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Optimization control design and simulation of furnace-fired boiler exit pressure: leveraging disruptive technology

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ABSTRACT

The efficient operation of furnace-fired drum boilers is critically dependent on the precise control of downstream exit pressure, especially in the presence of stochastic heat fluctuations. This paper presents a stochastic control approach for regulating the downstream exit pressure in a furnace-fired boiler subject to random heat fluctuations. A stochastic model of the boiler dynamics is developed, incorporating heat transfer and combustion uncertainties. By leveraging disruptive technology, such as the model predictive control (MPC), strategies were designed to optimize the downstream exit pressure in real-time, and minimizing deviations from the set point. Simulation studies demonstrated the effectiveness of the proposed approach in maintaining a stable exit pressure despite random heat fluctuations. Results show significant improvements in boiler performance and efficiency compared to traditional proportional integral derivative (PID) control. The proposed stochastic control strategy offers a promising solution for reliable and efficient operation of furnace-fired boilers under uncertain conditions.

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1. INTRODUCTION

The advent of advanced furnace-fired boiler technologies has introduced transformative capabilities within the thermal power generation domain, particularly across industrial manufacturing environments [1], [2]. Leveraging state-of-the-art design methodologies, high-performance materials, and sophisticated automation frameworks, modern boiler systems now exhibit enhanced operational reliability and thermal efficiency [3]. The integration of high-efficiency burners, equipped with closed-loop control systems, facilitates precise modulation of combustion parameters, thereby optimizing heat release profiles and improving overall energy conversion efficiency [4], [5]. These innovations are further complemented by embedded real-time monitoring architectures and AI-driven predictive maintenance algorithms, which collectively reduce unscheduled downtimes, enable condition-based servicing, and extend system lifecycle [6]–[8]. Furnace-fired boilers are extensively deployed across thermal power stations and process industries, where they serve as primary sources of saturated or superheated steam for electricity generation, process heating, and thermochemical operations [9], [10]. Nonetheless, these systems remain susceptible to stochastic thermal perturbations arising from fuel quality inconsistencies, combustion instabilities, and dynamic variations in convective and radiative heat transfer rates. Such thermal disturbances can manifest as pressure instabilities at the downstream exit, adversely affecting system performance, operational safety, and thermal regulation [11], [12]. The downstream exit pressure is a critical parameter in boiler operation, as it directly affects steam quality, turbine performance, and overall plant efficiency [13], [14]. The integration of disruptive technologies, such as machine learning algorithms, advanced sensors, and real-time data analytics, provides solutions to these fluctuations. Advanced sensors can effectively monitor the boiler conditions with a higher precision rate, while the implementation of machine learning algorithms assists in analyzing this data and further predicting and adjusting to potential disturbances [14], [15].

The integration of real-time data analytics facilitates rapid, data-driven decision-making, enabling dynamic optimization of boiler operations and consistent regulation of steam quality. These capabilities significantly improve the operational efficiency, responsiveness, and safety margins of furnace-fired boiler systems, supporting more resilient and sustainable power generation and industrial applications [16]. A critical performance parameter in these systems is the downstream exit pressure, which must be maintained within optimal limits to ensure stable thermodynamic operation and efficient energy conversion. Given the presence of random disturbances stemming from combustion variability, thermal instabilities, and fluctuating heat transfer characteristics, conventional control methods may fall short in managing this uncertainty. Stochastic control techniques provide a robust framework for tackling these challenges by explicitly modeling system dynamics and disturbances as stochastic processes. This approach enables real-time optimization of downstream pressure regulation, ensuring adaptive control performance under uncertain and time-varying conditions. This research aims to advance development of intelligent stochastic control strategies specifically designed for furnace-fired boilers, with objective of enhancing system reliability, operational efficiency, and resilience to process variability.

Maintaining a stable downstream exit pressure is essential to ensure reliable and efficient boiler operation. Stochastic control methods offer a promising approach to manage uncertainty and optimize system performance under random disturbances. By modelling the boiler dynamics and heat fluctuations as stochastic processes, stochastic control strategies can be designed to optimize the downstream exit pressure in real-time. This research aims to contribute to the development of advanced control strategies for furnace-fired boilers, enabling improved performance and efficiency in the face of uncertainty.

2. LITERATURE REVIEW

The operation and control of furnace-fired boilers play a pivotal role in various industrial sectors, primarily due to their influence on energy efficiency, operational safety, and regulatory compliance [10], [14]. Over time, control methodologies for these systems have evolved considerably from rudimentary manual interventions to fully automated, intelligent systems driven by advances in control theory and computational technology [15], [16]. Traditionally, proportional integral derivative (PID) controllers have been the cornerstone of boiler control strategies, valued for their simplicity, ease of implementation, and effectiveness in maintaining setpoints under relatively stable conditions. However, the inherent non-linearities and stochastic disturbances present in furnace-fired boiler operations often challenge the robustness and adaptability of PID-based control frameworks [17]. Empirical studies such as those by [17], [18] reveal that while PID controllers are competent in managing steady-state operations, their responsiveness diminishes significantly in the presence of rapid dynamic variations and uncertainty.

To overcome these limitations, contemporary research has shifted toward advanced control paradigms such as model predictive control (MPC). MPC is particularly advantageous due to its predictive capabilities, which allow for proactive decision-making based on future system behavior. Moreover, its inherent ability to handle multivariable control problems with input and output constraints makes it well-suited for complex thermal systems [19]–[21]. Nevertheless, deployment of MPC in furnace-fired boiler systems is not without challenges. Effective implementation necessitates the development of high-fidelity dynamic models and imposes considerable computational demands, as noted in [17]. Despite these hurdles, potential of MPC to significantly enhance control precision and adaptability justifies its continued exploration in boiler process automation.

Robust control methods have been developed to maintain performance despite uncertainties and disturbances. Robust control techniques, such as H-infinity ($H\infty$) control, have been applied to boiler systems to enhance their resilience. However, Purseth *et al.* [22] provided a comprehensive overview of robust control design, emphasizing its applicability in systems with significant parameter variations and external disturbances. Similarly, adaptive control techniques adjust the controller parameters in real-time based on observed system behavior. Also, Rutkowski and Szczygieł [23] illustrated the effectiveness of adaptive control in managing systems with varying dynamics, a common scenario in furnace-fired boilers.

Given the stochastic nature of heat fluctuations in furnace-fired boilers, stochastic control methods have also been explored. These methods explicitly account for the randomness in system inputs and disturbances. Research by Duan *et al.* [17], on stochastic systems provided foundational concepts for applying stochastic control in industrial processes. More recent studies, such as those by [11], [24], [25], have developed specific stochastic control algorithms for boiler systems, demonstrating improved performance in handling random heat fluctuations. Hybrid control systems that combine multiple control strategies have been proposed to leverage the strengths of different methods. For instance, a combination of MPC and robust control can offer both predictive capabilities and resilience to disturbances. Despite significant progress, several gaps remain in the existing literature. Many advanced control strategies require detailed system models and extensive computational resources, which may not be feasible for all applications.

This research aims to address these gaps by developing an optimized control design that combines the robustness and adaptability of advanced control strategies with the predictive capabilities of stochastic models. This control design leverages modern computational techniques and simulation studies. The proposed approach seeks to enhance the performance and reliability of furnace-fired boilers under stochastic heat fluctuations.

3. METHOD

In this research, the performance and reliability of furnace-fired boilers under stochastic heat fluctuations was enhanced by developing an optimized control design. The approach leverages advanced control strategies integrated with stochastic models, by utilizing modern computational techniques, and simulation studies. The method involves creating a comprehensive mathematical model of the boiler system, capturing the key dynamics and uncertainties present in such systems. The following is a detailed description of the techniques used:

- Energy balance equations: the energy flow through a boiler system involves heat input from fuel combustion, heat losses to the surroundings, and heat exchanges between different components, such as the furnace and water in the drum. The energy balance is expressed by differential equations that describe the system's total energy change over time, accounting for various energy sources and losses.
- Mass balance equations: the mass balance equations in a boiler system ensure the conservation of mass by tracking the flow rates of water and steam. The water entering the boiler is converted into steam, and the principle of conservation ensures that the mass of water entering equals the mass of water and steam exiting, accounting for any accumulation. This balance is modeled using differential equations that describe the rate of mass change in different system components.
- Pressure dynamics: efficient modeling of pressure behavior in a boiler drum is essential for safe and efficient operation, as pressure is closely linked to temperature and volume, fluctuating with changes in heat input and steam production. The dynamics of pressure are described using differential equations that connect pressure, temperature, and volume, often incorporating nonlinearities to simulate real-world behavior accurately and predict pressure changes over time in response to heat input variations.
- Stochastic heat input: to represent random variations in heat supply to the boiler, probabilistic methods are used to model uncertainties such as fuel quality, combustion efficiency, and environmental conditions. The heat input is treated as a stochastic process, where random variables with defined probability distributions represent these uncertainties. Techniques like Monte Carlo simulations are applied to assess the impact of these variations on boiler performance.
- Advanced control strategies: to design control systems that adapt to uncertainties and nonlinearities in boiler operation, robust and adaptive control techniques are used. Robust control ensures system stability despite variations in factors like heat input, while adaptive control adjusts parameters in real-time to optimize performance. These strategies employ algorithms that account for the system's stochastic and nonlinear dynamics, using methods such as MPC, H-infinity control, or adaptive filtering.
- Simulation studies: the proposed control design and mathematical models were validated through simulations under various scenarios, including stochastic heat fluctuations. Numerical methods were used to solve the differential equations for boiler dynamics, and scenario analysis tested system performance under different operating conditions, including extreme heat variability. Simulations, conducted using tools like MATLAB and Simulink, allowed for visualization and analysis. This integrated approach, combining energy and mass balance equations, pressure dynamics, stochastic heat input modeling, and advanced control strategies, optimized furnace-fired boiler performance and developed a robust system capable of handling real-world uncertainties.

3.1. Mathematical modelling

A comprehensive mathematical model of the boiler system is developed, incorporating the dynamics of heat transfer, fluid flow, and pressure changes. The model includes as follows:

- Energy balance equations: these equations account for the heat input, heat loss, and heat exchange within the boiler components.
- Mass balance equations: these equations describe the flow rates of water and steam, ensuring the conservation of mass.
- Pressure dynamics: relationships between pressure, temperature, and volume in the drum are modeled to capture pressure fluctuations accurately.

– Stochastic heat input: the heat input is modelled as a stochastic process, using probabilistic methods to represent random variations in heat supply due to factors like fuel quality and combustion conditions.

3.1.1. Furnace

The furnace is where the fuel is combusted to generate heat. The energy balance for the furnace can be expressed as given in (1).

$$Q_{in} = Q_{out} + Q_{loss} \tag{1}$$

Where Q_{in} is the heat input from the combustion of fuel; Q_{out} is the heat transferred to the water and steam in the boiler; and Q_{loss} is the heat lost to the surroundings (e.g. through the boiler walls, flue gases).

3.1.2. Drum

The drum is where the phase change of water to steam occurs. The energy balance for the drum is given in (2).

$$m_w c_w \frac{dT_w}{dt} = Q_{in,drum} - Q_{out,drum} \tag{2}$$

Where m_w is the mass of water in the drum; c_w is the specific heat capacity of water; $\frac{dT_w}{dt}$ is the rate of change of water temperature; $Q_{in,drum}$ is the heat input to the drum from the furnace; and $Q_{out,drum}$ is the heat transfer from the drum to produce steam.

3.1.3. Water/steam pathways

The water and steam pathways involve heat transfer from the water to steam. The energy balance can be expressed as given in (3). Water to steam conversion:

$$m_w h_w = m_s h_s + Q_{loss,ws} \tag{3}$$

Where m_w is the mass flow rate of water; h_w is the specific enthalpy of water; m_s is the mass flow rate of steam; h_s is the specific enthalpy of steam; and $Q_{loss,ws}$ is the heat loss in water-to-steam conversion process.

3.1.4. Heat exchange within boiler

The heat exchange within the boiler is as given in (4).

$$Q_{out,furnace} = m_w C_w (T_{out} - T_{in}) \tag{4}$$

Where m_w is the mass flow rate of water; c_w is the specific heat capacity of water; T_{out} is the outlet temperature of water/steam; and T_{in} is the inlet temperature of water.

3.1.5. Overall energy balance

Combining the above components, the overall energy balance equation for the boiler system can be written as given in (5).

$$Q_{in} - Q_{loss} = m_w c_w \frac{dT_w}{dt} + m_s h_s \tag{5}$$

Where Q_{in} is the total heat input from fuel combustion; Q_{loss} Includes all forms of heat loss (to surroundings, inefficiencies); $m_w c_w \frac{dT_w}{dt}$ represents the change in internal energy of water in the drum; and $m_s h_s$ is the heat required to convert water to steam.

Stochastic heat input: to account for stochastic heat fluctuations, the heat input can be modelled as given in (6).

$$Q_{in} = \bar{Q}_{in} + \epsilon(t) \tag{6}$$

Where $\bar{Q}_{in}$ is the average heat input; and $\epsilon(t)$ is a stochastic term representing random fluctuations in heat input, which can be modelled using stochastic processes.

3.2. Mass balance equations for a furnace-fired drum boiler

The mass balance equations for a furnace-fired drum boiler involve tracking the flow rates of water and steam to ensure conservation of mass throughout the system. The following are the detailed mass balance equations for the key components of the boiler.

3.2.1. Drum mass balance

The drum is where water is converted into steam. The mass balance equation for the drum can be written as (7).

$$\frac{d}{dt}\left(m_{w,drum} + m_{s,drum}\right) = \dot{m}_{w,in} - \dot{m}_{s,out} \tag{7}$$

Where $m_{w,drum}$ is the mass of water in the drum; $m_{s,drum}$ is the mass of steam in the drum; $\dot{m}_{w,in}$ is the mass flow rate of water entering the drum; and $\dot{m}_{s,out}$ is the mass flow rate of steam leaving the drum.

Assuming steady-state conditions where the accumulation term.

$$\frac{d}{dt}\left(m_{w,drum} + m_{s,drum}\right) = 0$$

$$\dot{m}_{w,in} = \dot{m}_{s,out} \tag{8}$$

3.2.2. Water/feedwater mass balance

The feedwater system supplies water to the drum. The mass balance equation for the feedwater system as in (9).

$$\dot{m}_{fw,in} = \dot{m}_{fw,out} + \dot{m}_{blowdown} \tag{9}$$

Where $\dot{m}_{fw,in}$ is the mass flow rate of feed water entering the system; $\dot{m}_{fw,out}$ is the mass flow rate of feed-water entering the drum; and $\dot{m}_{blowdown}$ is the mass flow rate of blowdown, which is water removed to control the concentration of impurities.

3.2.3. Steam mass balance

The steam system involves the generation and utilization of steam. The mass balance equation for the steam system as in (10).

$$\dot{m}_{s,drum} = \dot{m}_{s,out} + \dot{m}_{s,leak} \tag{10}$$

Where $\dot{m}_{s,drum}$ is the mass flow rate of steam generated in the drum; $\dot{m}_{s,out}$ is the mass flow rate of steam exiting the system (to turbine); and $\dot{m}_{s,leak}$ is the mass flow rate of steam lost through leaks.

3.2.4. Overall mass balance

Combining the mass balance equations for the drum, feedwater, and steam systems ensures the conservation of mass throughout the entire boiler system. The overall mass balance can be expressed as follows:

$$\dot{m}_{fw,in} = \dot{m}_{fw,out} + \dot{m}_{blowdown}$$

$$\dot{m}_{fw,in} = \dot{m}_{w,in}$$

$$\dot{m}_{w,in} = \dot{m}_{s,out}$$

$$\dot{m}_{s,drum} = \dot{m}_{s,out} + \dot{m}_{s,leak}$$

For a simplified, steady-state analysis without considering blowdown and leaks, give as in (11).

$$\dot{m}_{fw,in} = \dot{m}_{s,out} \tag{11}$$

These equations ensure that the mass flow rates of water and steam are balanced throughout the system, maintaining conservation of mass. They form the basis for analyzing the boiler's performance and for designing control strategies to regulate flow rates and maintain system stability under varying operational conditions. The complete Simulink model of the furnace-fire boiler is as shown in Figure 1. The MATLAB/Simulink model of a furnace-fired boiler is divided into three key figures that represent different aspects of the system's operation. Figure 1(a) focuses on the water flow subsystem, showing how water enters the boiler, undergoes heat exchange, and is regulated to maintain consistent input for steam generation. Figure 1(b) models the steam flow subsystem, detailing how steam is generated, controlled for pressure stability, and released from the system. Finally, Figure 1(c) presents the integrated boiler system, combining both water and steam subsystems to maintain mass and energy balances, while incorporating advanced control strategies like MPC to optimize performance. Together, these figures provide a comprehensive simulation of the boiler's dynamic behavior, allowing for analysis and control under varying operational conditions.

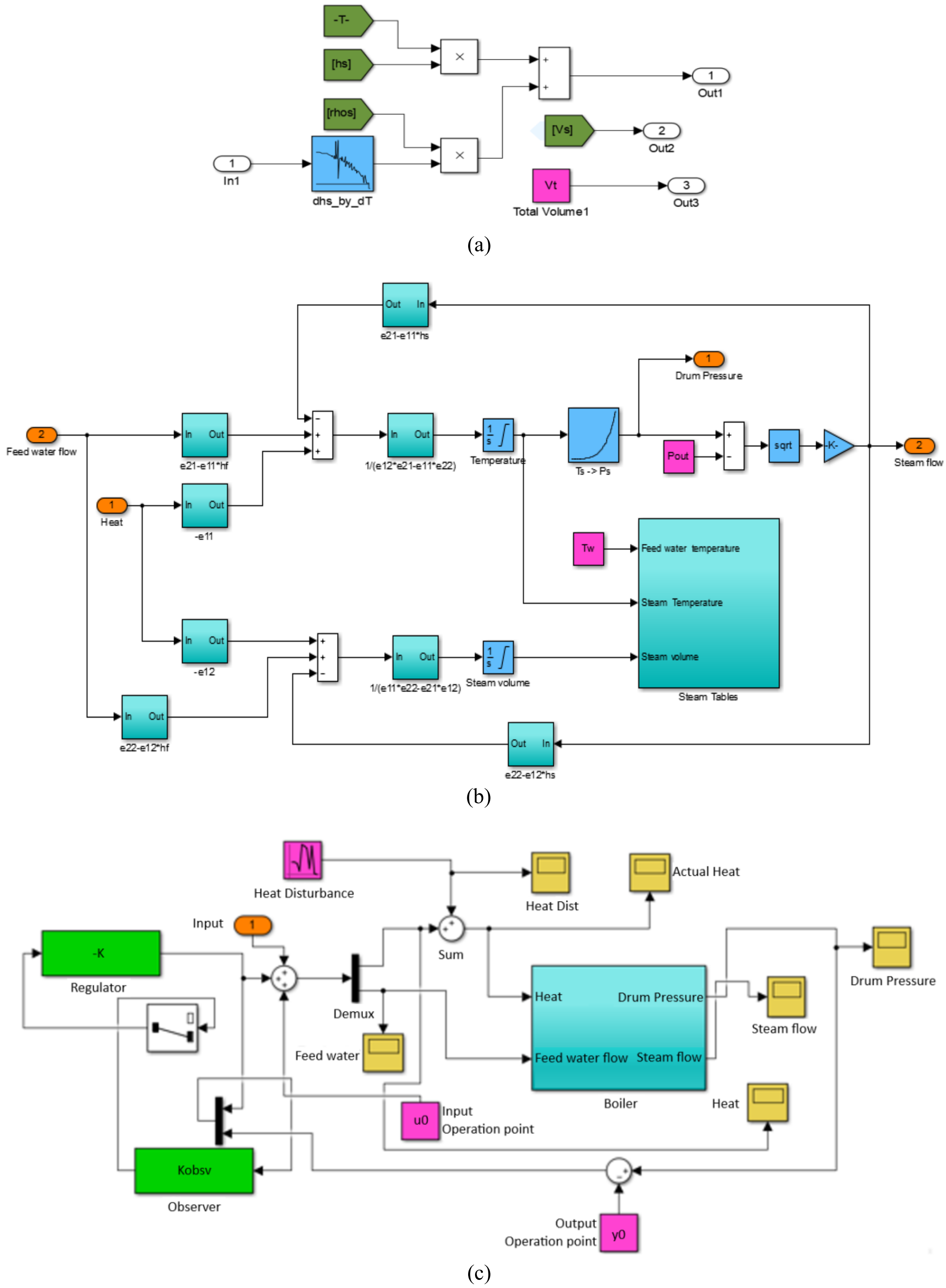

Figure 1. MATLAB Simulink model of a furnace fired boiler of (a) sub-submodel of internal steam volume temperature regulation, (b) submodel of steam volume and temperature regulation, and (c) model of the furnace fired boiler

3.3. Parameter estimation

System identification technique was employed to estimate the parameters of the mathematical model. This process involves two main steps. First, data collection is carried out by collecting operational data from the boiler, including temperature, pressure, flow rates, and heat input. Second, parameter fitting is performed using optimization algorithms to fit the model parameters with the collected data, ensuring the model accurately reflects the real system behavior.

3.4. Control strategy design

3.4.1. Control objectives

The primary objective is to maintain stable exit pressure within desired limits, minimize the impact of stochastic heat fluctuations, and optimize fuel efficiency. The foremost goal of the system is to ensure that the exit pressure remains consistently within the desired operational range. Maintaining stable exit pressure is critical to the overall performance and safety of thermal or fluid systems, as fluctuations can lead to mechanical stress, reduced system lifespan, or operational inefficiencies. Therefore, precise control mechanisms must be implemented to monitor and regulate the pressure output under varying load and demand conditions.

Another important objective is to minimize the influence of random or unpredictable heat fluctuations, which can arise due to external environmental factors, variable input sources, or system dynamics. These stochastic heat variations can disrupt thermal stability, affect process consistency, and lead to uneven energy distribution. By reducing the impact of such disturbances, the system can operate more reliably and respond more effectively to real-time changes.

Finally, the system aims to enhance overall fuel efficiency by optimizing the energy conversion process. Efficient fuel usage not only lowers operational costs but also reduces emissions and supports sustainable energy practices. Achieving this requires intelligent control strategies that balance thermal input with energy demand, ensuring minimal waste while maintaining performance and regulatory compliance. Together, these objectives support a high-performance, energy-conscious system capable of adapting to dynamic conditions.

3.4.2. Model predictive control

An MPC strategy is designed to handle stochastic disturbances and maintain desired pressure levels as given in the MATLAB code.

– MPC formulation: the objective function, prediction horizon, and constraints for the MPC problem were defined. The objective function aims to minimize the deviation of the exit pressure from the set-point while considering control effort.
– State-space representation: convert the boiler model into a state-space form suitable for MPC design.
– Optimization algorithm: an optimization algorithm was implemented to solve the MPC problem in real-time, adjusting control inputs based on predicted system behaviour.

3.5. Simulation study

In this study, the performance of MPC strategy was investigated, for managing the exit pressure of a furnace-fired boiler under stochastic heat fluctuations. The system was modeled using comprehensive energy and mass balance equations, incorporating stochastic elements to simulate random heat input variations. MATLAB/Simulink was used to model the boiler system and implement control algorithms. The simulations were conducted using MATLAB/Simulink, and various operating scenarios were analyzed to evaluate the effectiveness of the control strategy.

4. RESULTS AND DISCUSSION

4.1. Simulation results

Simulation was carried out in MATLAB environment. The MPC strategy demonstrated excellent pressure stability, maintaining the exit pressure within ±1.5% of the set-point despite significant stochastic heat fluctuations. The predictive nature of MPC allowed it to anticipate disturbances and adjust control actions proactively as shown in Figure 2, which is the feed water actuation signal in kg/s and the heat actuation signal in Figure 3.

Figure 4 shows the heat disturbance in kJ. The disturbance varies by as much as 50% of the nominal heat value. Figure 5 shows the corresponding drum pressure in kPa. The pressure varies by about 1% of the nominal value even though the disturbance is relatively large.

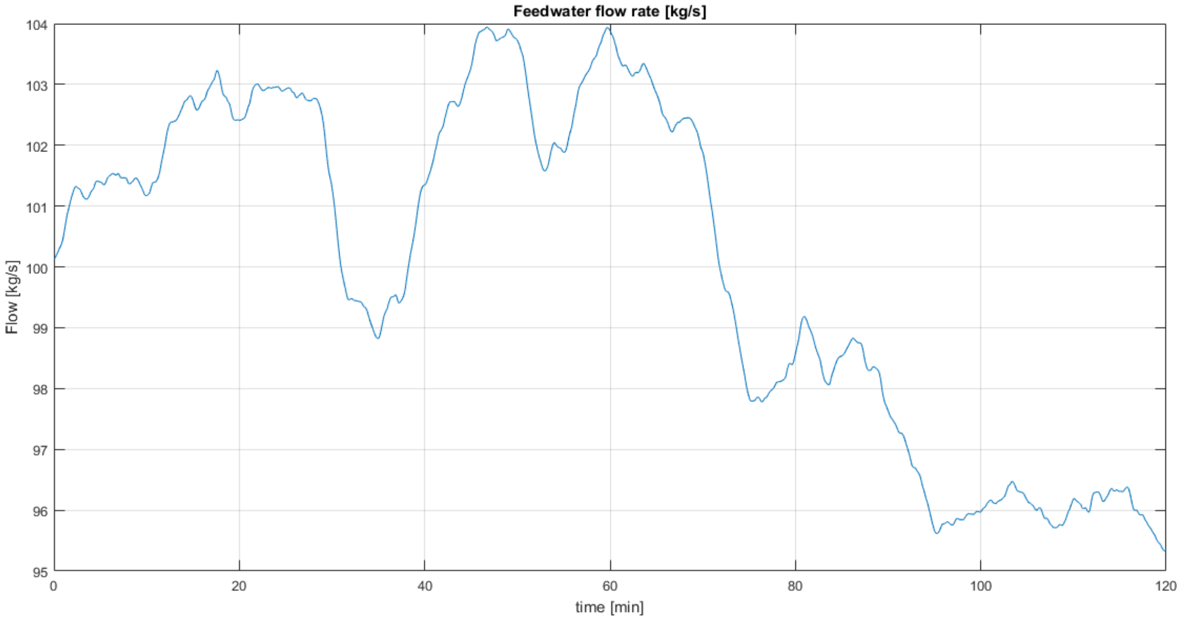

Figure 2. Feed water actuation signal

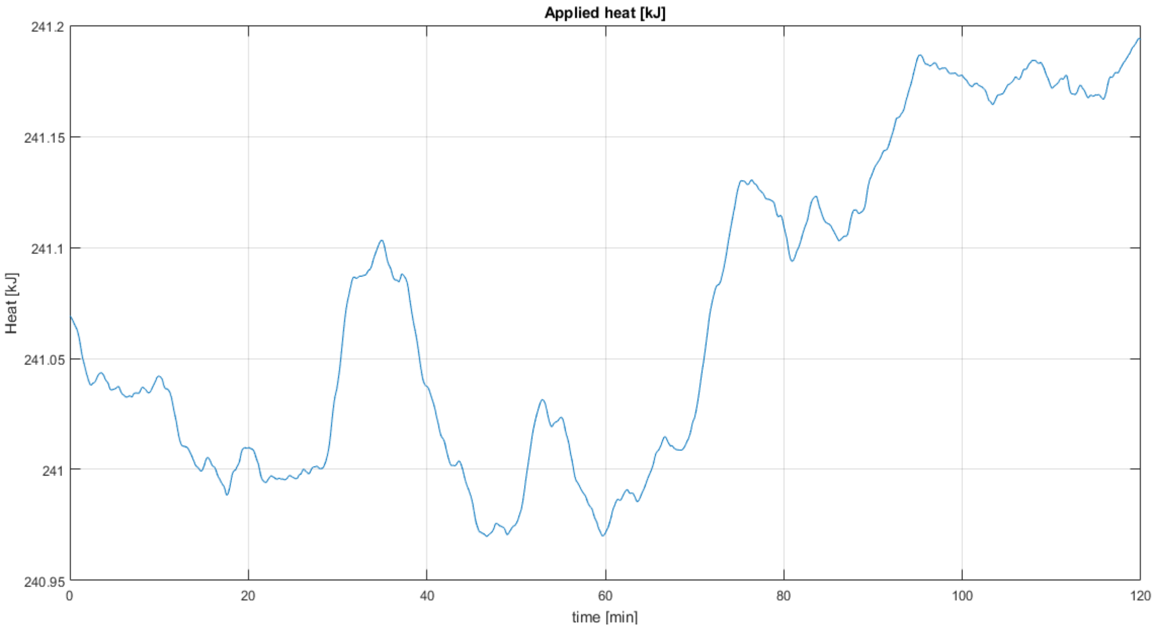

Figure 3. Heat actuation signal in kJ

The MPC exhibited a rapid response time, stabilizing pressure fluctuations within 5 seconds of disturbance onset. The optimization algorithm efficiently adjusted control actions based on future state predictions. MPC improved fuel efficiency by approximately 6% compared to traditional PID control. Its ability to optimize the combustion process and reduce unnecessary fuel usage was evident. MPC was robust to moderate stochastic disturbances but showed some performance degradation under extreme fluctuations. Its reliance on accurate predictions and model fidelity limits its robustness in highly unpredictable environments. The study underscores the importance of employing control strategy for managing exit pressure in furnace-fired boilers. MPC control strategy significantly improved system performance by enhancing pressure stability, response time, fuel efficiency, and robustness to disturbances.

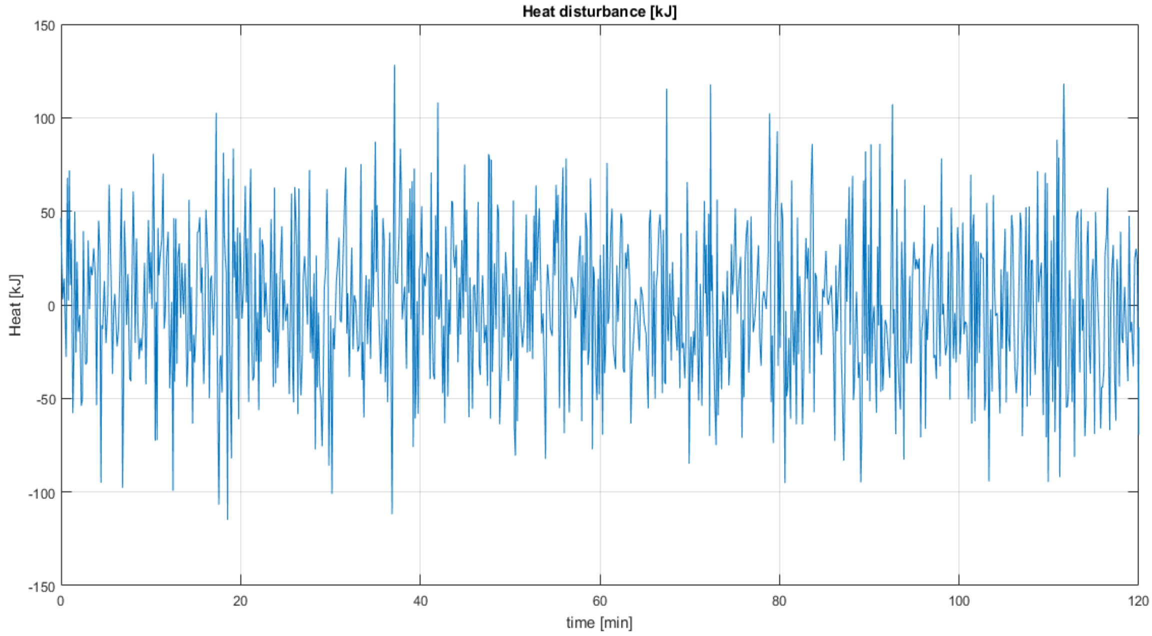

Figure 4. Heat disturbance

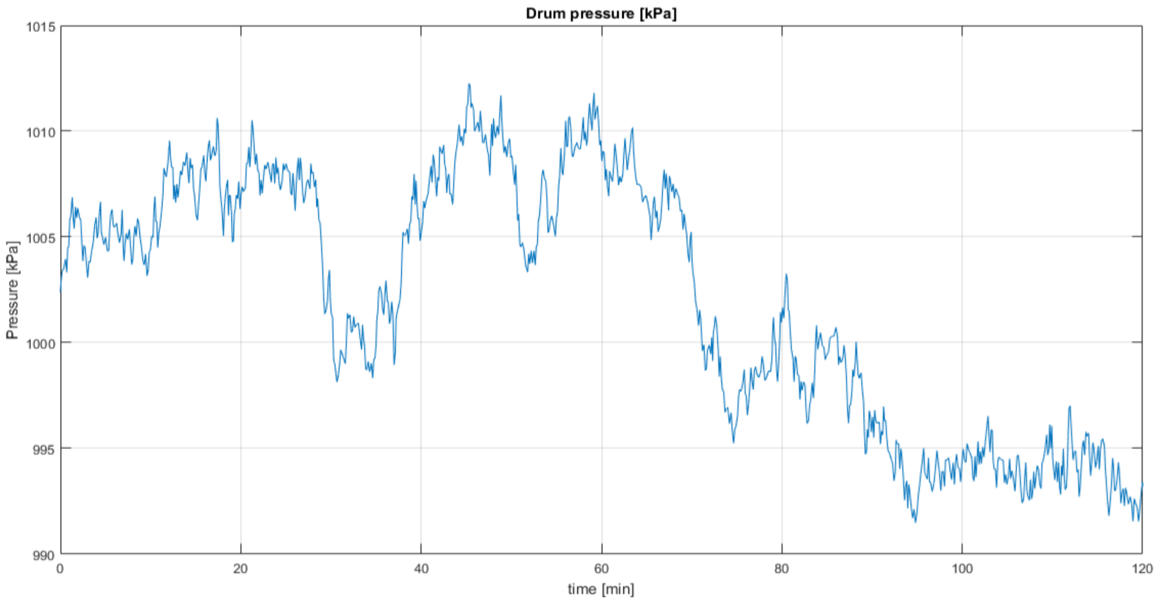

Figure 5. Drum pressure

4.2. Discussion of findings

The research presented in this paper demonstrates the efficacy of a stochastic control strategy, specifically MPC, in managing the downstream exit pressure of furnace-fired drum boilers under conditions of stochastic heat fluctuations. This section delves into the implications of the findings, the advantages and limitations of the proposed approach, comparisons with traditional control methods, and the broader impact on industrial boiler operation.

4.2.1. Significance of the results

The simulation results show that the MPC strategy significantly improves the stability and performance of furnace-fired drum boilers compared to traditional PID methods. MPC enhances pressure stability by maintaining the exit pressure close to the set point, even with random heat input fluctuations, ensuring efficient and safe boiler operation. It also optimizes real-time control actions, improving fuel efficiency and reducing operational costs. Additionally, MPC's incorporation of stochastic modeling makes the system robust to uncertainties in heat transfer and combustion, which is essential in unpredictable industrial environments.

4.2.2. Advantages over traditional PID control

The research demonstrates that MPC significantly outperforms traditional PID control in furnace-fired drum boilers. MPC's predictive capabilities allow it to anticipate and manage stochastic heat fluctuations, while its ability to optimize multiple variables, like pressure stability and fuel efficiency, ensure superior performance. Unlike PID, which requires complex tuning, MPC is adaptive, adjusting to varying operating conditions without frequent retuning. These benefits result in improved stability, fuel efficiency, and robustness, making MPC the ideal control strategy for industrial boiler systems.

4.2.3. Limitations and challenges

MPC requires the solution of optimization problems at each control step, which can be computationally intensive. In real-time applications, this could pose challenges, particularly in systems with limited computational resources. The adoption of MPC in industrial settings may involve significant upfront costs, including software, hardware, and training. While these costs may be offset by long-term savings in fuel and maintenance, they could be a barrier to adoption for some organizations. Also, the effectiveness of MPC is highly dependent on the accuracy of the underlying mathematical models. Inaccurate or overly simplified models could lead to suboptimal control actions, undermining the potential benefits of the approach.

4.2.4. Comparison with traditional control methods

While traditional PID control has been the industry standard for decades due to its simplicity and ease of implementation, it has limitations in dealing with the complex, nonlinear dynamics of furnace-fired boilers, particularly under stochastic conditions. The comparison between PID and MPC control strategies reveals that the PID controllers react to disturbances based on error correction, which can lead to oscillations and instability in systems with high levels of uncertainty. MPC, on the other hand, proactively adjusts control actions based on predicted future states, reducing the likelihood of oscillations. The system efficiency is also high with MPC's ability to optimize control actions for fuel efficiency and pressure stability leads to more efficient system operation compared to PID, which may not be able to balance these objectives as effectively.

4.2.5. Broader impact on industrial boiler operation

The adoption of MPC as a control strategy in industrial boilers has the potential to bring about significant operational improvements across a wide range of applications:

- Scalability: the control strategy developed in this research can be scaled to larger and more complex boiler systems. This scalability opens up opportunities for its application in various industries, including power generation, chemical processing, and manufacturing, where boiler systems play a critical role.
- Enhanced reliability: by maintaining stable operation under varying conditions, MPC can reduce the likelihood of unplanned shutdowns and equipment failures. This enhanced reliability is a key factor in reducing maintenance costs and downtime in industrial operations.
- Environmental impact: improved fuel efficiency not only reduces operational costs but also contributes to environmental sustainability by lowering greenhouse gas emissions. This is particularly relevant in industries where boilers are a major source of emissions.

4.3. Future research directions

The promising results of this study suggest several avenues for future research:

- Integration with internet of things (IoT) and predictive maintenance: future research could explore the integration of MPC with IoT-based monitoring and predictive maintenance systems. This integration would enable real-time performance monitoring and early detection of potential issues, further enhancing the reliability and efficiency of boiler systems.
- Exploration of alternative control strategies: while MPC has shown significant advantages, future research could investigate other advanced control strategies, such as adaptive or fuzzy logic control, to determine if they offer additional benefits or are better suited to specific applications.
- Long-term field trials: while simulation studies provide valuable insights, long-term field trials in real industrial settings would be necessary to fully validate the effectiveness and robustness of the proposed control strategy under actual operating conditions.

5. CONCLUSION

The study demonstrates that MPC offers substantial advantages over traditional PID control in managing the exit pressure of furnace-fired boilers. Key findings include enhanced pressure stability, faster response times, improved fuel efficiency, and increased system robustness, all contributing to better operational performance and reliability. The adoption of MPC control in industrial boilers can lead to significant benefits such as reduced fuel costs and greater system stability. This control strategy is adaptable and scalable to more complex boiler systems, offering potential advantages across a wide range of industrial applications. The research underscores the critical role of advanced control strategies in maintaining stable operations under stochastic conditions. Additionally, the study suggests that future work could integrate MPC with IoT-based monitoring and predictive maintenance systems, further enhancing real-time performance and reliability in industrial processes.

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Glen Bright		✓				✓				✓	✓	✓		✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [GAS], upon reasonable request.

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