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Performance Analysis of Linear Robust Model Predictive Control for Small-Scale Biomass Combustion Furnace

MSc Thesis for the Partial Fulfillment of

Master of Science in Electrical Automation and Control Technology Management

By,

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Performance Analysis of Linear Robust Model Predictive Control for Small-Scale Biomass Combustion Furnace

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By,

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DECLARATION

I, hereby declare that the work which is being presented during this thesis entitled "Performance Analysis of Linear Robust Model Predictive Control for Small-Scale Biomass Combustion Furnace" is that the original work of my very own and has not been presented for a master's thesis during this or other universities and everyone sources of materials used for this thesis work are fully acknowledged.

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

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ABBREVIATION

MPC	Model Predictive Control
MRAC	Model Reference Adaptive control
NMPC	Non-Model Predictive Control
LMPC	Linear Model Predictive Control
LRMPC	Linear Robust Model Predictive Control
LMI	Linear Matrix Inequalities
ID	Induced Draft
FD	Forced Draft
MISO	Multi Input Single Output
MIMO	Multi-Input Multi Output
SIMO	Single Input Multi Output
SISO	Single Input Single Output
PID	Proportional Integral Derivative
ROA	Regions Of Attraction
PI	Proportional Integral
ARX	Autoregressive with exogenous
ARMAX	Autoregressive Moving Average with Exogenous
MISiCFET	Metal insulator silicon carbide field-effect transistor sensors
PEMS	Predictive emission monitoring systems
RLMPC	Robust Linear Model Predictive Control
IMC	Internal Model Control

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ABSTRACT

Energy is that the greatest life-threatening consider the existence of all individuals on our planet. Among the varied sorts of energy sources, biomass is that the finest alternative for a secure and pollution-free source of energy. as compared to big systems, direct biomass combustion for small-scale burning furnaces is primarily liable to volatility in heat consumption. Linear model predictive control is a popular process control strategy in recent years. It predicts future control action and trajectories based on present input and output variables and future control signals. LMPC was developed through process control research. MPC uses an internet-based (real-time) optimization problem, a process model, and process data to predict future process behavior. This determines process input values. This study aims to improve the efficiency of a small-scale biomass burning furnace by incorporating a western renewable resource made from agricultural products, industrial byproducts, and household waste. This work will develop a linearized state space model for small-scale biomass furnaces. Model has 3 inputs, 3 outputs. According to the method analysis, the process in question has integrating type, negative gain, and high dimensionality. This complex process requires model predictive control. First, mathematical models of the system are considered when designing and analyzing a system. Due to the modeling methods used, this mathematical model can take many forms when viewed from the system structure's perspective. The IMC-designed multi-loop PI controller's performance is compared. A multi-loop PI controller's and the LMPC effectiveness is examined. Using IAE measures both controller operating efficiency is examined and LMPC have the value of 1.667e + 3 and PI have the value of 5.612e + 5. Based on the IAE result the LMPC controller response is better effective for the system. In simulation software, a linear model predictive controller and an estimating approach reinforced the control structure.

Key words: Biomass, Combustion Furnace, Optimization, LMPC, multi-variable process

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CHAPTER ONE

1. INTRODUCTION

1.1. THEORETICAL BACKGROUND

Electricity through electricity is produced by the conversion and transformation of obtainable energy, which is offered in diverse forms like several natural sources that include wind energy, the K.E. of water, the energy of fuels, and atomic energy of radioactive substances. Natural energy sources are one in all the foremost important inputs for any country's economic and monetary development. Conventional and nonconventional energy sectors are deemed crucial in various emerging countries to satisfy ever-increasing energy consumption, which necessitates massive investments to fulfill such demand. apart from non-conventional methods of electricity generation, conventional methods of power generation produce power by driving electrical machines with prime movers like diesel engines, gasoline engines, and vapor engines, which are wont to convert electrical to mechanical and mechanical to power. Nonconventional electricity generation refers to ways of generating power without the usage of prime movers. The subsequent characteristics will be wont to categorize power into differing types [1]:

- Primary and secondary energy.
- Marketable and non-Marketable energy.
- Renewable and nonrenewable energy

Renewable energy sources are also non-conventional energy sources that derive from constantly renewing natural resources like the sun's rays, the wind's speed, the water found in nature, the tides and waves, as well as geothermal and thermal heat. In the last twenty years, Ethiopia has achieved rapid and sustained economic process. the ability industry played a big role during this success, contributing significantly to the availability of enough electricity across the country. Clean, low-cost energy services are essential for social socio-economic development and improved life quality. within the future decades, a rise in global population and economic activity will lead to a rise in energy demand. Controlling biomass power plants is harder. Biomass fuel is formed from a range of waste streams, including wood waste, agricultural waste, and other bio-waste streams. Biomass fuel features a variable energy density, moisture content, and chemical characteristics because it's collected from waste streams. Despite its inconsistency, the fuel is usually free or available for a price, as against costly gas. The fuel poses challenges for powerhouse controllers, but it also makes biomass plants appealing as a source of renewable and sustainable energy. Small-scale biomass combustion furnace units are typically operating under varying process conditions. as an example, continuously changing heating demand and fluctuating fuel quality complicate the task to supply energy with high efficiency and low emissions. Unlike in large-scale biomass combustion furnaces, where sophisticated measurement and control systems are available, the shortage of cost-effective sensors and automation sets hard limits on small-scale control [2].

This, in turn, usually prevents the real-time optimization of the combustion processes under 1 MW, along with non-optimal process development. to beat problems in monitoring small-scale biomass combustion furnace processes, a soft sensor –approach might be considered [3]. during this methodology, the first process variables to be monitored are derived from the measurement of one or multiple secondary variables. Information from these inferential measurements is fused using mathematical models. As a result, the estimated value of a primary variable will be formed. The motivation for this sort of monitoring framework is evident in a very small-scale environment. Firstly, sensors are simpler making them more robust. Secondly, utilization of fast response in-situ sensors could assist to reduce time delays up to the mark. Thirdly, the data about absolute values of important process parameters will be of help in continuous emission and condition monitoring, including real-time efficiency calculations [4]. the aim of this investigation is to look at and develop advanced process monitoring methods for small-scale stoker-fired containers.

The research is targeted on small-scale biomass combustion furnace processes using wood chips. the event of the monitoring framework is predicated on the utilization of inferential measurements. Attention is paid to the reliability and adaptation features of the monitoring concept. The absence of those properties continues to be one among the key obstacles to the deployment of soppy sensors in industrial processes.

Data-based mathematical models utilizing soft computing methods are identified with analysis techniques utilizing data from a true small-scale combustion furnace process. the most aim of this research is to take care of the soundness of small-scale biomass combustion plants supported the planning.in order to stay the planning parameter, we should always optimize by changing input parameters that are fed to the furnace. the input material (waste) is that the critical factor for the soundness to come up with the expected level of energy [4].. Next, the idea of the proposed biomass combustion monitoring framework is briefly discussed. Finally, some results of the monitoring capability with the identified models are presented and analyzed.

1.1.1. Mechanisms of a Combustion System

Biomass-burning systems require multiple machineries for accurate control.[5] (see figure 1.1 below).

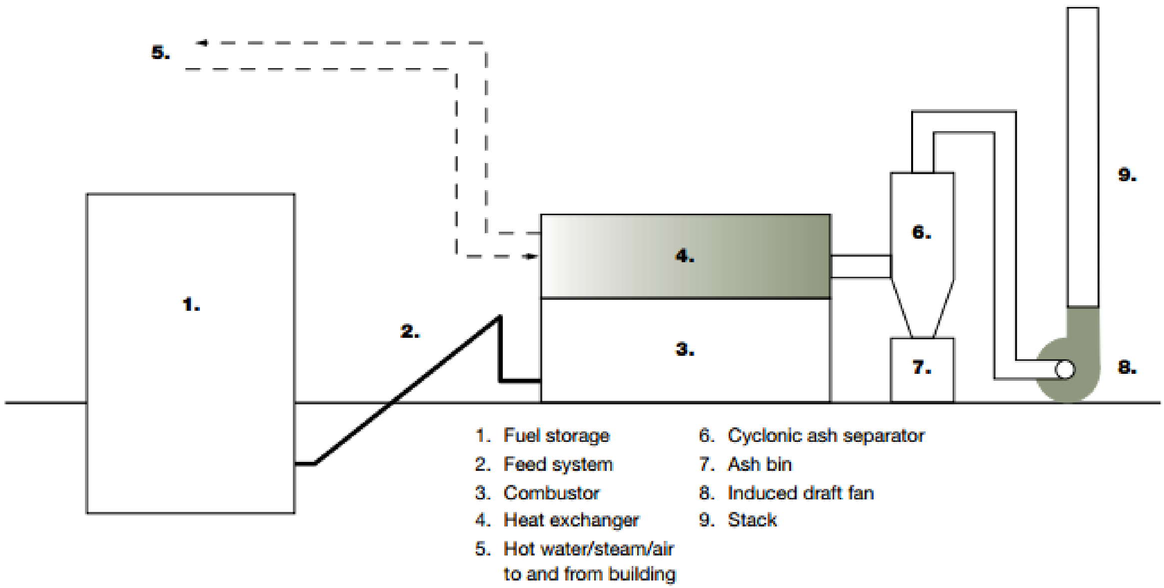


Fig 1.1: Components of a biomass combustion system.

1.1.2. **Fuel Storage**

Determining the fuel storage bin's capacity ensures enough gas between delivery. The institution should have enough fuel for winter break. "Walking floor" previews are the most mutual fuel delivery truck. Digging the storage holder into the crushed facilitates fuel unloading. The storage container should be solid and above freezing. Large amounts of fuel could freeze, damaging the delivery system's machinery. If the storage container isn't warm, the power company may use dried fuel (which is more costly and infrequently dusty) [5].

1.1.3. **Fuel Delivery**

Because the fuel delivery system is prone to problems, it must be carefully designed and operated. Moving floor or screw conveyors are used to draw fuel from the bin's bottom [5]. The fuel is then fed into the combustor using a calibrated metering device. Burn back protection devices prevent fires from escaping the combustor and spreading to the storage bin.

1.1.4. **Combustor**

The burner burns fuel by heating it and adding oxygen in the correct amounts. Various combustor designs combine fuel with air in a heated environment to completely consume it. Direct and gasifier combustors are the most important types [6].

1.1.4.1. **Direct Combustors**

Direct heat and dry single-chamber combustors. This is the most typical burner on the market, but there are variations in how fuel is injected and transported through it. Common types:

•Fixed-Grate; Fixed-Grate combustion systems gives fuel on a stationary, sloped grate and supply combustion air from lower and above. As the fuel burns, cinders falls through the grate and is removed. Fixed-grate combustion systems are still used today. These systems can handle variable-size fuel, but they can't control combustion air as exactly as others.

•Moving-Grate: Moving-Grate combustor, fuel slides or shakes along a metal grate, occasionally tumbling from one grade to another. This configuration precisely controls combustion air flow, but it necessitates unchanging fuel size and content.

•Auger Floor: An important part of a pellet stove because it’s responsible for feeding the pellets into the fire. Without it, the fire would quickly go out. Most pellet stoves have the auger located near the bottom of the stove.

•Fluidized-Bed: Fluidized-bed burner burns fuel by mixing fluid with heat, stirred particle. This configuration evenly heats the fuel, which speeds up combustion. It also gives the combustor more fuel options. The system is expensive to buy and maintain. Variations include the spreader and under-feed stokers. Each feed configuration has benefits and drawbacks, but successful design execution is more important [5].

1.1.4.2. **Gasifier Combustors**

Gasifier combustors have a two-step process. These burns fuel. Starting with oxygen-free space, biomass fuel is heated. Under suitable conditions, biomass chemically transforms into "syngas" or "producer gas." Syngas is made of methane, carbon monoxide, carbon dioxide, vapor, and a few other less significant components [3]. Second, combustible gas must be combined with air before being lit.

1.1.5. **Heat Exchanger**

The heat exchanger transfers heat from combustor to air or water for space heating or other uses. Heat exchangers must be managed carefully to maintain thermal efficiency [7].

1.1.6. **Ash Handling System**

The combustor's ash is removed in several places. Bottom ash is the heavier ash in the combustor. Wimbles can be removed manually or with help. [5]. Top ash is the lighter ash that collects on the combustor. Augers are used to remove top ash from the combustor.

1.1.7. **Pollution Control Devices**

Cyclonical separator is the only pollution control needed for many devices and are standard on most biomass combustors (see photo at right). Separators use rotating airflow to separate ash from combustor flue gas. User-friendly and reliable. The separator's ash container is large. Here it will stay until it's collected and discarded. If flue gas particle concentration remains high, a "bag house" may be needed. A bag house contains bag-shaped filters Flue gas is filtered to remove particulates. Cleaner air results. Cleaning filters and collecting ash is called "backflow." Electrostatic precipitators collect dust. Large, charged plates can prolong flue gas's charged particles with an electrical field. [8].Lastly, Scrubbers spray flue gas with water to remove pollutants and particulates. These expensive items are only needed in exceptionally secure locations.

Fig 1.2: Cyclonic separator [8]

1.1.8. **Stack**

Flue gases reach the surface through the stack. Sometimes a "induced draft fan" is needed to keep flue gas flowing steadily. If the flue gas is cool enough, moisture will separate and accumulated on the walls. This acidic "condensate" fluid might accelerate the flue's degeneration. Either the flue gas temperature should be kept high enough to prevent condensation, or the flue should be checked for corrosion protection. [7].

1.1.9. **Auxiliary Heating System**

Biomass burners perform best at or almost full capability. At the required level of heat is minimal, a burner cannot sustain the proper temperature for combustion. [5]. This problem may occur in the spring or fall, when a building's heat needs are minimal. The combustors "turndown ratio" is the smallest warmth output needed to sustain performance. This relates to the combustor's full load. Most often, a small "auxiliary furnace" that only provides heat when needed and at a lower turndown ratio than the biomass system is used (often about 20 percent of full load). Many firms preserve their older equipment as a backup when transitioning to reversible heating systems.

1.1.10. **Combustor Building**

The combustor holds equipment and fuel. Operation, maintenance, and fuel storage space are needed. Because trucks distribute fuel in "walking floor" trailers, truck access must be considered

1.1.11. **Control System**

The system monitors the item's performance and makes any required adjustments to ensure smooth, efficient, and risk-free process. Digital monitors and control systems are criteria for the systems, and they permit operator to make full burner evaluations [8].

1.1.12. **Maintenance**

Modern biomass combustors are more sophisticated than gas or oil furnaces, but they require less maintenance. Standard maintenance includes daily system checks and periodic ash cleaning. Many combustors must be manually initiated the minute or two times per heating season. Considering the power and coal used, grates should be cleaned often. Many systems need seasonal combustor and heat exchanger cleaning. [8].

1.1.13. **Flue Gas Heat Exchangers**

Used to improve efficiency, reduce heat loss, recover and de-funk flue gases, etc. The combustion air pre heater's convective heat transfer surface transfers heat from flue gas to combustion air [5].

1.1.13.1. **Combustion Air Preheater**

device example Flue gas goes through the combustion air pre heater after leaving the furnace. Before being burned, air goes through an air pre heater. Flue gas heat is transferred throug burner air way of the convective heat transfer area of the burned air pre heater. [5]. This heat convey freez the flue gas and the bag's air. Additional heat from combustion air fed into the furnace speeds up the combustion process. This reduces the amount of fuel used by a number of times heat has been delivered inside the burner air pre heater, increasing quality.

1.2. **BIOMASS CONTROL MECHANISM**

- There are basically five fundamental control strategies that are used in process control. They are: simple feedback control, feedforward plus feedback control, cascade control, ratio control, and feedforward control. In the control of boilers, all five of the fundamental control strategies are used. Many companies show all controllers on drawings as PID controllers. This is because vendor algorithms/function blocks for control are defined as PID controllers.

1.2.1.**PID control**

standard biomass control technique is presented in systems engineering. Biomass control involves regulating beat liquid level, mist weight, and mist temperature. Individually system variable has a one input and one output controller. The feed water is employed as the variable in a SISO system to adjust the beat level. Below are comparisons of PID and MPC controllers for beat level control

1.2.2. **Model Predictive control (MPC)**

Due to its predictability and applicability to a wide array of management difficulties, predictive strategies have gained popularity. In predictive control, a model predicts a process's future behavior. This control approach uses the quadratic set-point tracking error value function. This control method will benefit multivariable, adaptive, nonlinear, and limited control. Model-based Control was utilized to investigate small-scale bio-fired biomass systems' coupling and nonlinearities [9].

1.2.3. **Model Reference Adaptive control (MRAC)**

It resists disturbances and range mechanism parameters. Fuzzy adaptive PID control theory mixes PID and formal logic. This theory doesn't require a perfect mathematical description of the controlled item and adjusts to quick, modest overshoot and short transition. Fuzzy adaptive PID control theory mixes PID and formal logic [10].

1.3. **STATEMENT OF THE PROBLEM**

"Biomass combustion furnace" refers to a steam generator or boiler that uses biomass as heat. Inefficient biomass combustion furnace controls are used in some enterprises, such as programmable logic controllers coupled with PI controllers. The governing mechanism becomes inefficient. Depending on temperature, pressure, fuel flow, airflow, and steam drum level, biomass combustion can be nonlinear and multivariable. It's well-known. As a temporary process, it must be managed by predicting future values to generate an honest reference tracking response. Increasing biomass combustion efficiency requires modeling and control algorithms, according to studies. Due to the complexity of combustion dynamics, this could also result in considerable modeling inaccuracy. Some biomass combustion control approaches use linear system identification due to the system's nonlinearity. This causes poor control, which reduces accuracy. Past modeling and control techniques mainly covered one or two variables and ignored variable interactions. Most small-scale biomass combustion furnaces have the matter of fuel properties. The fuel comes from different sources of waste which has the properties of getting “different characteristics in terms of temperature to burn and moisture content”. The particular properties of the waste allow the furnace to lose its steady state more quickly, which affects the overall efficiency of the produced heat relative to the needed energy. Decoupling the system into one with a single input and output is important to address the PI controller and MPC problem, despite losing variables and interactions.

1.4. OBJECTIVE

1.4.1. General objective

The general objective of this research is to analyze the performance of linear robust model predictive control of small-scale biomass combustion furnaces to enhance heat production.

1.4.2. **Specific objective**

- To build a Mathematical model of biomass combustion furnace
- To simulate PI controller and linear MPC for biomass combustion furnace control design.

- To analyze PI controller and linear MPC MATLAB/Simulink simulation results of small-scale biomass combustion furnace

1.5. **SIGNIFICANCE**

Biomass combustion fuel performance depends on its temperature value, moisture content, chemical makeup, size, and density. These properties vary by fuel. Inherent fuel variations may also be important. If you have got access to acceptable feedstock, together with an area to store it, biomass combustion systems are often a horny option, saving you money compared to standard fuel systems.

1.6. **LIMITATION OF THE STUDY**

There is not enough environment to check and predict my simulation result on to real-time processing /implementation of my simulated data into the real-time process operation demonstrations workshop in my local industry because of many reasons and specifications of industry in my country. So supported such and the other reason I can’t implement my thesis work.

1.7. **METHODOLOGY**

This section looked for modeling and controlling flaws. Then, a computer file with local industrial documents played. This file logs furnace signals. Data gives input into MATLAB to judge and confirm a furnace model. Finally, the model was imported into SIMULINK to test controllers. Control techniques included the PI controller, RMPC, and nonlinear MPC (NMPC). Each method was evaluated based on the heats' temperature and quantity of switches.

1.8. **THESIS WORK STRUCTURE**

The thesis is organized as six chapters as follows:

<u>Chapter 1</u>: Presents the introduction, statement of problem, general objective, specific objective, benefits and drawbacks, significance, limitation of the study, and methodology for this research complete work.

<u>Chapter 2</u>: Presents the theoretical background and related work of furnace.

<u>Chapter 3</u>: Gives the modeling of biomass combustion furnace

<u>Chapter 4</u>: Presents the biomass combustion furnace control design.

<u>Chapter 5</u>: Presents the simulation result.

<u>Chapter 6</u>: Presents future work and conclusion.

CHAPTER TWO
LITERATURE REVIEW

2.1. **BACKGROUND**

Energy is that the most crucial think about the survival of all living beings on this planet. Among the assorted varieties of energy sources, biomass is that the finest alternative for a secure and pollution-free source of energy. as compared to big systems, direct biomass combustion for small-scale burning furnaces is primarily liable to volatility in heat consumption. Biomass is burned to obtain energy. Wood chips or individual pieces of pulp are used [1]. Wood chipping is an unusual and potentially lucrative fuel made from wood scraps. Burning biomass with less oxygen is excellent. Over airing the combustion chamber wastes energy. Insufficient air causes incomplete combustion, releasing combustible chemicals in the flue gases. Mostly carbon monoxide and volatile hydrocarbons. Flammable compounds in flue gas limit fuel efficiency and add to air pollution. Divide air into primary and secondary using the excess air ratio. This improves biomass burning. It's complicated. Wood chip supply and combustion require adjusting combustion air. Fuel's moisture content vary. [2,3]. Sensing monoxide emissions, oxygen content in flue gases, and fuel characterization will aid current control as a component of process control [4–6 In recent years, articles have discussed improving biomass combustion quality. Some of them were interested in the matter from an environmental perspective, especially with pollutant discharges [7], Unmanaged or poorly controlled biomass combustion can harm the environment more than coal or oil. Publications have resolved a disagreement about reducing NOx emissions. [8–12]. In these works, nitrogen oxides emissions, formation mechanisms, and control approaches are reviewed. Using experimental emission factor data, we also discuss fuel composition (particularly fuel-bound nitrogen), heating appliance type, and operation conditions. Monitoring, detecting, and lowering carbon monoxide emissions are discussed in [13], Various techniques for predicting CO emissions in a small-scale hardwood pellet biomass furnace are shown. These models predict CO emissions. This article examines small-scale biomass boilers' environmental impacts [7]. Compares the technical and economic aspects of small and medium-scale biomass energy production technologies [14], According to the article, biomass combustion is the most cost-effective option for smaller applications. Both and mention it [15] Locally produced biomass can save money and help the local economy. Recent developments in combustion control and heating network efficiency have reduced emissions from small biomass heating systems. Small biomass heating systems are a horny option, according to a study [15].]. In, a burnout control method supported continuous CO-O2 estimation. This was for small-scale biomass furnaces [16], Using a Kalman filter to examine the association between oxygen concentration and monoxide emissions. In, the pedagogical entropy technique for adaptive novelty detection in solid-fuel combustion was described [17]. This article also discusses modern control methods for biomass heating systems [18]. Using regulated variables like feed temperature and flue gas residual oxygen, this approach maintains good combustion conditions while maintaining the water temperature. Suction fan, primary and secondary air control valves, and boiler pump frequency are changed.

MPC is the most effective control approach since it follows input and state limitations [11]. MPC's biggest difficulty may be model uncertainty. Model MPC, or Predictive Control, provides optimal control and can handle system state and input constraints [12]. The MPC approach demands solving an optimum control problem with a finite horizon before each step. When the prediction model is uncertain, one of the hardest parts of developing an MPC is satisfying all the criteria reliably. Dynamic programming or Min-Max feedback can be used to find the best course of action for uncertain linear systems susceptible to additive disturbance. [13]. The MPC approach demands solving an optimum control problem with a finite horizon before each step. When the prediction model is uncertain, one of the hardest parts of developing an MPC is satisfying all the criteria reliably. Finding the appropriate course of action for uncertain linear systems with additive disturbance is an NP-hard tasks [14]. Building a robust MPC for uncertain linear systems with mismatched system dynamics matrices and additive disturbance is difficult [15]. Min-Max MPC algorithms are possible in this circumstance, but their computational complexity grows exponentially with the prediction horizon. When using affine state feedback, the zones of attraction are ellipsoidal and computationally tractable [10]. Polytopic, homothetic, and elastic tube MPC methods have been developed to reduce the conservatism of ellipsoidal ROA-based systems. Polytopic, homothetic, and elastic tube MPC with affine or piecewise affine feedback. Polytopic, homothetic, and elastic-tube MPC [9]. However, these strategies can increase in complexity while reducing conservatism. Alternatively, the work [12] System Level Synthesis ensures robust compliance with given limitations. This procedure may be more computationally efficient than methods in [12]. I present a unique robust MPC technique for linear systems in this additionmotivated research. This technique can handle mismatched system matrices and additive disturbance.

In areas having large furnaces supply heat for several facilities which exhibit a strongly changing individual heat demand throughout the day. But the aggregation of those single contributions comes together with a smooth and well-predictive total demand. Therefore, such a furnace comes together with a smooth and well predictive total demand. Therefore, such a furnace operates in a very steady state most of the time, which facilities highly efficient and emission-optimized combustion. Additionally, high output power and long operating life amid immense acquisition costs, justify sophisticated control strategies improving the general performance even further. In regions, heat supply is more likely to be organized in an exceedingly decentralized manner administered by small-scale furnaces with a nominal heat capacity of but 500KW [16]. Use an optimal control method, such as a linear model predictive controller, that can accept nonlinearities and limitations and whose optimization is increased by additional control requirements. Differences within the combustion chamber design, which influence the duration and mixing of air and volatiles, in addition because the position and proportion of primary and secondary air supply and fuel bed height, are possible reasons for the differences in NOx emissions observed between the furnace technologies [17]. Furthermore, the NOx emissions are full of the surplus air ratio used, i.e., NOx emissions increase with increasing lambda values. Therefore, an additional reduction of NOx emissions is feasible by a mixture of improvements within the technology and control strategies that enable complete combustion of the fuel at an occasional air ratio.Creating bio-energy production will help to alleviate energy poverty, gas emissions, and a range of other socio-economic factors. it'll also end in the use of the many teens, so addressing society's social concerns. Encouraging a sustainable agricultural system, tree plantations, and effective waste management will have a big impact on the country's power industry. We present an optimization-based constraint tightening technique for control synthesis. We employ worst-case constraint tightening tubes to offer an optimization-based tightening technique [18].

From the above literature the subsequent observations are made:

- More research and analysis of the biomass potential of agricultural, animal, and industrial waste is required.
- To investigate and examine the biomass potential of agricultural waste by optimizing the key factors that may influence the burning combustion furnace.
- Investigate and evaluate various organic wastes supported their physical and chemical qualities. There are a range of pretreatment procedures for various sorts of biomass combustion furnace

2.1.1. **Literature Gap Identified**

from the above literature the following gap is observed

- The production of improved heat rate.
- They have delayed reply and overshoot time
- The emission rate of different gas

CHAPTER THREE

3. MODELING OF SMALL-SCALE BIOMASS COMBUSTION FURNACE

3.1. **INTRODUCTION**

This chapter discusses modeling small-scale biomass combustion furnaces. I model a linear robust MPC furnace controller. It also shows modeling paradigms, methodologies, and procedures for recognizing MPC systems. Mathematical modeling is utilized to obtain input-output data and build the biomass combustion furnace model.

3.1.1. **Combustion Furnace Type**

The furnace has three hot zones, with the first two having the minimal reference hotness and the third having the maximal. Between zone 1 and two additional zones, a roof-mounted separator was built to increase the temperature difference. Each temperature zone had a three-part segment. Because heat flow between zones was strong and caused temperature discrepancies, the zones had to be divided. If each zone's temperature was the same, they wouldn't have been divided. Figure 3.1 depicts a furnace drawing. The arrows indicate where the furnace's bars enter and depart. Bars are loaded into zone one west and removed from zone three west. When a bar enters or leaves, a gate must be open, which affects the building's temperature. The room and furnace are the same temperature when the bars enter.

Fig 3.1: Sketch of layout of the furnace [19]

Figure 3.1 shows the furnace's top layout. Arrows illustrate where bars enter and exit the chamber, and flames show burners. Numbers indicate the number of sections. Horizontally transfer the bars into zone one's west. Depending on their length, the bars might occupy either of the three portions [20]. All zones' heats are parallel. Since changing the temperature locations is unlikely, the numbers and order will be considered unchangeable. Large bars could only be inserted every other segment. The bars are moved using a walking beam. When the walking beam advances the bars, the temperature zigzags. This 750-second pattern is easy to spot. Zone 1's western and eastern flue gas exhausts allow heat from zone 3 to enter zone 1. Even when the heats in east and west zone 1 are switched off, the temperature in zone 1 remains high because of the warmth streams.

A PI-controller in each furnace section managed the temperature. You can turn on or off the heaters. The PI-control controller's signal indicated, as a percentage, the section's heat capacity. [21]. Gradual increase to new reference temperature level. The steady movement in reference ensures that the temperature is correct throughout the entire region, not just near the sensor.

3.2. **BIOMASS COMBUSTION FURNACE**

BIOMASS Vapor generators include combustion furnaces. This type of vapor generator exploit burner as its major heat cause to change liquid to vapor for commercial purposes such as energy production, chemical reaction conductance, and heating. Continuous and huge operation. This technique warms water. This process requires fuel and oxygen to burn it. This produces flue gas and ash [22]. Figure 3.2 is a schematic of a typical combustion furnace system.

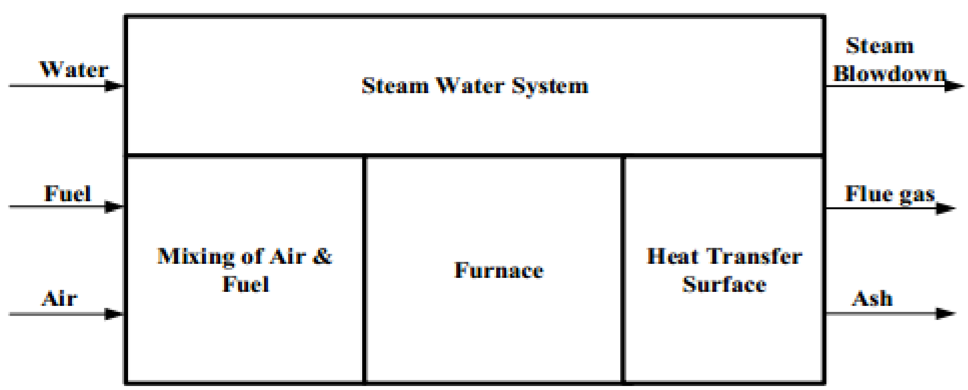


Fig 3.2: Basic block diagram

3.2.1. **System Description**

The combustion chamber or furnace is called the warmth transmission system because it releases heat. Time, temperature, and turbulence are needed for furnace combustion. Fans A furnace has ID and FD fans, abbreviated as ID and FD. Counterclockwise airflow from the ID fan creates undesirable pressure in the heater. FD fan moves combustion air through furnace. [21].

A biomass combustion system burns wood or collects to generate heat. business-scale schemes are dissimilar from household schemes because they (1) have automated feed and control systems and (2) must comply with strict emission rules. These two elements distinguish the two systems. When the combustor creates vapor or condensation, it's called a "furnace." Furnaces produce hot air. Compared to other heating systems, those that burn biomass emit fewer emissions, save money on overhead, and use renewable fuel. Biomass combustion systems help Pennsylvania commercial buildings. This document provides an overview of typical commercial biomass combustors and explores variables to consider when choosing one. If you want seeing install a biomass burner in your construction, you should learn how they work and enlist an experienced engineer for the look and installation. [22]. The thesis furnace may be a tempering furnace. "Tempering" is a method that the material (harden metal bars in our case) is heated to a given heat to get certain qualities, then cooled quickly to preserve them. This technology is common for steel products. To generate the desired fabric properties, the furnace must reach the reference temperature. Temperature profile affects these qualities.

Too much heat variance can ruin a set of treated material. The burner had three unique temperature zones, with the highest reference temperature in the zone where the bars emerged and the lowest in the zone where they entered. The batch's reference temperature is based on how stretched the bars will be in the heater, as mentioned in the work order. A movable beam will move the bar between heat zones.

Before or after using the walking beam, the oven doors were opened to demand out or in bars. Because the furnace was filled with cylindrical steel rods, the material could rotate. This thesis investigates the steel bar furnace, not its cooling method. Since the furnace was used throughout the thesis, all sample data was collected under real production settings. This prevented it from conducting experiments.

3.2.2. **Modeling of Biomass Combustion Furnace**

This study on modeling and identifying a biomass combustion furnace was used for linear robust model predictive control. System identification begins with selecting the system's input and output signals. Most applications need parameter control. Biomass furnace Thermostat: A way must be provided to control the mist temperature in different circuit sections to minimize overheating. Different tubes are impacted differently by flame radiation and hot gas movement. Keeping the temperature at the rated value will maximize fuel efficiency and save money [23].

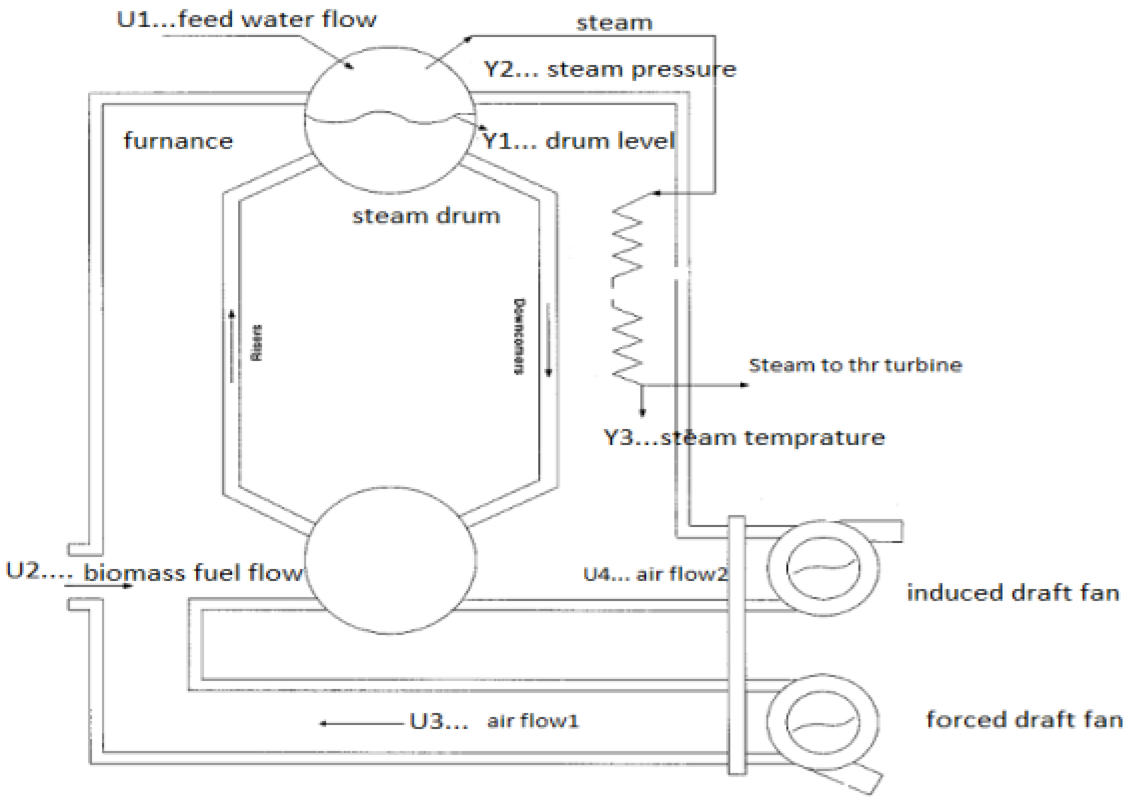


Fig 3.3: Input output description of biomass combustion [23]

Model shouldn't be too easy or sophisticated. If the prototypical is vary easy, it won't accurately characterize the researched system and won't achieve its goal. The model must not be too complicated to be useful [24].

Traditional modeling approaches cannot effectively use extra information, such as engineers' and operators' inaccurate and qualitative expertise. Traditional modeling has this issue. Modeling and controlling MPC systems are two main linear robust model predictive control approaches [24].

3.2.3. **Heat system**

The heating plant had a PI-controlled system. PI-control regulates four heats in zone 1 Mid, but only one in zone 2 West. The regulated heats were on or off. Because heaters could only function in two modes at once, the control signal is changed into a burning time. Multiplying the cycle time by the control signal determined the number of heating cycles. If the heating time was less than five seconds, it was lowered to zero and increased to the greatest possible value minus ten seconds. This was done to reduce device on/off times. A piece with two temps and a 50% control signal burnt on each other 50% of the time. If two heaters were set to 25%, neither would burn 25% of the time. Figure 3.1 depicts section 2 heating. The control signal for this section's four heats is

25%. The first heat finishes before the next one begins, etc. Figure 3.2 shows the same section at 60%, when the heat is more parallel. Since zone 1 and a few east's are already too hot, the system won't warm them today. A slight delay before the room's warming.

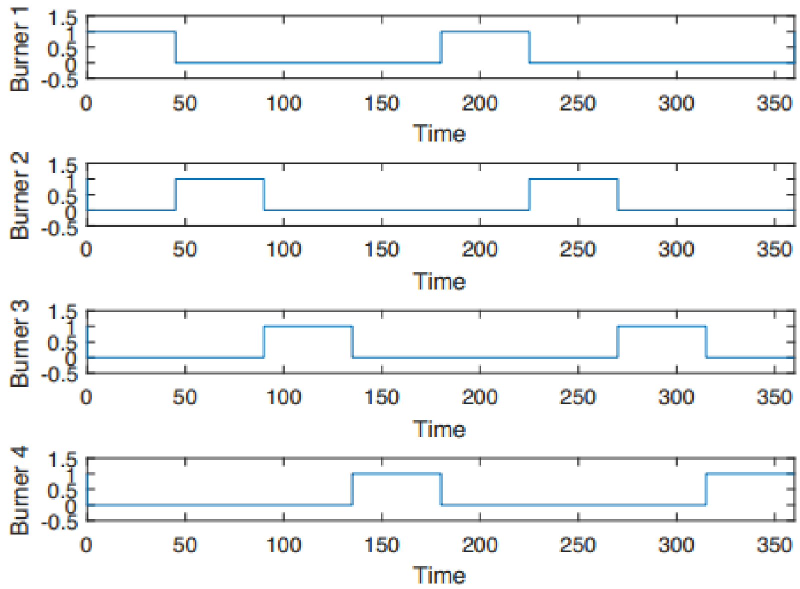


Fig 3.4: The heat beaves at an input of 0.25.1 represent the heat is high and 0 that it is low [25]

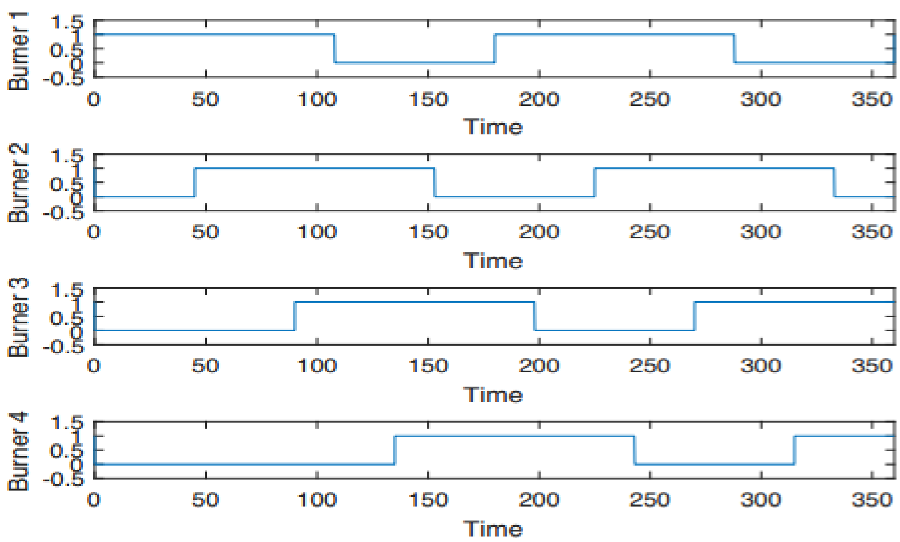


Fig 3.5: The heat behaves at an input of 0.6, 1 represents the heat is high and 0 that it is low [25]

3.3. **INPUT DATA COLLECTION MECHANISM**

In production, furnace data is collected. Feedback gathered the information. Direct, indirect, and hybrid input-output strategies are used to manage data collection during feedback. These include [26]. In this thesis, we took the straight route, ignoring input. The model was only a tool, given that the control design was most significant. In certain regions, high temperatures hampered data collection and input. Because the flames in those parts did not cause harm, there is no evidence in the data to doubt the connection between those flames and the resulting temperature. These flames are still modeled, but their parameter values are guesses. Including preliminary values for these attributes allows us to use flames in simulated situations.

3.4. **PARAMETER ESTIMATION**

The prediction error approach estimates model parameters [27]. The vector contains estimable parameters A, B, C, and D. it'll be utilized by the prediction y(t/θ) lay on at y(t-1).

The prediction error ε (t; θ) that the difference between the output y (t) and y (t/θ).

$$\in (t,\theta) = y(t) - \dot{y}(t/\theta) \qquad 3.1$$

The cost function aimed at numbers set with N trials is written as:

$$V_N(\theta) = \frac{1}{N}\sum_{t=1}^{N} \epsilon^2 \, (t,\theta) \qquad 3.2$$

$\hat{\theta}_N$ is given as the constraint which decreases the cost function:

$$\hat{\theta}_{N} = \arg\min V_N\,(\theta) \qquad 3.3$$

To perform the forecast error system in MATLAB I use PEM given by the SYSTEM IDENTIFICATION TOOLBOX. The function inputs are the system estimates numbers and the model's parameters. PEM allows users to weigh the loss function for various frequencies while evaluating focus. This study employed simulation and prediction. A loss function diminishes the one-step-ahead forecast. Simulations with a loss function that favors the input's highest-power frequency band.

3.4.1. **System Identification Toolbox**

System Identification creates mathematical models from dynamic system data. Adjusting model parameters to match measured output is the major strategy. An honest test compares the model's output to one tested with a different data set ("Validation Data"). Validity requires this comparison. "Residues" relate to data features the model couldn't reproduce. This couldn't be linked to other accessible information, such system input. Methods can be used to broad models. Popular models include ARX and ARMAX difference equation descriptions and linear state-space models. Parametric models require structure specification. This might be as simple as choosing a single integer to represent the model order, or it could include several alternatives. If the system is linear, you can estimate the impulse or step response with correlation analysis and the frequency response with spectral analysis. This allows comparisons to other estimated models. It includes typical methods for regulating linear model parameters.

3.5. SMALL-SCALE BIOMASS COMBUSTION MODEL

Small-scale combustion units are typically operating under varying process conditions. as an example, continuously changing heating demand and fluctuating fuel quality complicate the task to provide energy with high efficiency and low emissions. Unlike in large-scale combustion, where sophisticated measurement and control systems are available, the shortage of cost-effective sensors and automation sets hard limits to small-scale control [27]. This, in turn, usually prevents the real-time optimization of the combustion processes under 1 MW, along with non-optimal process development. to beat problems within the monitoring of small-scale combustion processes, a soft sensor –the approach may well be considered. during this methodology, the first process variables to be monitored are derived from the measurement of one or multiple secondary variables. Information from these inferential measurements is fused using mathematical models. As a result, the estimated value of a primary variable may be formed. The motivation for this sort of monitoring framework is obvious during a small-scale environment. Firstly, sensors are often simpler making them more robust. Secondly, utilization of fast response in-situ sensors could assist to attenuate time delays on top of things. Thirdly, the data about absolute values of important process parameters is of help in continuous emission and condition monitoring, including real-time efficiency calculations. the aim of this investigation is to look at and advance process monitoring methods for small-scale stoker-fired combustion furnaces. This research is targeted on combustion processes using wood chips. the event of the monitoring framework relies on the employment of inferential measurements [26]. Attention is paid to the reliability and adaptation features of the monitoring concept. The absence of those properties continues to be one in every of the foremost obstacles to the deployment of sentimental sensors in industrial processes. Data-based mathematical models utilizing soft computing methods are identified with analysis techniques utilizing data from a true combustion process. Data collection relies on the planning of the simulation –procedure. within the following sections, combustion process characteristics into consideration and also the applicability of present measurement technologies are first reviewed. Next, the idea of the proposed combustion monitoring framework is briefly discussed. Finally, some results of the monitoring capability with the identified models are presented and analyzed.

3.6. **MATERIAL AND METHODS**

3.6.1. **Furnace model**

The furnace model given here relies on physical principles and experimental design approaches to fill knowledge gaps. In the following sections, we'll cover the furnace's two stages of combustion, the non-linear difference equations used to build the regulator, and the native compassion analysis used to estimate the parameters.

3.6.1.1. **Biomass Combustion Process Description**

Tiny furnaces need mass and energy balances without scattered parameters to create a controller model. These balances help. By simplifying reaction kinetics and heat transfer, one can create an adequate process model with a few additional parameters. This is achievable because of reduced complexity. Figure 3.5 depicts the furnace's model able mass flows and temperatures. Wet biomass, first air from beneath the grate, and inferior air msa1 pouring into the freeboard overhead the grate are system inputs. Second stage combustion occurs in the freeboard. The extra air inlet msa_2 helps manage flue gas burnout and composition. The furnace's combustion residues mash and flue gas $m_f g$ are process-dependent mass fluxes. Because of its scale, the researched plant is designed to provide warmth for either an entire district or individual homes. Through the use of a water circuit, the consumers get their share of the thermal power that is generated when the fuel is burned. Because of this, the difference in temperature between the supplied water and the T_{sup}, and consequently the temperature of the water that is returned to the ocean The Tret measurement determines the plant's total power output. This means there is a trade-off among performance and emissions, and the oxygen absorption in flue gas O_2 reveals feedback and control adjustments. This shows that performance and greenhouse gas emissions are trade-offs. When oxygen is low, the furnace operates at near-maximum efficiency. Normal carbon monoxide levels are somewhat above the lowest possible level. [28]. High O_2 concentrations indicate enough oxygen for burning, but they also signal performance losses.

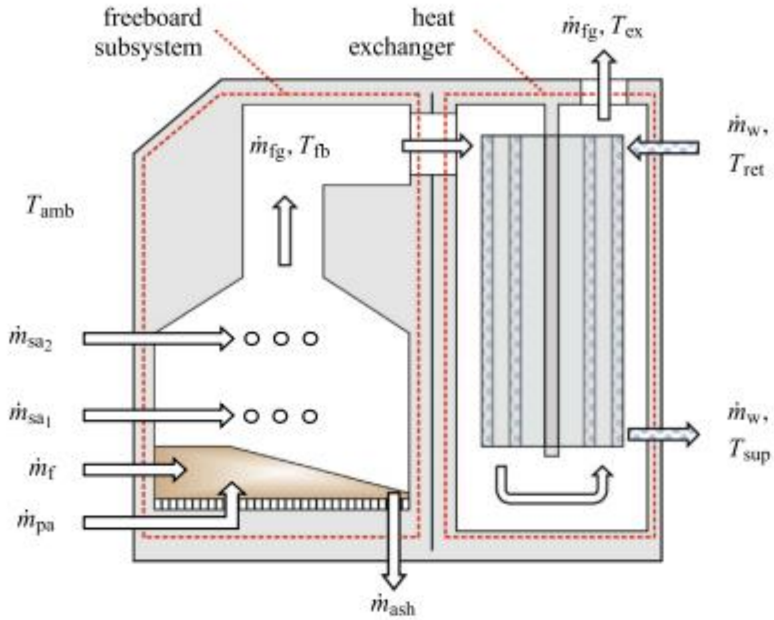


Fig 3.7: Lay out of the biomass burning model with relevant

Mass flows and heat of the form.

The furnace still's control strategy relies on the freeboard heat T_{fb} and the flue gas heat T_{ex}. This indicates combustion, emissions, wear, soot, and condensation. Don't mix the water circuit's capacity with the furnace's freeboard temperature. Thermal power replicates the amount of coal consumed throughout combustion, and the liquid circuit subject to on return liquid temperature, T_{ret}, and mass flow, m. Contributions to the heater and plant control, these two variables are held constant in the heater under consideration. These factors determine the water's temperature. T_{ex} monitors exhaust gas temperature. This state lowers the system's temperature threshold.

3.7.1.2. **Hard Mass Stability**

we may determine the present biomass fuel mass mb on the grate by:

$$\frac{dm_b}{dt} = \dot{m}_{f,dhd} - \dot{m}_{thd} - \dot{m}_{ash} \qquad 3.4$$

with the mass flow of dehydrated fuel $\dot{m}f, dhd$ (in kg/s) onto the grate,$\dot{m}thd$ thethermal breakdown of the fuel (in kg/s) and the grate rapidity reliant on removal of combustion remains mash (in kg/s). The dehydrated coal feed is given [28] by:

$$\dot{m}_{f,dhd} = (1-W_{H2O})\dot{m}_f \qquad 3.5$$

Where, W_{H2O}represents the mass segment of the liquid contented of the wet coal mass flow$\dot{m}f$(in kg/s). If the grate rapidity is continuous and slow, such that a complete exhaustion of the burnable mechanisms on the grate Is guaranteed, the relation:

$$\dot{m}_{ash} = \alpha_{ash}\,\dot{m}_{f,dhd}, \qquad 3.6$$

can be applied withα_{ash} as the residue content of the dehydrated coal. A simplified description of the thermal breakdown on the grate is obtainable in [28] as:

$$\dot{m}_{thd} = K1m_b(\dot{m}_{pa} - \dot{m}_{pao}) \qquad 3.7$$

Where, k1represents the burning percentage constant (in 1/kg),$\dot{m}pa$ the mass stream of prime air (in kg/s) and $\dot{m}_{pao}$ the weight improvement of the prime air (in kg/s).

3.7.1.3. Oxygen Absorption in Flue Gas

Determine the proportion of oxygen in combustion flue gas by [28] as:

$$KO_2\frac{dO_2}{dt} = 21\frac{\lambda-1}{\lambda} - O_2 \qquad 3.8$$

Using the O2-Sensor's time constant kO2 and air-to-fuel ratio λ [28] as:

$$\lambda = \frac{\dot{m}_a}{K_2 * L_{min} * \dot{m}_{thd}} \qquad 3.9$$

Where (m_a) is the whole air passing into the furnace (in kg/s), together with additional air, and L_{min} is the minimal air required for stoichiometrically complete combustion under ideal conditions. To compensate for measurements and the fact that laboratory conditions cannot be ensured in the furnace, the factor k_2 was determined through testing. Equation (3.5) yields accurate results for fixed and transient oxygen concentrations, although instantaneous active properties are not fully captured. The added state R_{thd} for the thermal decomposition rate m_{thd} is thus defined:

KR_{thd}

$$\frac{dR_{thd}}{dt} = \dot{m}_{thd} - R_{thd} \qquad 3.10$$

Experimentally determined time constant, kR_{thd}, is substituted into .

$$ko_2 \frac{do_2}{dt} = 21 \frac{\lambda-1}{\lambda} + \dot{R}_{thd} - O_2 \quad 3.11$$

Adding the thermal breakdown amount permits for explanation of the furnace's rapid oxygen dynamics.

3.7.1.4. **Freeboard Gas Temperature**

Unstable heat balance determines T_{fb}, or freeboard temperature.

$$m_g C_{p,g} \frac{d}{dt} T_{fb}(t) = \dot{Q}_{in}(t) + \dot{Q}_{comb}(t) - \dot{Q}_{gas}(t) - \dot{Q}_{rad}(t) \quad 3.12$$

With m_g as the gas mass in the chamber, $C_{p,g}$ optimum combustion gas temperature, $\dot{Q}_{in}$ the incoming enthalpy flow accompanied by the air and fuel mass flow, $\dot{Q}_{comb}$ the heat released by combustion, $\dot{Q}_{gas}g$ the enthalpy flow related to the gas mass leaving the freeboard, and $\dot{Q}_{rad}$ the heat loss due to radiation.

With $C_{p,a}$ and $C_{p,fuel}$ Depending on the air and fuel heat capacities, and T_{amp} as the ambient air temperature.

Since the flue mass gas flow $\dot{m}_f g$ is calculated according to

$$\dot{m}_f g(t) = \dot{m}_{thd}(t) + \dot{m}_a(t) \quad 3.13$$

The enthalpy flow related thereto is given by:

$$\dot{Q}_{gas}(t) = \dot{m}_f g(t) C_{p,g} T_{fb}(t) \quad 3.14$$

Results of the iterative identification process have indicated increased model performance by adapting the Stefan-Boltzmann radiation law in such a sense that temperature will no longer be of fourth rather third order. Yielding heat loss $\dot{Q}rad$ to be described by

$$\dot{Q}_{rad}(t) = K_{rad}\sigma(T_{fb}^3(t) - T_{amb}^3 \quad 3.15$$

With the Stefan Boltzmann constant σ and the factor K_{rad} representing the thermally effective surface.

3.7. **SMALL-SCALE COMBUSTION MONITORING**

3.7.1. **Characteristics of stoker-fired furnace systems**

Tiny stoker-fired furnaces share several problematic features that make monitoring and control challenging. During this scale, the technique's environment differs from the control's (Figure 3.9), causing fuel and cargo quality shifts. Because we lack real-time observations, fluctuations in fuel calorific value and energy consumption must be treated as unknown disturbances [29].

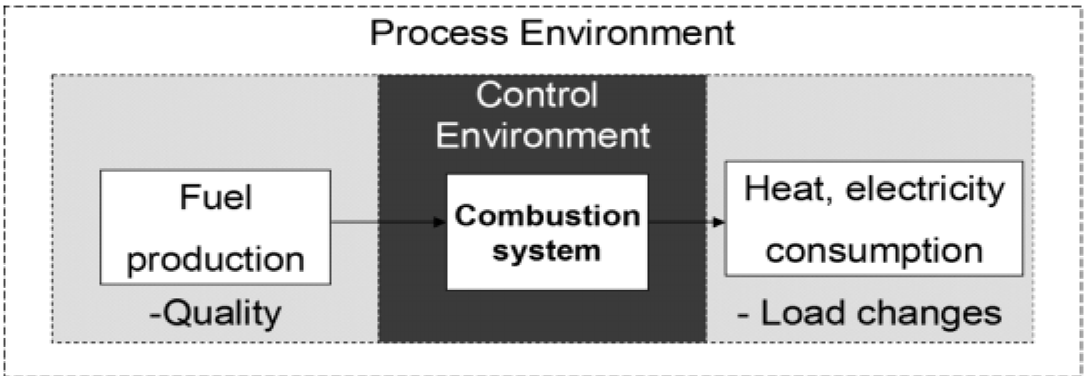


Fig 3.8: Control and process environment of a small-scale stoker combustion system

On the opposite hand, the little combustion units are volume products. This characteristic makes the method environment differ considerably and individually in each case. Small-scale process has also influenced variety of other factors, like the supply of cost-effective [29]:

- Materials and style for combustion chambers and grates,
- Energy storage units,
- Fuel feeding and dirt removal systems,
- Sensors and gas analyzers, and
- Control devices and actuators.

3.8. **Modeling of Biomass Combustions Furnace**

3.8.1. **Biomass Furnace**

The plant's biomass furnaces are water-tube heat furnaces. This heater has two systems. The furnace's water side is called the vapor–water system. The economizer preheated water is sent to the vapor beat to be heated by the down comers before entering the mud beat. The mud beat heats the water at the risers. In the vapor drill, saturated vapor-water is introduced and separated. The vapor next enters the primary and secondary superheaters. The vapor passes through two super heaters before entering the 6.306-MPa header. The two super heaters share a thermostat. This device blends secondary super heater vapor with lower-temperature water to modify temperature. The fuel-air flue is another system. Burns. This method combines fuel and oxygen before burning them in an oven. Combustion converts fuel energy into heat. Burning produces flue gases. Superheaters, risers, and downcomers release furnace gases. Figure 3.11 shows the furnace's composition. (where arrow indicates vapor–water movement). Figure 3.11 shows input variables.

- Feedwater rate (kg/s).
- Fuel rate of flow (kg/s).
- Attemperator spray rate (kg/s). and the principal output variables are
- Beat level (m).
- Beat pressure (map).
- Vapor temperature (c).

To operate effectively, the heating system must meet certain parameters.

- The header's force per unit area must be 6.306 MPa regardless of customer vapor needs.
- To avoid overheating the beat components or overflowing the vapor lines, the vapor beat must always contain the right amount of water.
- Temperature must be maintained to avoid super heaters from overheating and wet vapor from entering turbines.

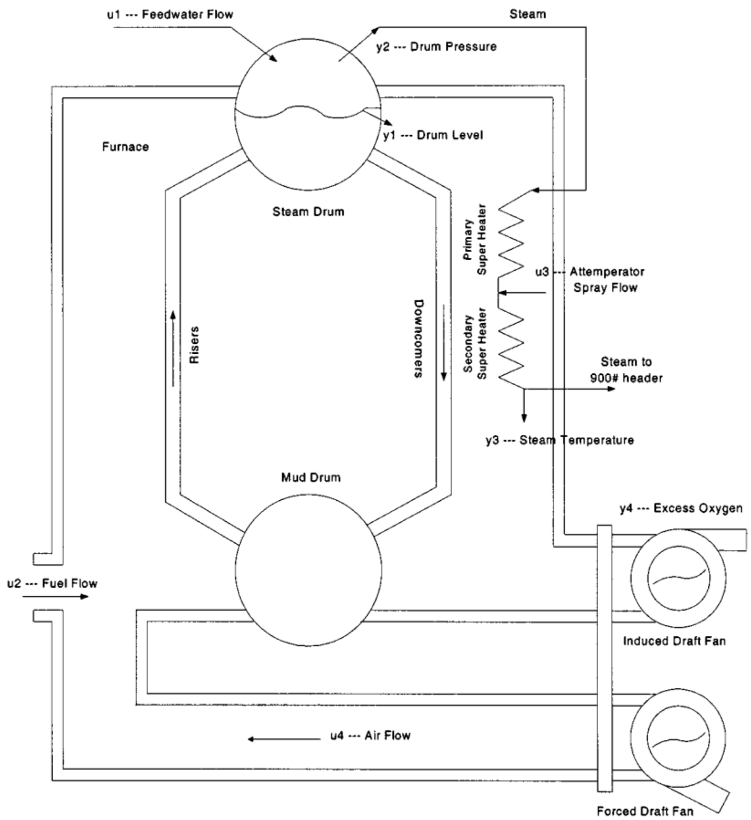


Fig 3.11: Biomass Furnace

At this operating point,

$$U0 = \begin{matrix} U10 \\ U20 \\ U30 \end{matrix} = \begin{matrix} 40.68 \\ 2.102, \\ 0 \end{matrix} \qquad Y0 = \begin{matrix} y10 \\ y20 \\ y30 \end{matrix} = \begin{matrix} 1.0 \\ 6.45 \\ 466.7 \end{matrix}$$

The usual vapor temperature setpoint is 499 C, while the operating point being assessed (466.7 C) is lower. The attemperator valve is closed, therefore spray flow isn't being used. Spray flow shouldn't be disregarded when constructing the plant's controller because 466.7 degrees Celsius isn't the only operational point. Vapor temperature is often higher than before the furnace is loaded. We suggested a 3 by 3 layout so the controller would work at larger spray flow rates. We found the LTI model using SYNSIM input-output data and MATLAB's Systems Identification Toolbox. Second-order models match input-output data. Pure delays were ignored.

CHAPTER FOUR

SMALL-SCALE BIOMASS COMBUSTION CONTROLLER DESIGN

4.1. **INTRODUCTION**

The chapter show the ultimate controller and with requirement was given for the controller. The various regulator are simulated with the model. It was derived in previous. The simulation result is going to be offered with both figures and tables.at the end, the topics ends with a discussion about the various controller and leads to the simulation.

4.1.1. **Requirement**

A new control design is created to minimize the heaters' on/off frequency and improve their temperature management. There are no predetermined constraints on switching frequency; nevertheless, reducing it will increase the heaters' era, allowing them to be used longer before being replaced [30]. Maximum temperature deviation from reference is 12 degrees Celsius. Zones 2 and 3 currently have adequate temperatures. In zone 1, section east is too hot. The walking beam causes a temperature reduction in zone 1's west and center. Zone 1 has the most potential to improve temperature regulation

4.2. **CONTROLLER**

In this part, the MATLAB/SIMULINK Simulations of the various controller whose idea was given in previous chapter are presented. It begins with the MPC controller and eventually the RLMPC controller.

4.3. **MODEL PREDICTIVE CONTROL DESIGN**

4.3.1. **Background**

Automation is found in all sectors of modern life, including technological, reproductive, productive, and safe and secure. Controllers must maintain internal control, increase productivity, and meet operational, safety, and environmental limits. It's tricky. By using an optimized model-based system, the method is manipulated under physical, environmental, and economical constraints and must be prepared to maintain a specific level of robustness to environmental disturbances and uncertainty in process measurements. This thesis examines Linear Model Predictive Control (LMPC) for small-scale biomass combustion furnaces. A traditional MPC comprises of future motions within control actions. These adjustments lower the controlled variables' variability while adhering to input and output limitations. Model predictive control (MPC) determines best future control actions by generating supported expected trajectories of controlled variables. Solving a constrained optimization problem takes into account the system's physical bounds, inputs, and outputs to identify control actions. Empirical linear models from experimental data or linearization of mechanistic (nonlinear) process models are used to support MPC applications in industry. This is typical. Despite how easy it is to run linear models in MPC, they can reduce plant performance. This is especially relevant when controlling a nonlinear dynamic approach. To make accurate predictions, use a nonlinear model. Model nonlinear The nonlinear model supported the development of Predictive Control, a predictive control system (NMPC). Article describes MPC. First, we provide background and MPC formulation. The MPC's adaptability, or flexibility, is a plus.

4.3.2. **MPC Theoretical Background**

Model predictive control relies on optimizing each sample instant. Optimization may be solved by implementing control signals today and in the future. The controlled system only receives the primary control signal from the sequence of signals. Repeating this method for each sample instant achieves feedback control. Because new measurements solve the optimization problem. The entire sequence would have open loop control. To predict the controlled system's future states accurately, a model must be built, which may be part of the optimization issue. MPC is often noticed since it optimizes each sample immediately in open loop.

4.3.2. **Description of the MPC**

MPC and a theoretical example are provided next. MPC aims to convey system states and contribution to 0 while considering dynamics and limits. Pricing's fundamental quadratic function has linear limitations.

$$minimize \ \sum_{j=1}^{N} \|x(k+j)\|_{Q1}^{2} + \|u(k+j-1)\|_{Q2}^{2} \quad 4.1$$

Focus to

$$X(K+i) = Ax(K+i) + BU(K+i) \quad 4.2$$

$$x_{min} \leq x_i \leq x_{max}$$

$$U_{min} \leq U_i \leq U_{max}$$

N represents the time period during which the prediction was made, which is utilized to determine the controller's improvement forecast. X_2Q is the Euclidean norm weighted by Q, x^T Qx. Change among Q1 and Q2 burden matrices affects controller behavior. If Q1 is large compared to Q2, system states will quickly converge to zero with enormous control inputs. If Q1 is small compared to Q2, control inputs will be minimum, but system states will take longer to meet to 0. Equality limitations model the controlled system dynamic. Inequality constraints limit system states and/or control signal. Safety requirements or saturation typically use these bounds. Model control led to MPC (IMC). MPC helps process industry confront restrictions effectively. Based on controlled and regulated parameters, the MPC predicts point tracking behavior or disturbance rejection. At each sampling period, the control system designer calculates MPC. These calculations employ current data and projected output predictions. An MPC controller must be able to execute point calculations and control calculations, which must take process limitations and explicitly set parameters into consideration. By observing a succession of control moves inside the controlled variable, an MPC controller ensures the system reaches its destination efficiently [30] the controllers are used extensively in industries due to their ability to deal optimally with input /output procedure limitations (better and lesser values for specific variables). One must remain to securely function the arrangement by constraining it to a very restricted area of procedure, such as a extreme valve opening. MPC controllers are widely employed in process industries because they can handle input/output limitations (upper and lower values for specific variables). MPC controllers regulate input/output process limitations (higher and lower values for variables) optimally, hence they're used in process industries.

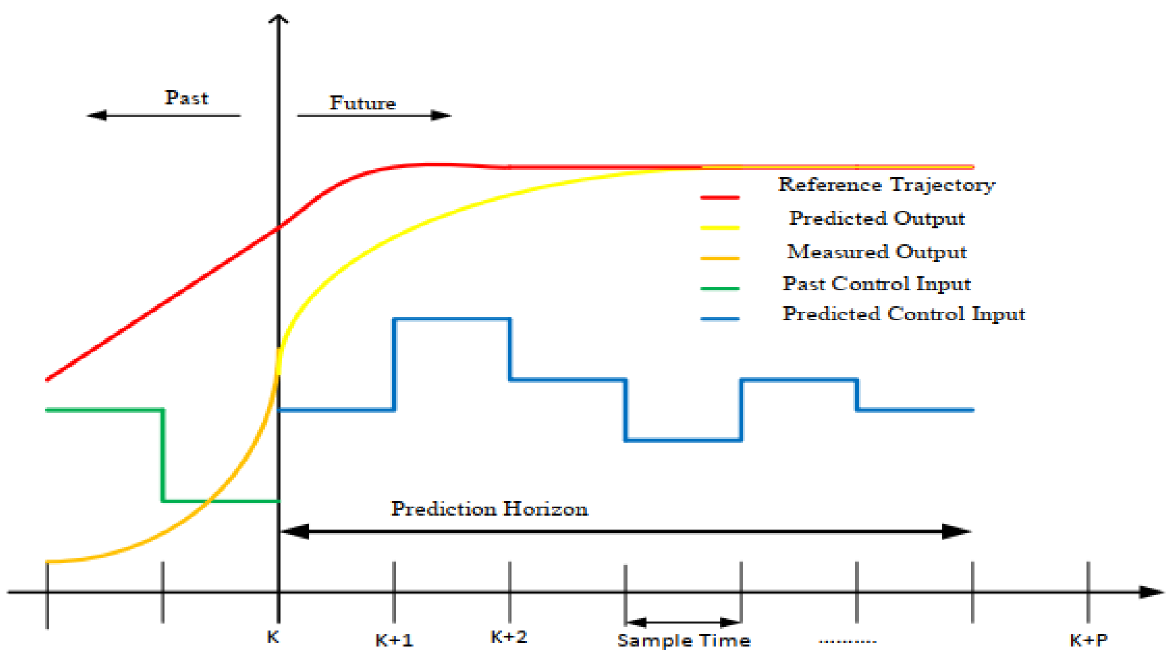


Fig 4.1: Basic concept of MPC

We'll minimize projected deviations from the reference trajectory to support control computations. Step K via an objective function supports result forecasts across a calculation prospect of P time steps, and this objective function is decreased by operated variable quantity finished an effect horizon of M control movements. MPC solves an optimization problem by stepping k across an objective function over P time steps. [30]. MPC computes the simplest control strategy to meet goals over time when backed by a process model. MPC synthesis is well-studied. This is a major difference between MPC and other formats. MPC evaluates upcoming fault due to a defined control path using a receding horizon, whereas typical control systems act based on prior iteration error. MPC analyzes error across a longer time horizon than standard control methods.

4.3.3. **Principle of MPC**

At each repetition of the algorithm k, where k = 1, 2, 3,..., the variable's future values are as follows and is calculated on-line.

$u\ (k + p|k)$ M is the control horizon represents the value of the modified variable at the instant k + p was calculated.

as well as the vector storing future variable increases. can be resolved as.

$$J(k) = \sum_{P=1}^{N} \left(y^{sp}\left(k + \frac{p}{k}\right)\right) - \hat{y}(k + p/k))2Q + \sum_{p=0}^{m-1}\ (\Delta u(k + p/k))2R \qquad 4.3$$

Where, the path of these two result variables (k) and $\Delta u(k)$ online because of an optimization difficulty. Minimized objective (cost) functions have two parts. First, the difference between the output variable's anticipated trajectory and the set point's trajectory across N predictions. Control mistakes anticipate the difference. Second, inputs' M-period change rate. The second step slows the pace of change for the modified variables. Cost function:

Where, R>0 is a weighting coefficient (the greater its value, the lower the increments of the manipulated variable and, hence, the slower control).

$y_{sp}\ (k + p|k)$ is the set point rate at sample instant of $k + p$.

$\hat{y}\ (k + p|k)$ is the forecast rate of the output variable at immediate time of $k + p$.

For p = 1, 2,..., N, successive output forecasts are obtained using a dynamic model of the process. It is assumed that

$u\ (k + p|k) = u\ (k + M - 1|k)$ For $P = M, \ldots$,(It mean that $\Delta u\ (k + M|k) = \cdots = \Delta u\ (k + N|k) = 0$).

$u\ (k + p|k) = u\ (k + M - 1|k)$ For $P = M, \ldots, N$ (It mean that $\Delta u\ (k + M|k) = \cdots = \Delta u\ (k + N|k) = 0$).

Every MPC technique uses a moving horizon, sequential online optimization, and a dynamic model to make predictions. Essential fading horizon. This algorithm assesses the current value of modified variables and future control policy. Model predictive control can locate the longer-term control sequence, improving control precision.

4.3.4. **Main parts of MPC**

- Acts and predictions Model predictive control considers long-term implementation, unlike PID. Predicting outcomes helps reduce unanticipated unpleasant occurrences.
- Models support predictions. The model must show the output's dependence on the up-to-date amount variable and up-to-date and upcoming inputs. Models provide system predictions. Only the proper model with accurate forecasts should be employed. Choosing this in-put the anticipated inputs are nominated as those minimalizing a specified cost function. The value function would be as easily mutually can flee with for the quantified efficiency.
- The system should settle before the receding horizon. Otherwise, performance is low and important events are missed. The forecast horizon should include all major dynamics (For example, the settling time).
- If we need a well tuned controller, we necessity a precise model.
- MPC will all times yield steady control (at minimum for the nominal), therefore the essential findings are a strategy to steadiness input activity, loop efficiency, sensitivity, and reaction speed. Weighting tuning and matrices are key to attaining equilibrium. Tuning is usually easy if the relative importance of each loop's performance can be determined.
- Control algorithms are concerned with constraints. The chosen algorithm will depend on a variety of profit-related variables including sampling time. MPC considers limits systematically, improving performance.
- MPC combines feed-forward and constraint handling. This enables methodical use of future demands.
- MPC algorithms can build multivariable (MIMO) systems systematically. It enables methodical MIMO system construction [31].

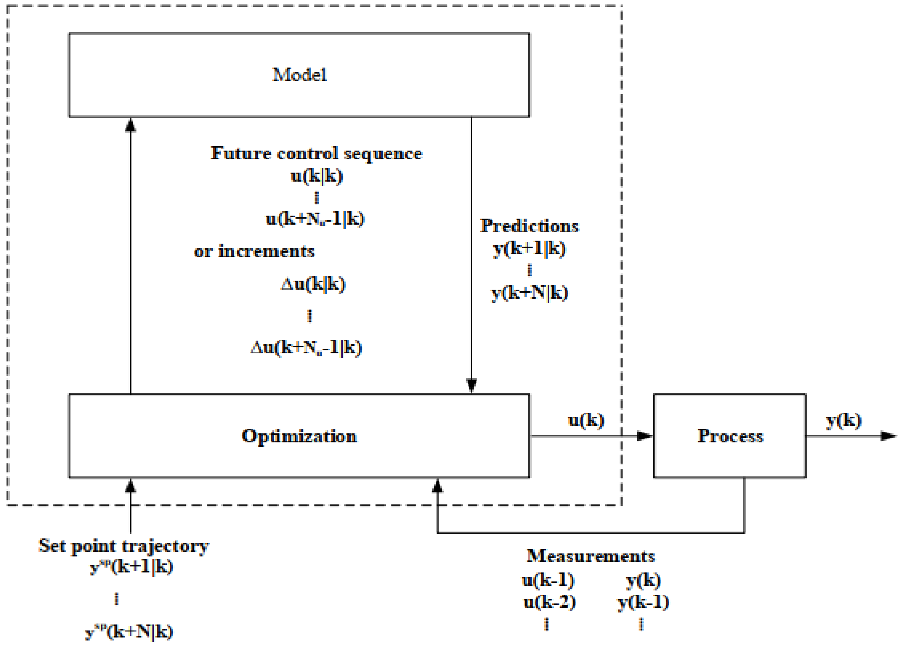


Fig 4.2: The structure of the MPC algorithm

4.4. **MPC Algorithms**

MPC uses several algorithms. This study used GPC. It's more trustworthy than over-parameterization or unknown-length waits. It can handle plant control issues with suitable design variables. The user sets these variables depending on plant knowledge and desired control. GPC minimizes a multistage cost function by anticipating future control signals. Sequence calculation does this. Optimize a quadratic function measuring the distance between expected system output and a few forecasted reference sequences. Optimize a quadratic function assessing control effect. Both are quadratic [32]. GPC exchanges ideas with predictive controllers. It's adaptive to unstable and non-minimum phase plants and considers control increment weighting [33]. If there are no constraints, it presents an analytical answer. The MPC method is utilized to manage the Biomass Combustion Furnace because it is a subset of the GPC algorithm.

4.2.1. **MPC**

The MPC formulation provided in Chapter 3 used a linear model, quadratic equation cost function, and linear limitation. MPC malleability allows for a nonlinear internal model, a more complicated cost function, and nonlinear limitations. The optimization problem can be tough, but the concept remains the same. The model must be rewritten to separate regulated inputs, such warmth, from disruption inputs, like doors and walking beam. Because the walking beam is activated at a predetermined time, the disturbance inputs are known in advance. If a bar has to be charged or discharged, the gates will open before or after the walking beam is activated. Input disturbances are known. In order for the MPC controller to calculate control signals, the formulation did not contain zone 1 temperature restrictions.

The heating plant in the heat systems division converts this controller's signals. It's possible to transform the MPC control signal like the PI control signal. MPC controls heating elements directly. The choice was made because heat would hamper the MPC controller's performance. Second, the MPC controller inner model of the system would include heat. This could make optimizing a time-varying utility more complex. The signal restriction must be changed because temperatures are binary. If the switch controls the temperature, (0 - 1)2 equals (1- 0)2 = 1. This allows the controller to be programmed to optimize for a given switch-reference temperature relationship.

The examined boiler to be controlled by an mpc have the following set point for controlled variables y1, y2, and y3 equal to 1 meters , 6711.7 kpa and 500 0 c ,respectively. The mpc tuning parameters for the controller design are specified as follows in the below table.

Table 4.1. Tuning parameters for mpc

Tuning parameters	Value
Control horizon	1.0
Forecast horizon	10
Control horizon	3
Weight for input	0.1
Weight for drum pressure	1
Weight for steam output	1
Weight for water level,	1
Robustness	0.8

CHAPTER FIVE

5.1. SIMULATION AND RESULT ANALYSIS

The open loop unit step input response of the linearized model at the conventional load is shown in Figure 5.1. the extent response indicates that the behavior is integrating type. this is often also verified by checking the eigenvalues of the system matrix A. The eigenvalues of the system matrix are as follows:

-0.8440 + 0.0000i

-0.0174 + 0.0073i

-0.0174 - 0.0073i

0.0000 + 0.0000i

-0.0111 + 0.0000i

The fourth eigenvalue is zero which suggests that the pole at the origin. Hence the method has integrating type response. Also, the temperature response incorporates a negative gain. This analysis indicates that the process has complex behavior like integrating type and negative gain.

5.1.1. **Multi-loop PI controller response**

The multi-loop PI controller designed using the IMC method is considered for performance comparison. The multi-loop PI controller transfer function is as follows:

$$K(s) = \begin{bmatrix} 212\left(1+\frac{1}{62.2424s}\right) & 0 & 0 \\ 0 & 0.01\left(1+\frac{1}{35.23s}\right) & 0 \\ 0 & 0 & -0.015\left(1+\frac{1}{4s}\right) \end{bmatrix}.$$

The control system response for the set-point changes in pressure (y2) as 100 and temperature (y3) as 20 is shown in Figure 5.2. It should be noted that there are not any setpoint changes in level. Because the extent isn't changed during the operation, and it's maintained at a relentless level the least bit operating points. The multi-loop PI controller response is shown in Figure 5. 3.

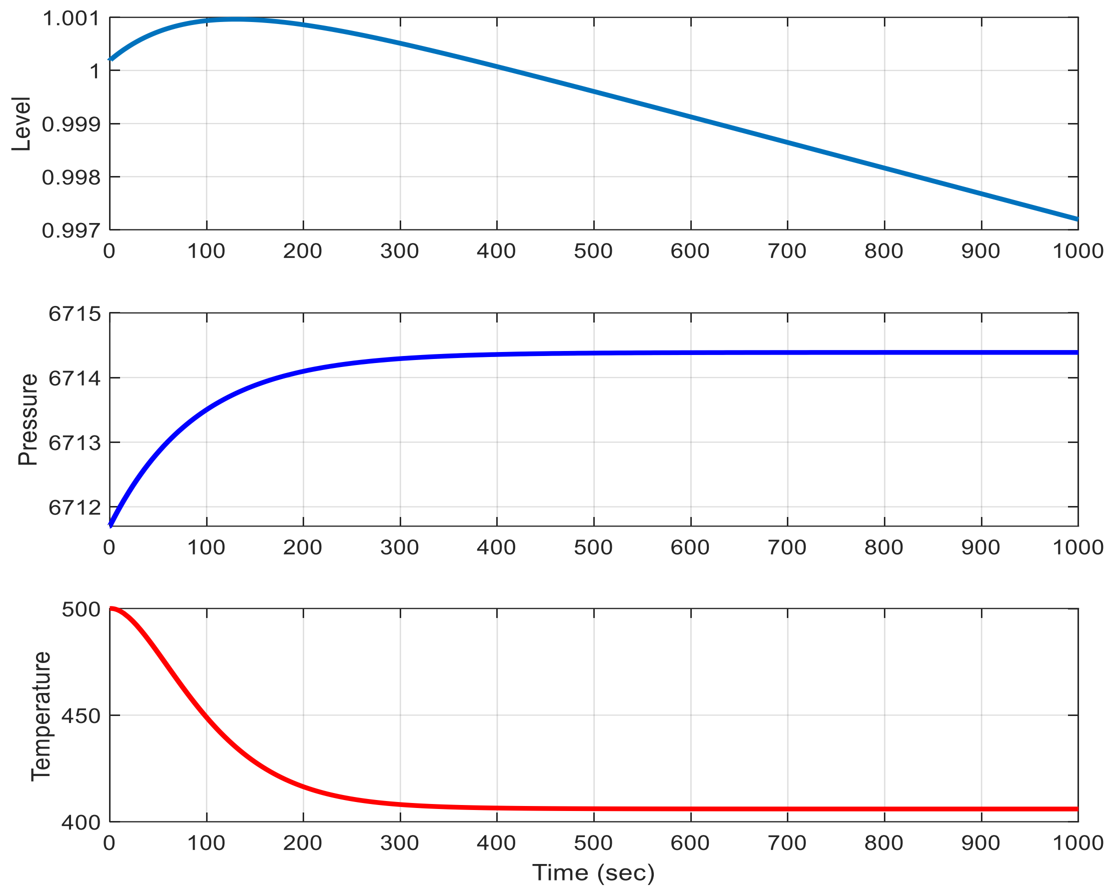
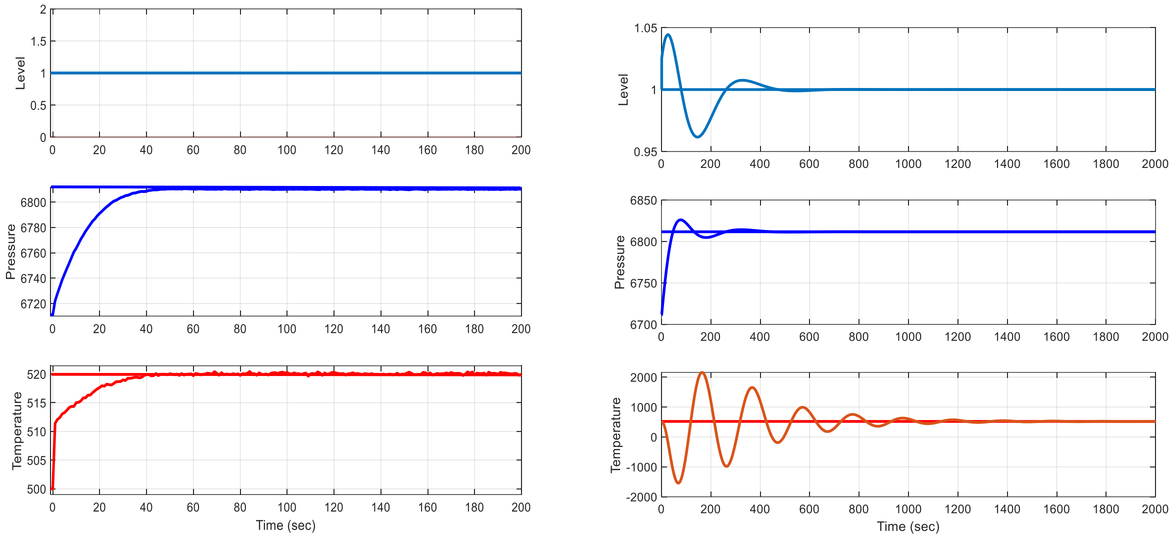


Fig 5.1: Open loop step response

A multi-loop PI controller's effectiveness is examined. The temperature system shows a more oscillatory response. Also, the extent is disturbed during the setpoint changes in pressure and temperature.

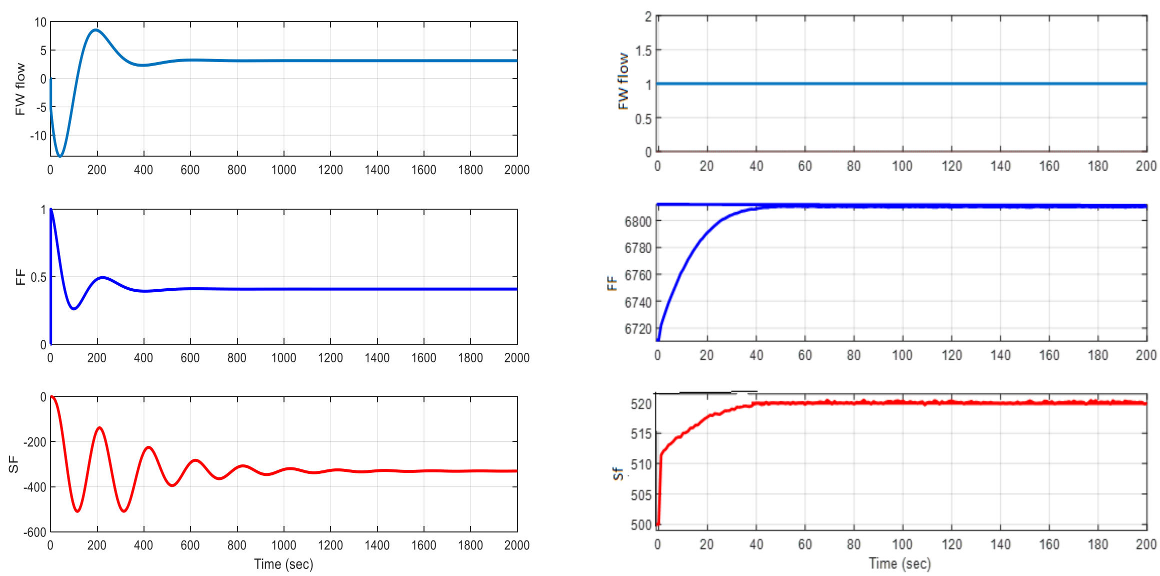
5.1.2. **CONTROLLER RESPONSE**

The closed-loop system response of MPC for the set-point changes in pressure (y2) as 100 and temperature (y3) as 20 is shown in Figure 5.4. The corresponding controller response is shown in figure 5.5. The capacity of the MPC controller is analyze. The temperature response encompasses a smooth and quick response without oscillation compared to a multi-loop PI controller. The MPC controller response is best than the multi-loop PI controller.



(a) (b)

Fig 5.2: Closed loop response OF(a) model predictive controller (b)multi loop PI controller



(a) (b)

Fig 5.3: controller response (a)PI response (b)LMPC response

5.2 PERFORMANCE COMPARISON

Integral Absolute Error (IAE) measurements are used to compare Multi-loop PI controller and MPC operating efficiency. Table 5.1 lists each control strategy's computed IAE. MPC controller IAE is lower than multi-loop PI controller IAE. In multivariable, difficult procedures, the MPC controller outperforms the multi-loop PI controller.

Table 5.1: Performance comparison of MPC and Multi-loop PI control schemes

Controller	IAE
Multi-loop PI	5.612e+5
MPC	1.667e+3

CHAPTER SIX

CONCLUSION AND FUTURE RECOMMENDATION

6.1. **Conclusion**

This research creates a linearized state space model for small-scale biomass furnace operations. The typical has 3 inputs and three outputs. the amount response indicates that the behavior is integrating type. Also, the temperature response encompasses a negative gain. the method analysis indicates that the process has complex behavior like integrating type, negative gain, and high dimensional. The model predictive control scheme is intended for this complex process. The control system response of MPC for the set-point changes is simulated. The IMC-designed multi-loop PI controller's performance is compared. Analyze multi-loop PI controller performance. The temperature system shows a more oscillatory response. Also, the amount is disturbed during the setpoint changes in pressure and temperature. The capacity of the MPC controller is analyze. The temperature response features a smooth and quick response without oscillation compared to a multi-loop PI controller. The MPC controller response is healthier than the multi-loop PI controller.

6.2. **Recommendation**

The followings aspects may be considered for the future work:

- The MPC controller is designed for the normal operating point, it may be designed for other operating points.
- The MPC controller performance may be compared with other advanced control schemes.

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