynamics effectively.

To achieve satisfactory control performance, the parameters of the MPC controller need to be properly tuned. This process involves adjusting the weights and constraints in the cost function, as well as the prediction and control horizons. Tuning can be performed through simulation and iterative refinement, considering performance metrics such as rise time, settling time and overshoot.

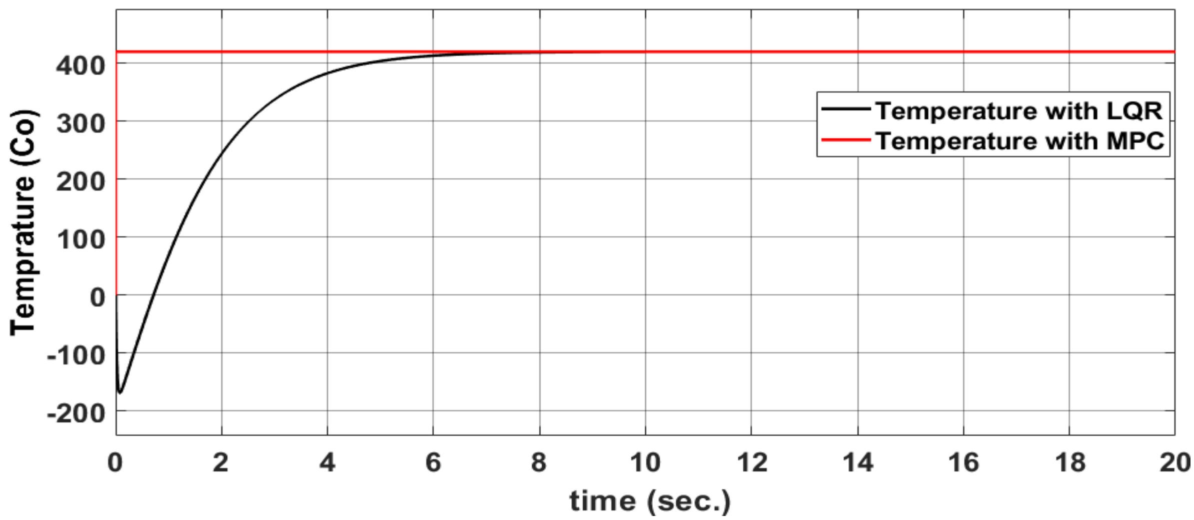


Figure 5.6 system response with MPC in comparison with LQR for steam temperature.

In Figure 5.6, the system response with the Model Predictive Controller (MPC) is compared to the response with the Linear Quadratic Regulator (LQR) controller. The graph focuses on the temperature parameter, with a reference value of 420 degrees Celsius.

The graph shows the response of the system over time for both controllers. The MPC controller achieves a settling time of 0.3955 seconds, a rise time of 0.1966 seconds. On the other hand, the LQR controller exhibits a settling time of 5.908 seconds, a rise time is very large seconds.

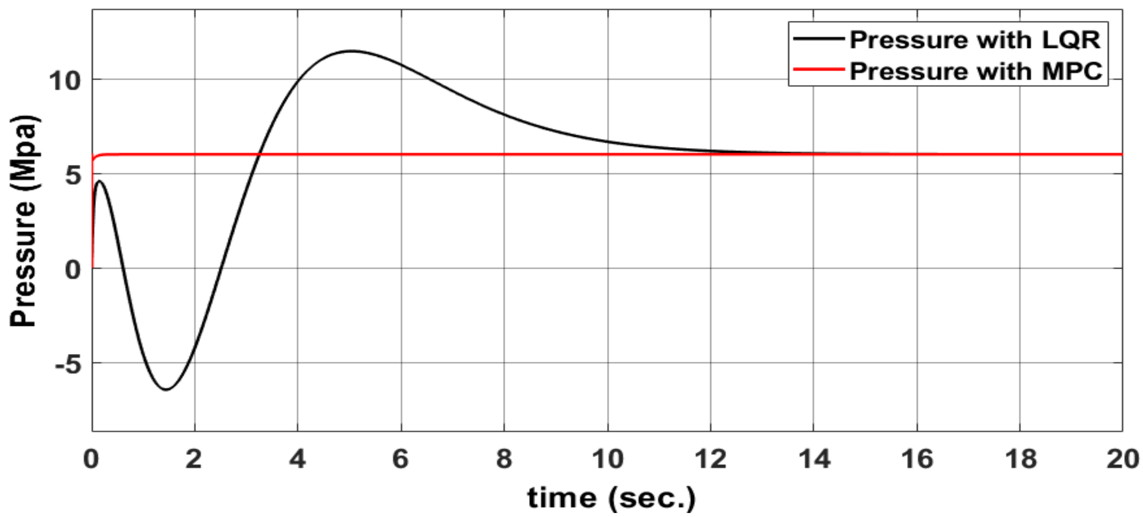


Figure 5.7 system response with MPC in comparison with LQR for steam pressure.

Figure 5.7, it presents the system response for the pressure parameter with the MPC and LQR controllers. The reference pressure value is set at 6 mega pascals. As with the previous graph, the MPC controller demonstrates a settling time of 0.0901 seconds, a rise time of 0.0195 seconds, and an overshoot of 0. In contrast, the LQR controller shows a settling time of 12.507 seconds, a rise time of very large seconds, and an overshoot of 12.70.

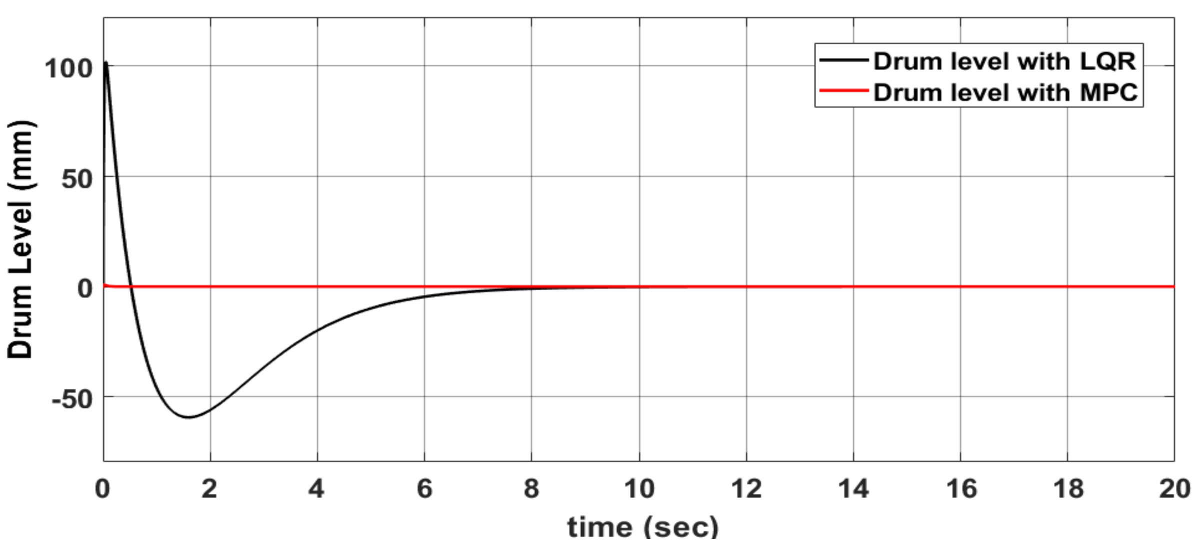


Figure 5.8 system response with MPC in comparison with LQR for Drum Level.

Figure 5.8 pertains to the system response for the drum water level parameter, with a reference value of zero millimeters. The MPC controller achieves a settling time of 0.5223 seconds, a rise time of 0.1741 seconds, and an overshoot of 0. Conversely, the LQR controller exhibits a settling time of 8.003 seconds and an overshoot of 0.

Table 5.1 Performace analysis for steam boiler parameter.

Parameters		Settling time	Rise time
Temerature	MPC	0.3955	0.1966
	LQR	5.99	-
Pressure	MPC	0.0901	0.0195
	LQR	12.05	-
Drum Level	MPC	0.5223	-
	LQR	0.1741	8.302

Through the comparison of these graphs and the associated performance metrics, the advantages of the MPC controller over the LQR controller can be observed. The MPC controller demonstrates significantly improved settling time, rise time, and overshoot for all three parameters, namely temperature, pressure, and drum water level.

The reduced settling time indicates that the MPC controller reaches the desired reference value faster, resulting in faster control response. The decreased rise time suggests that the MPC controller achieves stability and tracks the reference value more quickly. Moreover, the reduced overshoot implies that the MPC controller provides better control precision, minimizing deviations from the reference value.

Overall, the simulation results highlight the superior performance of the MPC controller compared to the LQR controller in regulating the steam boiler system. The MPC controller's predictive capabilities, combined with its ability to handle constraints contribute to its improved control performance and enhanced system stability.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The waste-to-energy (WtE) steam boiler is a critical component of the thermal power plant, as it provides a sustainable and efficient way to generate energy from waste materials that would otherwise be disposed of in landfills. Developing an effective control strategy for the WtE steam boiler can help to maximize the environmental benefits of the process, by reducing waste and optimizing energy production.

This study aims to achieve precise control over pressure, temperature, and drum level in steam boilers. The integration of RBF-ARX modeling and MPC offers a robust control framework that can effectively handle the nonlinear dynamics of steam boiler systems. This advanced control strategy enables accurate prediction and regulation of pressure, temperature, and drum level, leading to improved control performance and stability. The precise control over key variables helps enhance overall energy efficiency. This leads to cost savings and a reduced environmental impact.

By maintaining these variables within desired ranges, the risk of equipment failures, accidents, and hazardous conditions is minimized, promoting a safe working environment. The RBF-ARX modeling technique allows for accurate system identification, capturing the underlying dynamics of the steam boiler. It also focuses on integrating advanced control techniques and a system identification method demonstrates the practical application of cutting-edge technologies in the field of steam boiler control.

6.2. Recommendation

While there are several studies on modeling and optimizing steam boilers using system identification modeling, there is a need for further research on the application of this approach to improve the efficiency of steam boilers in industrial facilities. Specifically, there is a need for research on the use of system identification modeling to identify and optimize the parameters that affect the efficiency of steam boilers, such as fuel type, combustion process, and heat transfer. Additionally, there is a need for research on the integration of system identification modeling with other optimization techniques, such as neural networks and fuzzy logic, to improve the accuracy and efficiency of the models.

It is recommended to validate the proposed RBF-ARX-based MPC control system through extensive testing in a real-world steam boiler environment. This will help validate the effectiveness and performance of the control strategy under various operating conditions and system dynamics. Conduct a comparative analysis of the proposed RBF-ARX-based MPC control system with other existing control strategies, such as PID control. This will provide insights into the strengths and advantages of the RBF-ARX approach and help quantify its performance improvements over conventional methods.

In addition the future work also focuss on not only regulate pressure, temperature, and drum level but also optimize the overall system performance in terms of energy efficiency, emissions reduction, and cost optimization.

By addressing these recommendations and exploring future work directions, the study can contribute to the continued advancement and optimization of steam boiler control systems, ultimately leading to safer, more efficient, and sustainable industrial processes.

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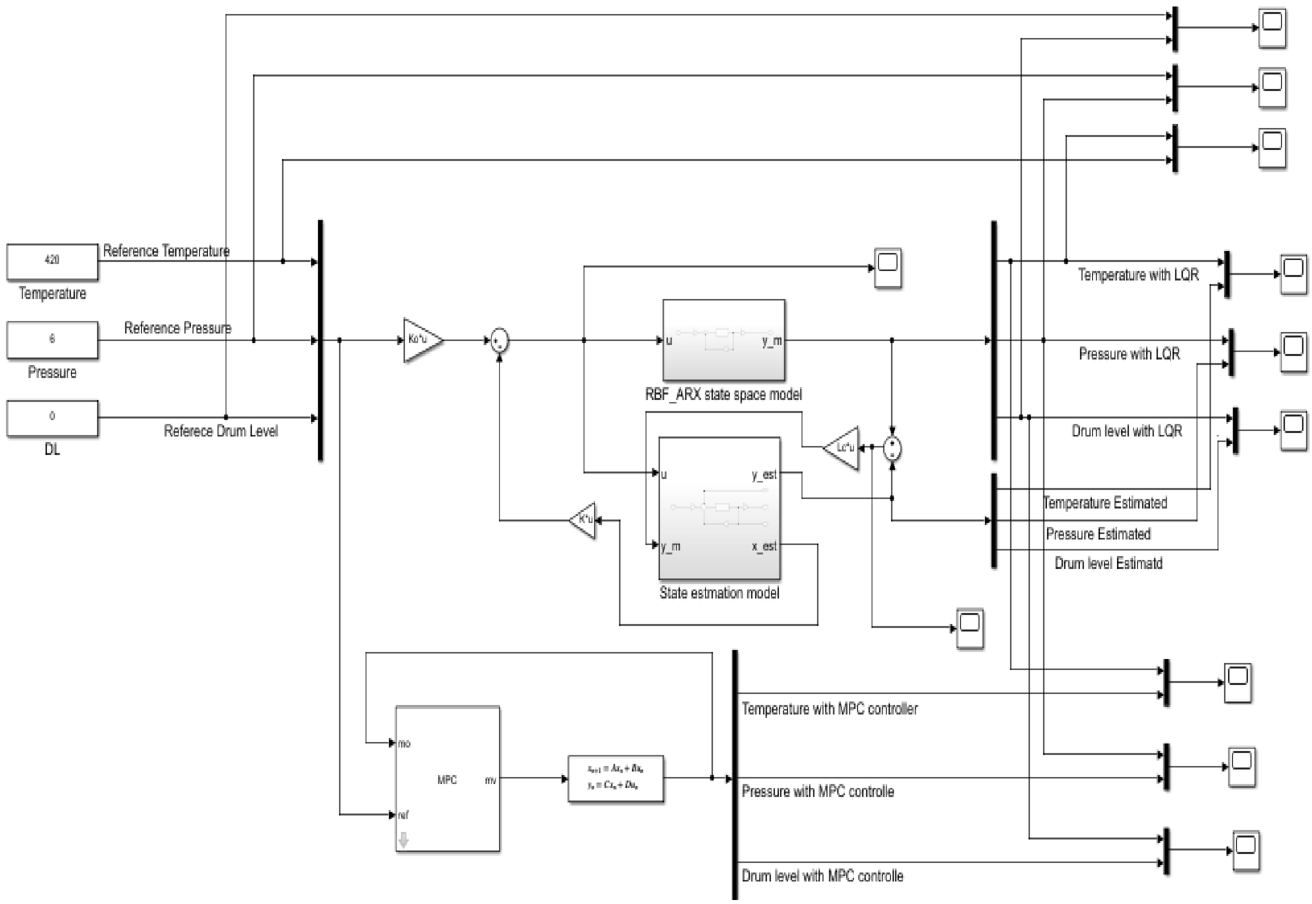
Appendex I



420
Temperature
Reference Temperature
6
Pressure
Reference Pressure
0
DL
Referece Drum Level
Ko*u
u
y_m
RBF_ARX state space model
Lc*u
u
y_est
y_m
x_est
State estmation model
K*u
Temperature with LQR
Pressure with LQR
Drum level with LQR
Temperature Estimated
Pressure Estimated
Drum level Estimatd
mo
MPC
mv
ref
Temperature with MPC controller
Pressure with MPC controlle
Drum level with MPC controlle

Appendex II

```
echo off;
clear;
close all;
clc;
Ts=0.01;
load mn_input
load mn_output
mn_input=mn_input;
mn_output=mn_output;
% mn_input(:,1)=mn_input(:,1)/1000;
ref_val=[420,6,0];
%training the RBF-ARX model
[subsystemone,MSE1]=Training1(mn_input,mn_output);
[subsystemtwo,MSE2]=Training2(mn_input,mn_output);
[subsystemthree,MSE3]=Training3(mn_input,mn_output);
%validating the model
[VMSE1]=Validating1();
[VMSE2]=Validating2();
[VMSE3]=Validating3();
 [Den1,Num_U11,Num_U21,Num_U31,Num_U41]=RBFARXtest1(Ts);
[Den2,Num_U12,Num_U22,Num_U32,Num_U42]=RBFARXtest2(Ts);
[Den3,Num_U13,Num_U23,Num_U33,Num_U43]=RBFARXtest3(Ts);
% Combining the dynamic systems state space models
num = cell(3,4);
den = cell(3,4);
num{1,1} = Num_U11; den{1,1} = Den1;
```

```
num{1,2} = Num_U21; den{1,2} = Den1;
num{1,3} = Num_U31; den{1,3} = Den1;
num{1,4} = Num_U41; den{1,4} = Den1;
num{2,1} = Num_U12; den{2,1} = Den2;
num{2,2} = Num_U22; den{2,2} = Den2;
num{2,3} = Num_U32; den{2,3} = Den2;
num{2,4} = Num_U42; den{2,4} = Den2;
num{3,1} = Num_U13; den{3,1} = Den3;
num{3,2} = Num_U23; den{3,2} = Den3;
num{3,3} = Num_U33; den{3,3} = Den3;
num{3,4} = Num_U43; den{3,4} = Den3;
sys_tf = tf(num, den,0.01*Ts)
sys = ss(sys_tf);
[A,B,C,D] = ssdata(sys)
% checking whether the system is cotrollable/observable
CO=rank(ctrb(A,B));
OV=rank(obsv(A,C));
% LQR controller design for the system and state estimator design
R=0.5*eye(4);
R_y=50*eye(3);
Q=5000*(C')*C;
Klqr=lqrd(A,B,Q,R,Ts);
Lc=lqrd(A',C',Q,R_y,Ts)';
A_c=A-B*Klqr;
sys_c=ss(A_c,B,C,D);
step(sys_c);
%optimal set point tracking
Ko=-pinv(C*pinv(A-B*Klqr)*B);
%mpc test
p = 10;
m = 5;
```

```
mpcobj = mpc(sys, 0.01*Ts, p,m);
% Set the MV and OV ScaleFactors
mpcobj.MV(1).ScaleFactor = 1;
mpcobj.MV(2).ScaleFactor = 1;
mpcobj.MV(3).ScaleFactor = 1;
mpcobj.MV(4).ScaleFactor = 1;
mpcobj.OV(1).ScaleFactor = 1;
mpcobj.OV(2).ScaleFactor = 1;
mpcobj.OV(3).ScaleFactor = 1;
% Define the MPC weights
mpcobj.Weights.MV = [0.0 0.0 0.0 0.0];
mpcobj.Weights.MVRate = [0.1 0.1 0.1 0.1];
mpcobj.Weights.OV = [5000 50000 5000];
mpcobj.Weights.ECR = 1000;
% Define the MPC constraints
mpcobj.MV(1).Min = -inf;
mpcobj.MV(1).Max = inf;
mpcobj.MV(2).Min = -inf;
mpcobj.MV(2).Max = inf;
mpcobj.MV(3).Min = -inf;
mpcobj.MV(3).Max = inf;
mpcobj.MV(4).Min = -inf;
mpcobj.MV(4).Max = inf;
mpcobj.OV(1).Min = -inf;
mpcobj.OV(1).Max = inf;
mpcobj.OV(2).Min = -inf;
mpcobj.OV(2).Max = inf;
mpcobj.OV(3).Min = -inf;
mpcobj.OV(3).Max = inf;
review(mpcobj)
% Simulate the MPC controller
```

```
Tstop = 20;
num_sim_steps = round(Tstop/Ts);
sim(mpcobj,num_sim_steps,r)

%% To Train the model

function [subsystemone,MSE1]=Training1(input,output)
Y1=output(:,1);
U=input;
ust=U(1:length(U)/2,:);         % training data
yst=Y1(1:length(U)/2,1);
usv=U(length(U)/2 +  1:end,:);         % validating data, validated in 'Validating.m'
ysv=Y1(length(U)/2 + 1:end,1);

global Order_y
global Order_u
global N_Center
global D_Center
global N_lag
global N_S
global gamma0
global beta

Order_y=3;
Order_u=3;                                   %
N_Center=1;
D_Center=2;
N_lag=max(max(Order_y,Order_u),D_Center);
N_S=size(ust,1)-N_lag;
%% SNPOM
scale=max(yst)-min(yst) ;
center0=min(yst)+rand(2*N_Center*D_Center,1)*scale;
```

```
x0=center0;

options=optimset(@lsqnonlin);
opt_temp=optimset(options,'DiffMaxChange',0.00001,'DiffMinChange',0.00000001,'Displ
    ay','iter','Jacobian','off',...
     'LargeScale','off','MaxFunEvals',100000,'MaxIter',30,'TolFun',1e-4,'TolX',1e-
    8,'Algorithm','levenberg-marquardt');
options=opt_temp;
tic                % timing start
[optimcenter,resnorm]=lsqnonlin(@ObjFun,x0,[],[],options,ust,yst);  % traning
toc                % timing end
MSE1 =resnorm/N_S     % print MSE
save 'model1paras' beta optimcenter Order_y Order_u N_Center D_Center gamma0 ust yst
    usv ysv N_S N_lag
subsystemone=struct('Order_y',Order_y,'Order_u',Order_u,'N_Center',N_Center,'D_Center
    ',D_Center,'center',optimcenter,'gamma0',gamma0,'beta',beta);
save 'themodel1' subsystemone;
'End Training'
%% for traning data
[X,Y]=LSM_Data(yst,ust,optimcenter)
y_pre=X*beta;
error=Y-y_pre;
figure('Name','Subsystem One Training Result','NumberTitle','off');
subplot(2,1,1)
hold on
plot(Y,'k-')
plot(y_pre,'b--')
title(''Tempreature Training'')
legend('Model O/p','Actual O/P')
subplot(2,1,2)
stem(error)
```

```
title("Training Error")
figure('Name','System Inputs','NumberTitle','off');
subplot(2,2,1)
plot(ust(:,1),'r-')
title("Training Airflow one Input")
subplot(2,2,2)
plot(ust(:,2),'r-')
title("Training Airflow two Input")
subplot(2,2,3)
plot(ust(:,3),'r-')
title("Training water flow Input")
subplot(2,2,4)
plot(ust(:,4),'r-')
title("Training Stoker Speed Input")
MSE=sum(error.^2)/size(y_pre,1);
['Training MSE1 = ' num2str(MSE)]

%% for validating data
[X,Y]=LSM_Data(ysv,usv,optimcenter);
y_pre=X*beta;
error=Y-y_pre;
figure('Name','Subsystem One Validation Result','NumberTitle','off');
subplot(2,1,1)
hold on
plot(Y,'k-')
plot(y_pre,'b--')
title("Tempreature Validation")
legend('Model O/p','Actual O/P')
subplot(2,1,2)
stem(error)
title("Validation Error")
```

```
figure('Name','System Inputs','NumberTitle','off');
subplot(2,2,1)
plot(usv(:,1),'r-')
title("Validation Airflow one Input")
subplot(2,2,2)
plot(usv(:,2),'r-')
title("Validation Airflow two Input")
subplot(2,2,3)
plot(usv(:,3),'r-')
title("Validation water flow Input")
subplot(2,2,4)
plot(usv(:,4),'r-')
title("Validation Stoker Speed Input")
VMSE=sum(error.^2)/size(y_pre,1);
['Validating MSE1 = ' num2str(VMSE)]
'End Validating'
end

%% For RBF-ARX model

function [Den1,Num_U11,Num_U21,Num_U31,Num_U41]=RBFARXtest1(Ts)
inputvector=zeros(1,4*Order_u + Order_y+1);
for t=N_lag+1:N_lag+N_S
W=ARXModel([yst(t-1),yst(t-2),yst(t-3)],subsystemone);
for i=1:Order_u
inputvector(i+Order_y + 1)=ust(t-i,1);
inputvector(i+Order_y + 1*Order_u + 1)=ust(t-i,2);
inputvector(i+Order_y + 2*Order_u + 1)=ust(t-i,3);
inputvector(i+Order_y + 3*Order_u + 1)=ust(t-i,4);
end
y_pre_by_arx(t)=sum(inputvector.*W);
end
```

```
y1_pre_by_arx=y_pre_by_arx(N_lag+1:N_lag+N_S);
figure('Name','Temperature Prediction','NumberTitle','off');
plot(y1_pre_by_arx);
title('Predicted Value of Tempreature by RBF ARX')
'End Testing'
Den1=[1,-W(2:Order_y+1)];
Num_U11=[W(Order_y + 0*Order_u +2:Order_y + 1*Order_u +1),zeros(1,Order_y-
    Order_u)];
Num_U21=[W(Order_y + 1*Order_u +2:Order_y + 2*Order_u +1),zeros(1,Order_y-
    Order_u)];
Num_U31=[W(Order_y + 2*Order_u +2:Order_y + 3*Order_u +1),zeros(1,Order_y-
    Order_u)];
Num_U41=[W(Order_y + 3*Order_u +2:Order_y + 4*Order_u +1),zeros(1,Order_y-
    Order_u)];
end
```

Appendex III

The Collected Input and output data.

Primary air (m3/h)	secondary air (m3/h)	water flow (t/h)	Fuel (t/h)	Temperature (°C)	Pressure (Mpa)	DrumLevel (mm)
32669.0677	1614.32	42.7724	26.0831	32669.0677	1614.32	42.7724
32669.2997	1613.5826	42.7782	26.0808	32669.2997	1613.5826	42.7782
32669.5294	1612.8219	42.7841	26.0785	32669.5294	1612.8219	42.7841
32669.757	1612.0376	42.7903	26.0762	32669.757	1612.0376	42.7903
32669.9825	1611.2291	42.7967	26.0739	32669.9825	1611.2291	42.7967
32670.2059	1610.3961	42.8034	26.0716	32670.2059	1610.3961	42.8034
32670.427	1609.5385	42.8103	26.0693	32670.427	1609.5385	42.8103
32670.646	1608.6558	42.8175	26.0671	32670.646	1608.6558	42.8175
32670.8628	1607.7479	42.8249	26.0648	32670.8628	1607.7479	42.8249
32671.0775	1606.8146	42.8326	26.0625	32671.0775	1606.8146	42.8326
32671.2899	1605.856	42.8406	26.0603	32671.2899	1605.856	42.8406
32671.5002	1604.872	42.8489	26.0581	32671.5002	1604.872	42.8489
32671.7084	1603.8628	42.8575	26.056	32671.7084	1603.8628	42.8575
32671.9146	1602.8286	42.8664	26.0538	32671.9146	1602.8286	42.8664
32672.119	1601.7697	42.8756	26.0518	32672.119	1601.7697	42.8756
32672.3217	1600.6866	42.8851	26.0497	32672.3217	1600.6866	42.8851
32672.523	1599.5797	42.895	26.0478	32672.523	1599.5797	42.895
32672.7232	1598.4499	42.9051	26.0459	32672.7232	1598.4499	42.9051
32672.9227	1597.2979	42.9156	26.044	32672.9227	1597.2979	42.9156
32673.122	1596.1248	42.9264	26.0423	32673.122	1596.1248	42.9264
32673.3216	1594.9316	42.9376	26.0406	32673.3216	1594.9316	42.9376
32673.5222	1593.7197	42.949	26.039	32673.5222	1593.7197	42.949
32673.7244	1592.4904	42.9609	26.0376	32673.7244	1592.4904	42.9609
32673.9291	1591.2456	42.973	26.0362	32673.9291	1591.2456	42.973
32674.1373	1589.9868	42.9855	26.035	32674.1373	1589.9868	42.9855
32674.35	1588.7162	42.9983	26.0339	32674.35	1588.7162	42.9983
32674.5683	1587.4357	43.0114	26.033	32674.5683	1587.4357	43.0114
32674.7936	1586.1478	43.0249	26.0322	32674.7936	1586.1478	43.0249
32675.0271	1584.8548	43.0387	26.0315	32675.0271	1584.8548	43.0387
32675.2704	1583.5594	43.0528	26.0311	32675.2704	1583.5594	43.0528
32675.5251	1582.2645	43.0672	26.0308	32675.5251	1582.2645	43.0672
32675.793	1580.9728	43.0818	26.0307	32675.793	1580.9728	43.0818
32676.0759	1579.6878	43.0968	26.0309	32676.0759	1579.6878	43.0968

32676.3757	1578.4125	43.112	26.0312	32676.3757	1578.4125	43.112
32676.6946	1577.1504	43.1275	26.0318	32676.6946	1577.1504	43.1275
32677.0347	1575.9051	43.1432	26.0326	32677.0347	1575.9051	43.1432
32677.3983	1574.6801	43.1591	26.0336	32677.3983	1574.6801	43.1591
32677.7876	1573.4791	43.1752	26.0349	32677.7876	1573.4791	43.1752
32678.205	1572.306	43.1916	26.0365	32678.205	1572.306	43.1916
32678.6529	1571.1646	43.208	26.0384	32678.6529	1571.1646	43.208
32679.1337	1570.0589	43.2246	26.0405	32679.1337	1570.0589	43.2246
32679.6499	1568.9928	43.2414	26.0429	32679.6499	1568.9928	43.2414
32680.2039	1567.9703	43.2582	26.0456	32680.2039	1567.9703	43.2582
32680.798	1566.9953	43.2751	26.0486	32680.798	1566.9953	43.2751
32681.4345	1566.0716	43.292	26.052	32681.4345	1566.0716	43.292
32682.1156	1565.2032	43.309	26.0556	32682.1156	1565.2032	43.309
32682.8434	1564.3938	43.3259	26.0596	32682.8434	1564.3938	43.3259
32683.6197	1563.6469	43.3428	26.0639	32683.6197	1563.6469	43.3428
32684.4463	1562.9661	43.3596	26.0685	32684.4463	1562.9661	43.3596
32685.3245	1562.3546	43.3763	26.0735	32685.3245	1562.3546	43.3763
32686.2556	1561.8158	43.3929	26.0788	32686.2556	1561.8158	43.3929
32687.2405	1561.3525	43.4094	26.0844	32687.2405	1561.3525	43.4094
32688.2798	1560.9677	43.4257	26.0903	32688.2798	1560.9677	43.4257
32689.3736	1560.6637	43.4417	26.0966	32689.3736	1560.6637	43.4417
32690.522	1560.4429	43.4575	26.1033	32690.522	1560.4429	43.4575
32691.7243	1560.256	43.4731	26.1102	32691.7243	1560.256	43.4731
32692.9795	1560.1616	43.4883	26.1175	32692.9795	1560.1616	43.4883
32694.3149	1560.1607	43.5038	26.125	32694.3149	1560.1607	43.5038
32695.6982	1560.2541	43.5189	26.1329	32695.6982	1560.2541	43.5189
32697.1271	1560.4422	43.5337	26.1411	32697.1271	1560.4422	43.5337
32698.5986	1560.7252	43.5479	26.1496	32698.5986	1560.7252	43.5479
32700.1092	1561.1029	43.5617	26.1584	32700.1092	1561.1029	43.5617
32701.6549	1561.5746	43.5751	26.1675	32701.6549	1561.5746	43.5751
32703.2312	1562.1395	43.5879	26.1769	32703.2312	1562.1395	43.5879
32704.8329	1562.7962	43.6002	26.1866	32704.8329	1562.7962	43.6002
32706.4545	1563.5432	43.612	26.1966	32706.4545	1563.5432	43.612
32708.0898	1564.3784	43.6233	26.2068	32708.0898	1564.3784	43.6233
32709.7319	1565.2995	43.634	26.2173	32709.7319	1565.2995	43.634
32711.3738	1566.3039	43.6441	26.2279	32711.3738	1566.3039	43.6441
32713.0076	1567.3885	43.6536	26.2388	32713.0076	1567.3885	43.6536
32714.6251	1568.5502	43.6625	26.2499	32714.6251	1568.5502	43.6625
32716.2177	1569.7853	43.6709	26.2612	32716.2177	1569.7853	43.6709
32717.7763	1571.0899	43.6786	26.2726	32717.7763	1571.0899	43.6786
32719.2913	1572.46	43.6858	26.2841	32719.2913	1572.46	43.6858
32720.7529	1573.8909	43.6923	26.2959	32720.7529	1573.8909	43.6923
32722.1509	1575.3781	43.6982	26.3077	32722.1509	1575.3781	43.6982

32723.4749	1576.9165	43.7035	26.3196	32723.4749	1576.9165	43.7035
32724.7141	1578.5009	43.7082	26.3316	32724.7141	1578.5009	43.7082
32725.8577	1580.1261	43.7123	26.3436	32725.8577	1580.1261	43.7123
32726.8947	1581.7863	43.7159	26.3558	32726.8947	1581.7863	43.7159
32727.8139	1583.4759	43.7188	26.3679	32727.8139	1583.4759	43.7188
32728.6041	1585.1891	43.7211	26.38	32728.6041	1585.1891	43.7211
32729.2544	1586.9199	43.7229	26.3922	32729.2544	1586.9199	43.7229
32729.7537	1588.6621	43.7241	26.4043	32729.7537	1588.6621	43.7241
32730.0912	1590.4097	43.7247	26.4164	32730.0912	1590.4097	43.7247
32730.2562	1592.1563	43.7249	26.4284	32730.2562	1592.1563	43.7249
32730.2382	1593.8958	43.7245	26.4403	32730.2382	1593.8958	43.7245
32730.0272	1595.6217	43.7236	26.4521	32730.0272	1595.6217	43.7236
32729.6136	1597.3277	43.7222	26.4638	32729.6136	1597.3277	43.7222
32728.988	1599.0078	43.7204	26.4754	32728.988	1599.0078	43.7204
32728.1417	1600.6556	43.7181	26.4868	32728.1417	1600.6556	43.7181
32727.0664	1602.2652	43.7154	26.4981	32727.0664	1602.2652	43.7154
32725.7546	1603.8306	43.7123	26.5092	32725.7546	1603.8306	43.7123
32724.1991	1605.346	43.7088	26.5201	32724.1991	1605.346	43.7088
32722.3936	1606.8057	43.705	26.5307	32722.3936	1606.8057	43.705
32720.3326	1608.2043	43.7008	26.5411	32720.3326	1608.2043	43.7008
32718.0111	1609.5364	43.6963	26.5513	32718.0111	1609.5364	43.6963
32715.425	1610.797	43.6916	26.5612	32715.425	1610.797	43.6916
32712.5712	1611.9812	43.6865	26.5708	32712.5712	1611.9812	43.6865
32709.4472	1613.0844	43.6813	26.5801	32709.4472	1613.0844	43.6813
32706.0514	1614.1024	43.6758	26.5892	32706.0514	1614.1024	43.6758
32702.3832	1615.0308	43.6701	26.5979	32702.3832	1615.0308	43.6701
32698.4429	1615.8661	43.6643	26.6062	32698.4429	1615.8661	43.6643
32694.2315	1616.6047	43.6584	26.6142	32694.2315	1616.6047	43.6584
32689.7512	1617.2435	43.6524	26.6218	32689.7512	1617.2435	43.6524
32685.0049	1617.7794	43.6462	26.6291	32685.0049	1617.7794	43.6462
32679.9962	1618.21	43.6401	26.636	32679.9962	1618.21	43.6401
32674.7296	1618.5328	43.6339	26.6425	32674.7296	1618.5328	43.6339
32669.2106	1618.7461	43.6277	26.6486	32669.2106	1618.7461	43.6277
32663.4454	1618.8482	43.6215	26.6542	32663.4454	1618.8482	43.6215
32657.4409	1618.8379	43.6153	26.6595	32657.4409	1618.8379	43.6153
32651.205	1618.7141	43.6093	26.6643	32651.205	1618.7141	43.6093
32644.7461	1618.4762	43.6033	26.6687	32644.7461	1618.4762	43.6033
32638.0734	1618.1239	43.5974	26.6727	32638.0734	1618.1239	43.5974
32631.1967	1617.6573	43.5917	26.6762	32631.1967	1617.6573	43.5917
32624.1264	1617.0766	43.5861	26.6792	32624.1264	1617.0766	43.5861
32616.8735	1616.3825	43.5807	26.6818	32616.8735	1616.3825	43.5807
32609.4494	1615.5759	43.5755	26.684	32609.4494	1615.5759	43.5755
32601.8658	1614.658	43.5705	26.6857	32601.8658	1614.658	43.5705

32594.1352	1613.6304	43.5657	26.6869	32594.1352	1613.6304	43.5657
32586.2698	1612.4948	43.5612	26.6877	32586.2698	1612.4948	43.5612