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Research/Technical Note

Design of Multi-Input Multi-Output Non-linear Model Predictive Control for Main Steam Temperature of Super Critical Boiler

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Abstract

Flexible operation of coal-fired power plants is becoming increasingly necessary for successful integration of large-scale renewable power generation into the power grid. The maximum ramp rate and the number of load cycles are generally limited by the thermal stress experienced by the boiler pressure parts, turbine metallurgy and creep and fatigue of critical thick-walled components Main steam temperature is a critical operating parameter that must be controlled within acceptable limits for safe operation. Main steam temperature deviation beyond acceptable limit has impact on boiler pressure parts and turbine material of construction due to creep and fatigue effect. Base load operating units do not require steep ramp rate and hence recommended ramping rates are kept low within the safe operating zone in comparison to the flexible operation of the units with wide range load change width. Thermal stresses are caused by the temperature changes inside the thick-walled components and turbine steam admission parameters. Hence, the quality of main steam temperature control plays a vital role in flexible operation of the coal fired units. Conventional cascaded PID temperature control loop architecture performs well at steady state condition within a limited variation of load change at low ramp rate but it acts slowly and performs poorly at transient operating conditions of flexible operation of the boiler turbine with wide range load variation and load cycle with high ramp rate and remains far from rated conditions. In this paper, a Multi-Input Multi-Output (MIMO) Non-linear Model Predictive Control (MPC) design for regulation of the main steam temperature of a Once-Through supercritical Boiler is proposed. The controller is based on a non-linear dynamic model which incorporates dynamics of the variables of interest. It has the capability to operate effectively across a wide load range while maintaining main steam temperature within acceptable limits. A notable advancement in this design of MPC is the incorporation of coal flow demand and feedwater flow demand as additional control inputs alongside primary and secondary spray flows. In simulation test cases, the MPC controller demonstrates satisfactory performance and computational efficiency.

Keywords

Dynamic Optimization, Main Steam Temperature Control, Model Predictive Controller, Once Through Boiler Turbine System, Parameter Estimation

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1. Introduction

The boiler turbine unit plays a critical role in thermal power plants by converting the chemical energy of fuel into mechanical energy and then into electrical energy. The boiler produces high-pressure and high-temperature steam, which drives the turbine to generate electricity. Precise regulation of the electric power output of the boiler-turbine system is necessary to meet grid and load demands, while maintaining internal variables such as steam pressure and temperature within the desired range. Ensuring reliable control of superheated steam temperature is essential for the efficient and safe operation of coal-fired thermal power plants.

Various control strategies have been developed to achieve these objectives, ranging from the early Model Predictive Heuristic Control (MPHC) introduced in 1978 [1], to the widely used Proportional–Integral–Derivative (PID) control scheme [2]. Although PID control, often implemented as cascade control, has been successful in many industrial applications, it has limitations when applied to Multiple-Input Multiple-Output (MIMO) systems. Therefore, more advanced control strategies such as Model Predictive Control (MPC) have been chosen for nonlinear and highly complex systems like the boiler-turbine unit. MPC refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. At each control interval, the MPC algorithm optimizes future plant behaviour by calculating a sequence of future manipulated variable adjustments [3]. Other algorithms, such as Dynamic Matrix Control (DMC) [4, 5] and Generalized Predictive Control (GPC) [6], have also been proposed. Nonlinear model predictive control, coupled with successive online model linearization and quadratic optimization, shows promise [7, 8]. Fuzzy Model Predictive Control with hierarchical MPC architecture, which approximates nonlinear characteristics with a linear feedback controller, has also shown advancements [9]. Another significant milestone in recent years is the development of closed-loop robust MPC with bi-level optimization for boiler-turbine system control, addressing uncertainties [10].

In this paper, the control of superheated steam temperature in a Once Through Boiler (OTB) unit, through a nonlinear MIMO process implemented with MPC. MPC is a control algorithm that calculates control inputs based on the predicted behaviour of process outputs over a time horizon. The algorithm calculates future control inputs to minimize the difference between predicted control outputs and set point values over the prediction horizon. Only the first calculated control input is applied in each calculation step. This process is repeated at subsequent sampling times with prediction horizons of the same length but shifted one step forward. This concept is known as the principle of a receding horizon [11].

The aim of this study is to propose an MPC design for temperature control of the boiler turbine system. The paper is organized as follows: Firstly, we provide a description of the OTB unit under investigation, followed by a detailed explanation of its dynamic mathematical model using available design data. Subsequently, the process model based on this information is simulated under different scenarios for validation. We outline a general MPC framework and elaborate on the MPC specifications of our model. The control performance of the proposed MPC is demonstrated through various simulated test cases. Finally, we conclude by observing that MPC exhibits good set point tracking and smooth control.

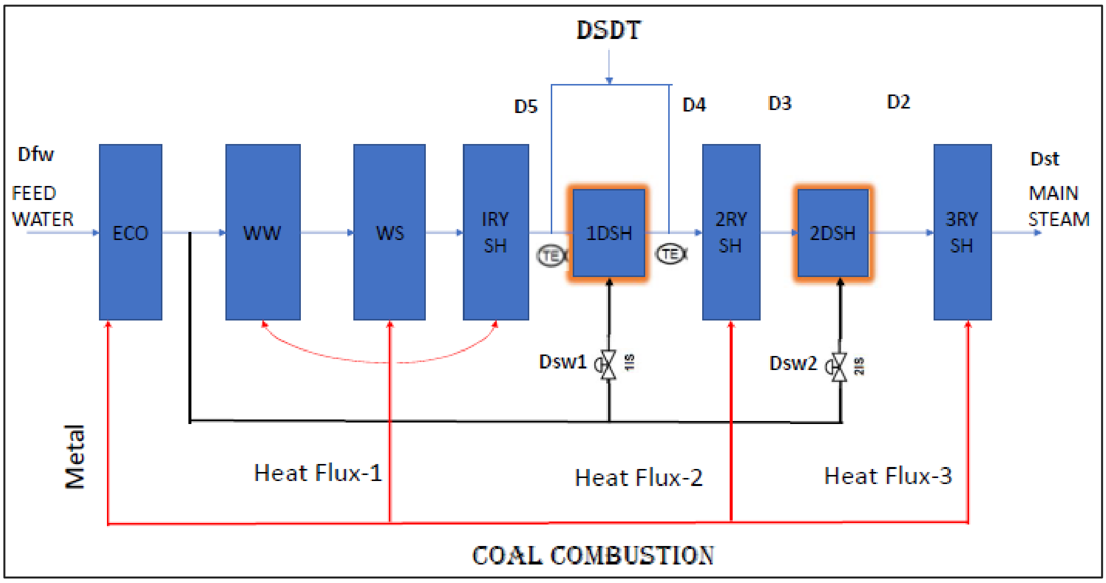


Figure 1. *Diagram of once through boiler section.*

2. OTB Unit Description

In this research, a comprehensive analysis of a 660 MW Once Through Boiler Turbine (OTBT) pulverised coal-fired unit, situated in India, is conducted. At its core, the unit consists of an ultra-supercritical sliding-pressure once-through boiler. This steam is channelled into an ultra-supercritical single reheat condensing steam turbine, a critical component ensuring the conversion of thermal energy into mechanical work.

The primary focus of this study lies in the development of a robust control strategy, supported by meticulous parameter identification using authentic operational data. This approach, grounded in empirical evidence and advanced analytical techniques, paves the way for the successful implementation of Model Predictive Control (MPC) during the operational phase of the plant.

The simplified structure diagram of a 660 MW USC OTBT coal-fired unit is portrayed in Figure 1 [12].

3. Dynamic Mathematical Model

The development of a mathematical model for the system involves deriving equations based on fundamental principles, such as conservation laws or physical laws governing the system's behaviour and utilizing grey-box modelling technique. The nonlinear model evolved after parameter identification and function fitting is relatively simple and provides a quantitative representation of the system, facilitating the analysis and prediction of its dynamic response. It serves as a valuable tool for simulation studies, control system design, and optimization. By manipulating the model equations, we can explore different scenarios, investigate system behaviour under varying conditions, and evaluate the effectiveness of different control strategies.

The model structure is described herein as a set of differential algebraic equations (1) (DAEs) [12]. The state variables, output variables, control inputs, parameters, and nonlinear functions associated with the system outlined below are also summarized in Tables 1 and 2.

$$\frac{dx_1}{dt} = \left(\frac{-1}{c_0}\right) x_1 + \left(\frac{1}{c_0}\right) u_1 \tag{1}$$

$$\frac{dx_2}{dt} = \left(\frac{h_{fw}-d_{11}}{c_{11}}\right)(u_2 - u_4 - u_5) + \left(\frac{d_{11}-h_5}{c_{11}}\right) f_2 u_3 + k_{11}\left(\frac{x_1}{c_{11}}\right)$$

$$\frac{dx_3}{dt} = \left(\frac{h_{fw}-d_{12}}{c_{12}}\right)(u_2 - u_4 - u_5) + \left(\frac{d_{12}-h_5}{c_{12}}\right) f_2 u_3 + k_{11}\left(\frac{x_1}{c_{12}}\right)$$

$$\frac{dx_4}{dt} = D_3\left(\frac{h_4 - x_4}{c_2}\right) + k_{12}\left(\frac{x_1}{c_2}\right)$$

$$\frac{dx_5}{dt} = \left(\frac{h_2-d_{21}}{c_{31}}\right) D_2 + \left(\frac{d_{21}-x_6}{c_{31}}\right) f_1 u_3 + k_{13}\left(\frac{x_1}{c_{31}}\right)$$

$$\frac{dx_6}{dt} = \left(\frac{h_2-d_{22}}{c_{32}}\right) D_2 + \left(\frac{d_{22}-x_6}{c_{32}}\right) f_1 u_3 + k_{13}\left(\frac{x_1}{c_{32}}\right)$$

$$\frac{dx_7}{dt} = \left(\frac{x_7}{c_4}\right) + k_2\left(\frac{x_6 - h_{fw}}{c_4}\right) f_1 u_3$$

$$\frac{dx_8}{dt} = \left(\frac{-1}{c_0}\right) x_8 + \left(\frac{1}{c_0}\right) u_2$$

$$h_{fw} = h_1(x_1)$$

$$h_{sw1} = h_2(x_1)$$

$$h_{sw2} = h_3(x_1)$$

$$h_5 = l x_3$$

$$P_5 = x_2 - g_1$$

$$P_3 = x_2 - g_2$$

$$D_5 = f_2 u_3$$

$$D_4 = D_5 + u_4$$

$$h_4 = \frac{D_5 h_5 + u_4 h_{sw1}}{D_4}$$

$$D_3 = D_4$$

$$D_2 = D_3 + u_5$$

$$h_2 = \frac{D_3 x_4 + u_5 h_{sw2}}{D_2}$$

$$y_1 = x_5$$

$$y_2 = x_3$$

$$y_3 = x_7$$

$$y_4 = T_1(x_2, x_4)$$

$$y_5 = T_2(x_5, x_6)$$

Table 1. *Variables of dynamic mathematical system.*

Variables	Symbol	Description
State	x_1	Coal Flow
	x_2	Water Separator Pressure
	x_3	Water Separator Enthalpy
	x_4	Platen Superheater Enthalpy
	x_5	Main Steam Pressure
	x_6	Main Steam Enthalpy
	x_7	Load
	x_8	Feedwater Flow
Output	y_1	Main Steam Pressure
	y_2	Water Separator Enthalpy
	y_3	Load
	y_4	Platen Superheater Temperature
	y_5	Main Steam Temperature
Control	u_1	Coal Flow Demand
	u_2	Feed Water Flow Demand
	u_3	Throttle Valve Opening
	u_4	Primary Spray Water Flow
	u_5	Secondary Spray Water Flow

Table 2. *Parameters of dynamic mathematical system.*

Static Parameters	Dynamic Parameters	Non-linear functions
h_{fw}	c_0	f_1
h_{sw1}	c_{11}	f_2
h_{sw2}	c_{12}	g_1
k_{11}	d_{11}	g_2
k_{12}	d_{12}	T_1
k_{13}	c_2	T_2
k_2	c_{31}	h_1
l	c_{32}	h_2
	d_{21}	h_3
	d_{22}	
	c_4	

For parameter identification and nonlinear regression of the model, steady state data of variables at various loads is required. In this regard, we utilize the design data available for analysis as presented below in Table 3.

Table 3. *Design data at various operating points.*

N_e (MW)	693	660	528	396	330
r_B (kg/s)	116.94	111.67	91.39	71.39	61.39
P_m (MPa)	29.01	28.76	23.08	17.55	14.83
h_m (kJ/kg)	2700.97	2710.51	2796.43	2811.22	2821.18
h_3 (kJ/kg)	3324.68	3326.49	3400.75	3448.79	3475.93
p_{st} (MPa)	26.48	26.48	21.28	16.18	13.63
h_{st} (kJ/kg)	3489.01	3489.01	3536.14	3580.95	3602.78
D_{fw} (kg/s)	544.44	513.61	405.28	303.61	254.72
u_B (kg/s)	116.9	111.6	91.39	71.39	61.39
D_{sw1} (kg/s)	13.61	12.86	14.19	10.64	8.92
D_{sw2} (kg/s)	13.61	12.86	14.19	10.64	8.92
D_{st} (kg/s)	544.4	513.6	405.2	303.61	254.72
T_{st} (Deg C)	603	603	603	603	603
D_5 (kg/s)	517.22	487.8	376.8	282.33	236.89
h_5 (kJ/kg)	2899.6	2881	2932	2944	2950.15
P_5 (MPa)	28.41	28.21	22.64	17.21	14.55
P_3 (MPa)	27.96	27.8	22.31	16.99	14.36
h_{fw} (kJ/kg)	1350.7	1328	1260	1181	1133.32
h_{sw} (kJ/kg)	1544.3	1521	1444	1378	1348.25
T_3 (Deg C)	556	556	560	557	557

3.1. Estimation of Static Parameters

A total of 8 static parameters $h_{fw}, h_{sw1}, h_{sw2}, k_{11}, k_{12}, k_{13}, k_2$ and l need to be identified in this system. Static parameters used in the model are calculated from the steady state running of data and nonlinear regression analysis [12]. The parameters that have been fitted are as follows:

$$h_{fw} = h_1(x_1) = 375.08x_1^{0.2686} \tag{2}$$

$$\begin{aligned} h_{sw1} &= h_2(x_1) = 561.35x_1^{0.2113} \\ h_{sw2} &= h_3(x_1) = 561.35x_1^{0.2113} \end{aligned} \tag{3}$$

$$l = (1.4 \times 10^{-5})x_1^2 - 0.002095x_1 + 1.122232 \tag{4}$$

Table 4 below lists the determined values of k_{11}, k_{12}, k_{13} and k_2 parameters at various load conditions.

Table 4. *Values of k_{11}, k_{12}, k_{13} and k_2 at different loads.*

Load (MW)	k_{11}	k_{12}	k_{13}	k_2
693	6840.04	2112.2	973.238	0.5945
660	6802.2	2124.209	955.46	0.5955
528	6900.91	2223.99	902.299	0.5728
396	6951.02	2328.16	869.96	0.5434
330	7025.99	2323.5	836.59	0.5248

The above data fits quadratic equations for k_{11}, k_{12}, k_{13} and k_2 as stated subsequently,

$$k_{11} = 7524.247 - 10.66722x_1 + 0.03986892x_1^2 \tag{5}$$

$$k_{12} = 2373.388 + 1.25306x_1 - 0.03049282x_1^2 \tag{6}$$

$$k_{13} = 741.1336 + 1.258423x_1 + 0.006044255x_1^2 \tag{7}$$

$$k_2 = 0.3491689 + 0.003678727x_1 - 0.00001338697x_1^2 \quad (8)$$

Based on steady-state simulations, it has been observed that k_{11} influences x_3, k_{12} affects x_4, k_{13} has an impact on x_6 and k_2 influences x_7.

3.2. Estimation for Dynamic Parameters

The determination of dynamic parameters is pivotal for ensuring the accuracy and effectiveness of the mathematical models employed. In this study, the focus was on 11 dynamic parameters $c_0, c_{11}, c_{12}, d_{11}, d_{12}, c_2, c_{31}, c_{32}, d_{21}, d_{22}$ *and* c_4.

Experimental data from load swing tests of the 660 MW unit was utilised for parameter estimation. The method consists of minimising a least squares objective function defined over the difference between the model predicted values and observed data. The optimization process was guided by a set of box-constrained parameters, ensuring the optimization remained within realistic boundaries aligned with the physical constraints of the system.

Subsequently, a cost function is formulated, which internally invokes the Ordinary Differential Equation (ODE) solver to generate solutions for comparison against the empirical data. To quantify the disparity between model predictions and actual data, we employ an optimized version of the L2 distance, serving as our loss function.

This approach allows simultaneous estimation of multiple parameters and is implemented in the Python programming language Leveraging the library's specific algorithms, we optimize these parameters starting from an initial guess, informed by prior experience or expert opinion. Furthermore, our methodology allows for the specification of upper and lower parameter bounds, in addition to initial guess, all of which are incorporated into the optimization function. Consequently, the optimization process yields the below mentioned parameter values that best align with the empirical data.

$$c_0 = 152, c_{11} = 110475, c_{12} = 197128$$

$$d_{11} = 103, d_{12} = 2004, c_2 = 89912, c_{31} = 2667932$$

$$c_{32} = 44805, d_{21} = 236, d_{22} = 3001, c_4 = 10 \quad (9)$$

3.3. Estimation of Non-linear Functions

Nonlinear functions involved in our system can be estimated with the aid of following equations at the steady state [12].

$$f_1 = \frac{D_5}{u_t} \quad (10)$$

$$f_2 = \frac{D_{st}}{u_t} \quad (11)$$

$$\begin{aligned} g_1 &= (x_2 - P_5)/1000 \\ g_2 &= (x_2 - P3)/1000 \end{aligned} \quad (12)$$

Consequently, suitably fitting the functions f_1, f_2, g_1 and g_2 as,

$$f_1 = 4985.00315x_5/(0.0619873x_6 - 128.448) \quad (13)$$

$$f_2 = 2621.9901/(0.0587h_5 - 117.69) \quad (14)$$

$$g_1 = 2.9897 \times 10^{-7}x_2^2 + 0.00000748x_2 + 0.0001 \quad (15)$$

$$g_2 = 4.4353 * 10^{-7}x_2^2 + 0.000018 + 0.000105 \quad (16)$$

For the calculation of the steam temperature T_3 and T_{st}, we have adopted a bilinear fitting method. In this regard we define,

$$\begin{aligned} T_1(P_5, h_5) &= \kappa_1(p_5^2) + \beta_1 P_5 + \gamma_1 \\ T_2(P_{st}, h_{st}) &= \kappa_2(p_{st}^2) + \beta_1 P_{st} + \gamma_2 \end{aligned} \quad (17)$$

where the intermediate functions are identified as,

$$\begin{aligned} \kappa_1 &= -1.292 * 10^{-7}x_4^2 + 0.000980 * x_4 - 1.878 \\ \beta_1 &= 6.5093 * 10^{-6}x_4^2 - 0.0524 * x_4 + 108.138 \\ \gamma_1 &= 1.8054 * 10^{-5}x_4^2 + 0.335 * x_4 - 887.064 \\ \kappa_2 &= -1.15034 * 10^{-7}x_6^2 + 0.000878 * x_6 - 1.6941 \\ \beta_2 &= 6.31422 * 10^{-6}x_6^2 - 0.0509 * x_6 + 105.32 \\ \gamma_2 &= 3.9667 * 10^{-6}x_6^2 + 0.4311 * x_6 - 1050.743 \end{aligned} \quad (18)$$

4. Process Model Validation

An algorithmic framework can be devised to implement the process model simulation in the Python programming language, considering the complex system of equations described above. This entails the handling of both differential equations and algebraic equations, resulting in a higher index differential algebraic system of equations (DAEs) as given in (1). Through meticulous index reduction techniques and subsequent structural simplifications, the DAEs can be transformed into a system of ordinary differential equations (ODEs) amenable to numerical solution using readily available solvers within diverse software environments. Numerous sophisticated numerical integration methodologies exist, designed to accommodate the inherent stiffness of equations encountered in practice. However, the selection of an appropriate integration technique necessitates a judicious balance between the desired level of accuracy and the computational resources allocated [13, 14].

To verify the integrity of the developed process model and estimated parameters, our primary focus lies in conducting a comprehensive evaluation of open-loop simulations. This involves examining the model's response to induced variations in input variables. In consequence, the steady-state simulation and step response of the system, utilizing the design data, discussed below.

4.1. Steady State Simulation

The process model is simulated under steady and unwavering initial conditions, specifically tailored to a load of 660 MW. Through an open loop simulation spanning a duration of 5000 seconds, the resulting outputs are meticulously observed, as visually presented in Figure 2. The comprehensive analysis includes graphical representations of the eight state variables, denoted as $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8$ and the output variable MST (y_5). Notably, these plots are generated utilizing appropriate libraries in Julia [15] , with the observed variables positioned on the y-axis and the simulation time interval accurately depicted along the x-axis.

The steady state simulation is conducted with utmost precision, ensuring accurate and reliable results. By carefully establishing and maintaining consistent initial conditions corresponding to a 660 MW load, the simulation captures the system's behaviour under these specific circumstances. The obtained outputs are carefully observed and analysed. The generated plots depict the eight state variables and the output variable MST, showcasing the intricate dynamics of the simulated process. These results are a testament to the fidelity of the simulation and provide valuable insights into the steady state behaviour of the system under examination.

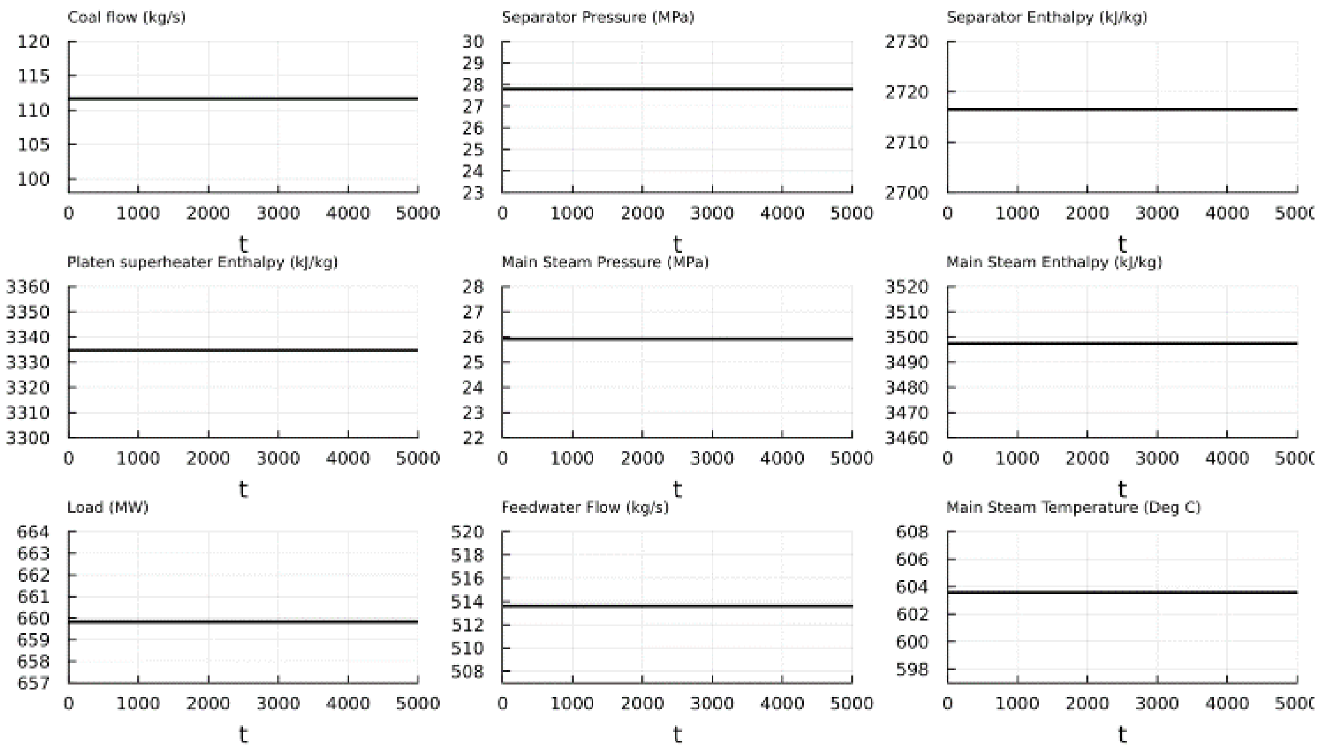


Figure 2. *Open loop steady state response of system variables.*

4.2. Step Response

Under steady and consistent initial conditions, the process model is simulated at a load of 660 MW for a duration of 5000 seconds. To evaluate the system's response, a step change is introduced in the control inputs of coal flow and feedwater flow after 500 seconds. Specifically, both inputs are subjected to an instantaneous increase of 14 kg/s, causing coal flow to transition abruptly from 111.6 kg/s to 125.6 kg/s, and feedwater flow to escalate from 513.6 kg/s to 527.6 kg/s. The consequential effects of these step changes on the state variables and the output variable MST are thoroughly analysed and graphically presented in Figure 3 and Figure 4, respectively. These visual representations provide valuable insights into the dynamic behaviour of the system as influenced by the enforced step changes in control inputs.

The conducted simulation, encompassing steady state conditions and step changes in control inputs, has yielded insightful results. By simulating the process model under consistent initial conditions at a 660 MW load, and subsequently introducing step changes in coal flow and feedwater flow, the impacts on the system's state variables and output variable MST have been thoroughly analysed. They are in line with the expected response.

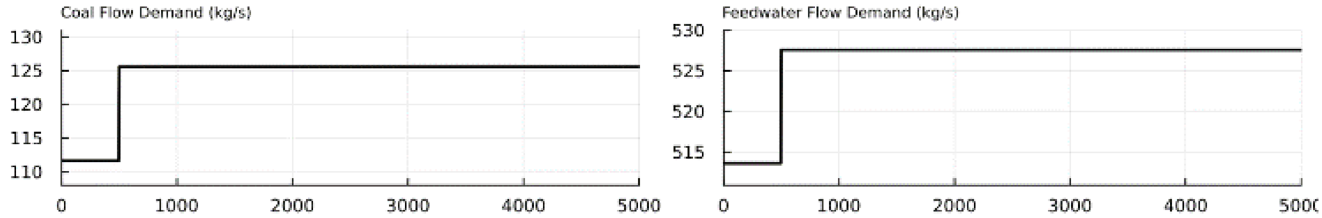


Figure 3. *Step applied in control inputs coal flow u1 and feedwater flow u2.*

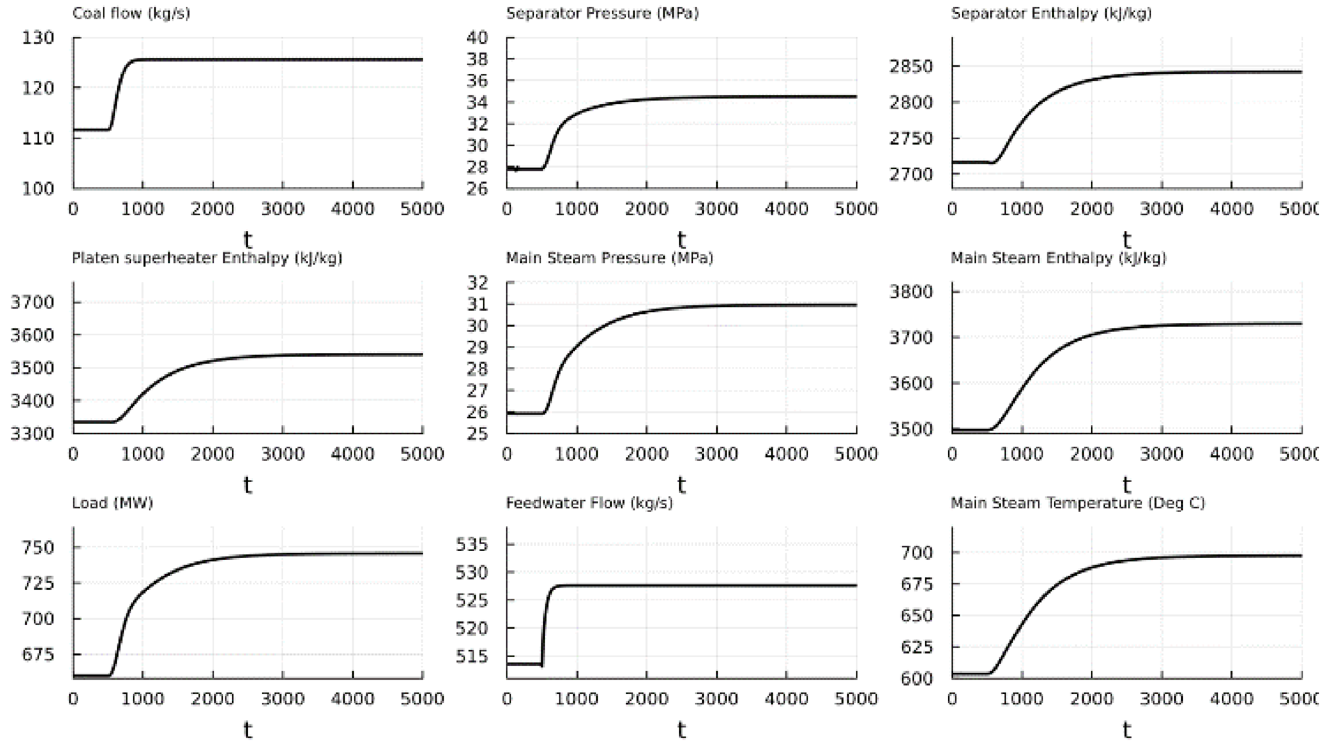


Figure 4. *Step response of state variables and output variable y5.*

5. Model Predictive Control Design

5.1. Overview on Model Predictive Control

Model Predictive Control (MPC) is an advanced and effective control technique specifically designed to address complex multivariable control problems. It is grounded in the integration of control and optimization objectives, process constraints, and the dynamic model of the system under consideration. Particularly suitable for large-scale control problems with multiple inputs and multiple outputs, MPC enables effective management of constraints placed on both inputs and outputs.

The fundamental concept of MPC can be succinctly summarized as follows: Assuming a sufficiently accurate dynamic model of the process is available, MPC utilizes the model and current measurements to forecast future values of the outputs. By considering these predictions alongside the measurements, the appropriate adjustments to the input variables can be calculated. Crucially, MPC considers the input-output relationships as represented by the process model, coordinating changes across individual input variables. The calculations performed in MPC are based on the current measurements and predictions of future output values. The primary objective of MPC is to determine a sequence of control actions that optimally guide the predicted response towards the desired set point in a proficient manner [16].

5.2. MPC Implementation

We utilize a dynamic optimization specialized package in Python to implement MPC. This package serves as a prominent algebraic modelling language for both linear and nonlinear programming applications, providing a comprehensive set of features. These features include automatic differentiation, ODE discretization using orthogonal collocation on finite elements, and bundled large-scale solvers, Moreover, the package facilitates the development and application of advanced control strategies, such as model predictive control and real-time optimization, offering valuable tools for control and optimization tasks in various domains.

Optimization problems are typically composed of variables, equations, and objectives. In line with our chosen model variable definition, the fundamental types employed are constants, parameters, variables, and intermediates. These variable types are subject to stringent boundary conditions, showcasing their distinctive characteristics within the optimization framework. In the context of MPC, the overarching objective is to minimize the disparity between the set point of the controlled variable and the model predictions, as shown below.

$$\underset{x,u}{Min}\|x - x_{sp}\| \quad (19)$$

where x denote state variable, u inputs and x_{sp} is the desired set point or target condition for that state. The objective is typically a l_1-norm or l_2-norm. There are efficient solvers for optimization that can be customized. The popular open-source interior-point solver IPOPT is a generic solver often used.

5.3. MPC Specifications for Boiler Turbine System

We present a novel control design for the dynamic model of an OTBT unit. The proposed control strategy aims to maintain main steam temperature across a wide range of loads. Specifically, this paper presents a notable advancement in the design of our MPC system, focusing on the incorporation of coal flow and feedwater flow as additional controllers alongside spray flows. Our research reveals that relying solely on spray flows for main steam temperature control in a 660 MW ultra-supercritical (UTC) power plant is insufficient. While spray flows exhibit satisfactory performance under minor load fluctuations, they fail to maintain optimal control in scenarios involving significant load swings and varying load profiles.

A time horizon of 1000 seconds is established, discretized into 100 equally spaced intervals of 10 seconds each. To address the specific requirements of our case, a multiple objective function is defined, taking into account both load and temperature set points. The primary objective is to achieve smooth control of the MST within a designated dead band around the set point, particularly when a load set point change is introduced. As such, MST (y_5) and load (x_7) are chosen as CVs. The dead band range for MST is specified as $603 \pm 1°C$, while for load it is defined as $Ne_{sp} \pm 1000kW$, with representing the desired load set point in kilowatts. The l_1-norm is selected as for the objective function formulation. Additionally, we assume that both CVs are measured. Time constant for MST response is set to be 150s. Regarding the load, the time constant is determined through a quadratic function fitted to the step size of the load set point change. The load reference trajectory is adjusted to realign with the variable's initial condition with each cycle, while the initial conditions are set to start at the bounds of the dead band, creating a consistent target over the horizon for MST. These CV options were finalized based on a series of experiments prioritizing smooth control of MST.

Assuming that all state variables have been measured, we designate eight state variables (SVs) to incorporate their measurements and adhere to non-negativity constraints. As we exclude throttle valve regulation from this model, we consider this control input as a constant parameter, along with other dynamic parameters of the model. The remaining control inputs—coal flow, feedwater flow, primary spray flow, and secondary spray flow—are manipulated as manipulated variables (MVs) to achieve the desired control set by the objective function. Among the N-move control sequence that minimizes the objective, only the initial move is executed. Upon the availability of another measurement, the problem's parameters are updated, and a new optimization problem is formulated to determine the subsequent control action. This iterative optimization process, utilizing an objective function that is modified through process feedback, constitutes one of the fundamental features of MPC. Additionally, there are constraints on MV movements to prevent infeasible conditions, such as significant jumps in MV values. It is important to note that our prediction horizon and control horizon are equivalent in duration.

6. Closed Loop Simulation with MPC

A closed loop simulation refers to a computational process in which a feedback loop is established between a controller and a dynamic system or process model. The simulation involves iteratively exchanging information between the controller and the model to evaluate the system's behaviour under varying conditions. The controller receives measurements from the system, uses them to calculate control inputs, and then feeds these inputs back to the model. The model simulates the response of the system to these inputs, and the process is repeated to observe how the system behaves over time. The closed loop simulation allows for the evaluation and optimization of control strategies, as well as the assessment of system performance and stability.

In the context of a closed loop simulation utilizing the proposed MPC model, the measured state variable values are inputted into the MPC controller. Subsequently, the controller computes the optimal control inputs required to guide the controlled variables (CVs) towards a desired trajectory. The resulting manipulated variable (MV) values are then employed by the process model to advance to the subsequent iteration.

The subsequent discussion presents the outcomes and findings derived from this closed loop simulation.

6.1. CASE 1: Load Ramp Down

To investigate the system's behaviour, a test case is performed by initializing our model under the operating conditions of 660 MW. Subsequently, a ramp-down response is initiated by modifying the load set point to 560 MW, resulting in a substantial 100 MW change. The impact of this load change on the state variables is analysed and depicted in Figure 5 and Figure 6, respectively.

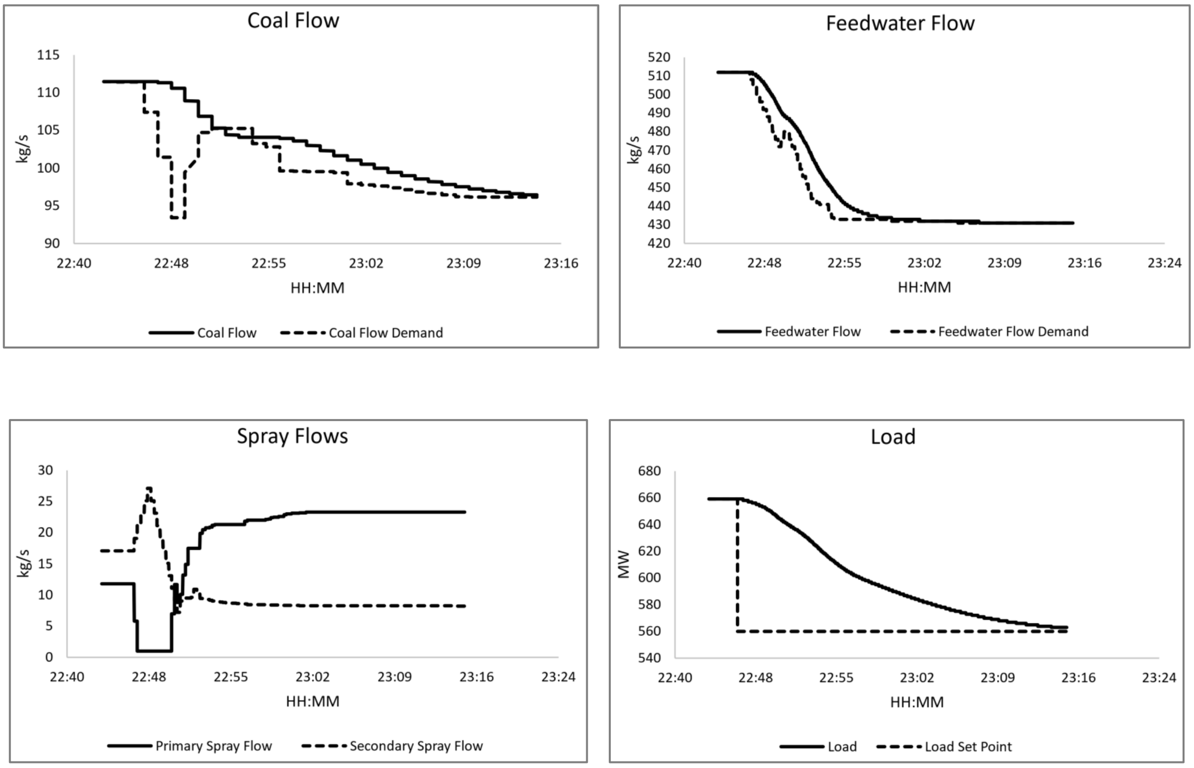


Figure 5. *Closed loop response of system variables with load ramp down.*

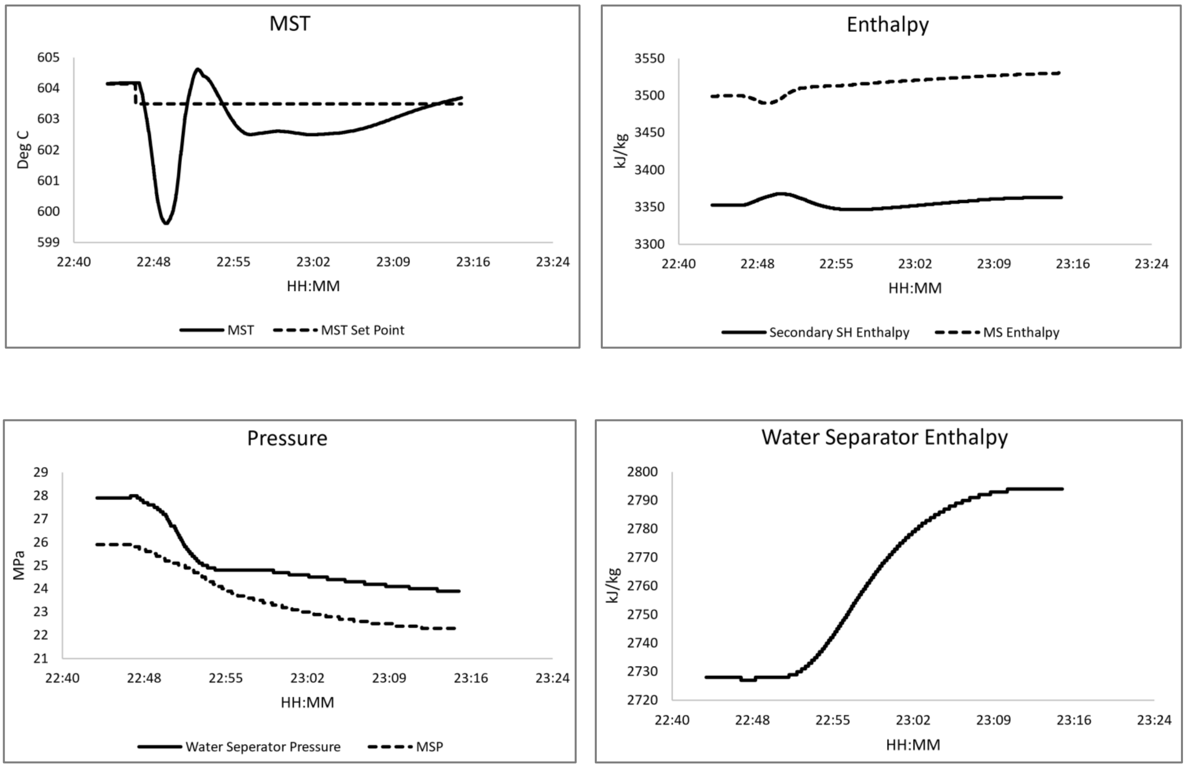


Figure 6. *Closed loop response of state variables with load ramp down.*

The conducted closed-loop simulation test case involving a load ramp-down scenario results portrays the predicted behaviour of state variables and MST in response to the ramp. The results obtained from the real-time simulation, as depicted in Figures 5 and 6, demonstrate the system's response to the load change. It can be concluded that the employed control strategy, within the framework of the proposed closed-loop MPC model, successfully managed the load ramp-down scenario. The simulation results validate the effectiveness of the control approach in achieving the desired control objective and maintaining stability in the system.

6.2. CASE 2: Load Ramp Up

In continuation, we conducted a reverse of the previous test case by initializing our closed-loop model under the operating conditions of 560 MW. Subsequently, a ramp-up response was initiated by modifying the load set point to 660 MW, resulting in a significant 100 MW change. The impact of this load change on the state variables is discussed below and can be inferred from Figure 7 and Figure 8.

The simulation test case involving a load up-down scenario yields results that portray the predicted behaviour of state variables and MST in response to the ramp. The analysis of these results provides evidence supporting the model's ability to accurately track the desired trajectory. These observations significantly contribute to the understanding of the system's response and confirm the effectiveness of the employed control strategy in managing the load ramp-up scenario.

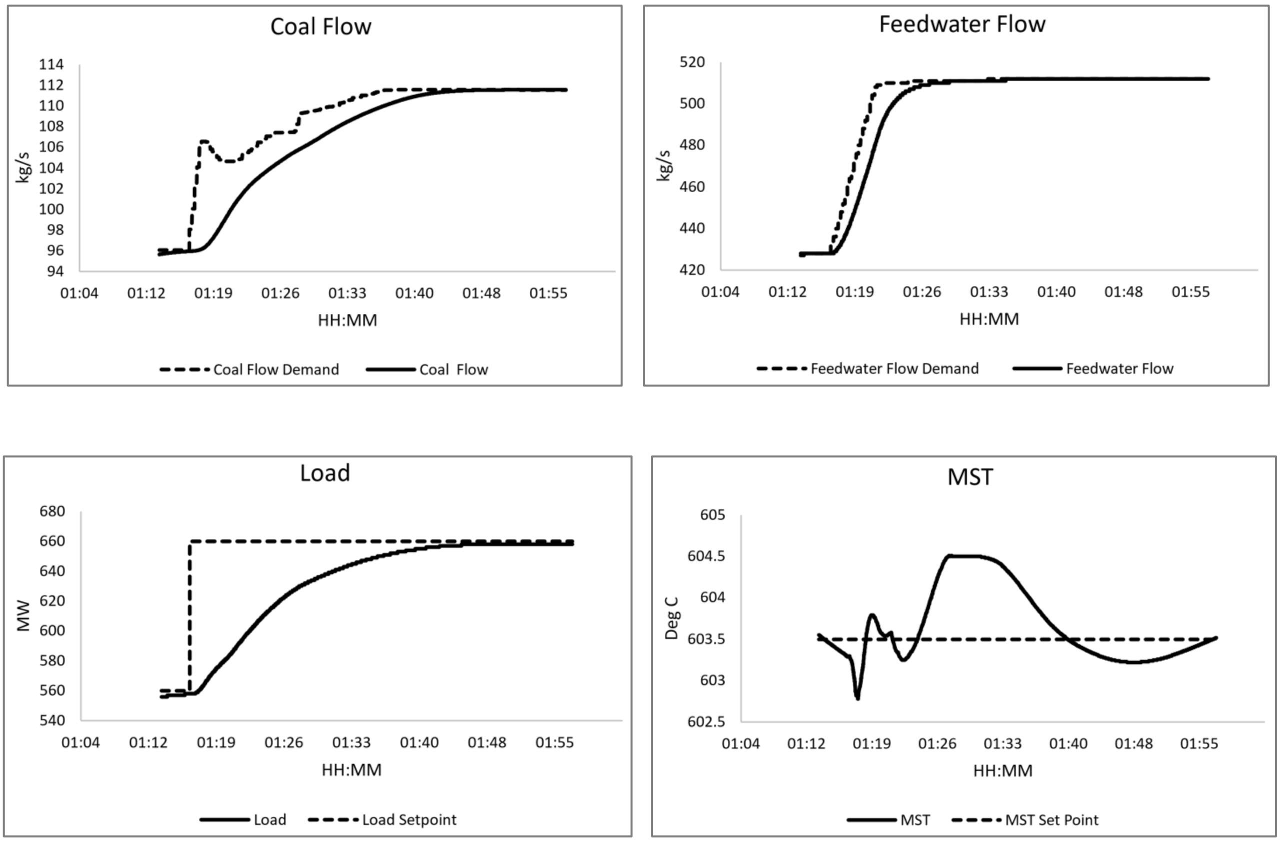
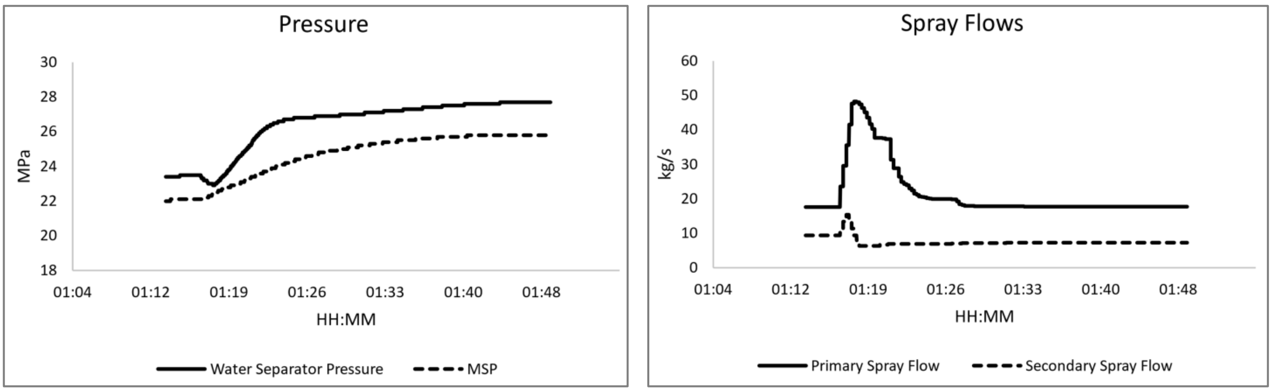


Figure 7. *Closed loop response of state variables with load ramp up.*



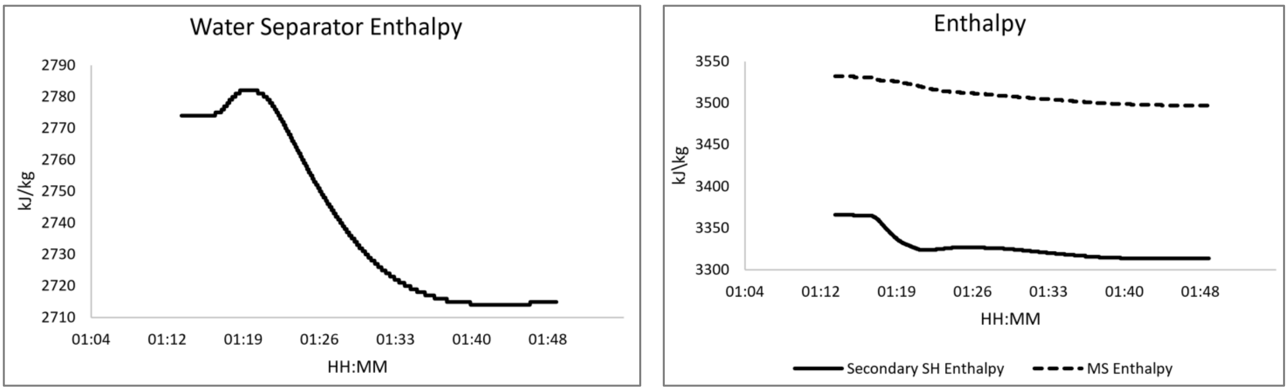


Figure 8*. Closed loop response of state variables with load ramp up.*

6.3. General Test Case

Here we present a comprehensive general test case, where the model is initialized at steady conditions with a load of 660 MW and MST) set point of 603 ℃. The load profile designed for the experiment follows a specific sequence:

660 MW -> 528 MW -> 396 MW -> 363 MW -> 330 MW -> 363 MW -> 396 MW -> 528 MW -> 660 MW

These load points represent the varying load levels during the simulation and serve as reference values for evaluating the system's behaviour. The results of the test case are presented and visualized in Figure 9 and Figure 10, respectively.

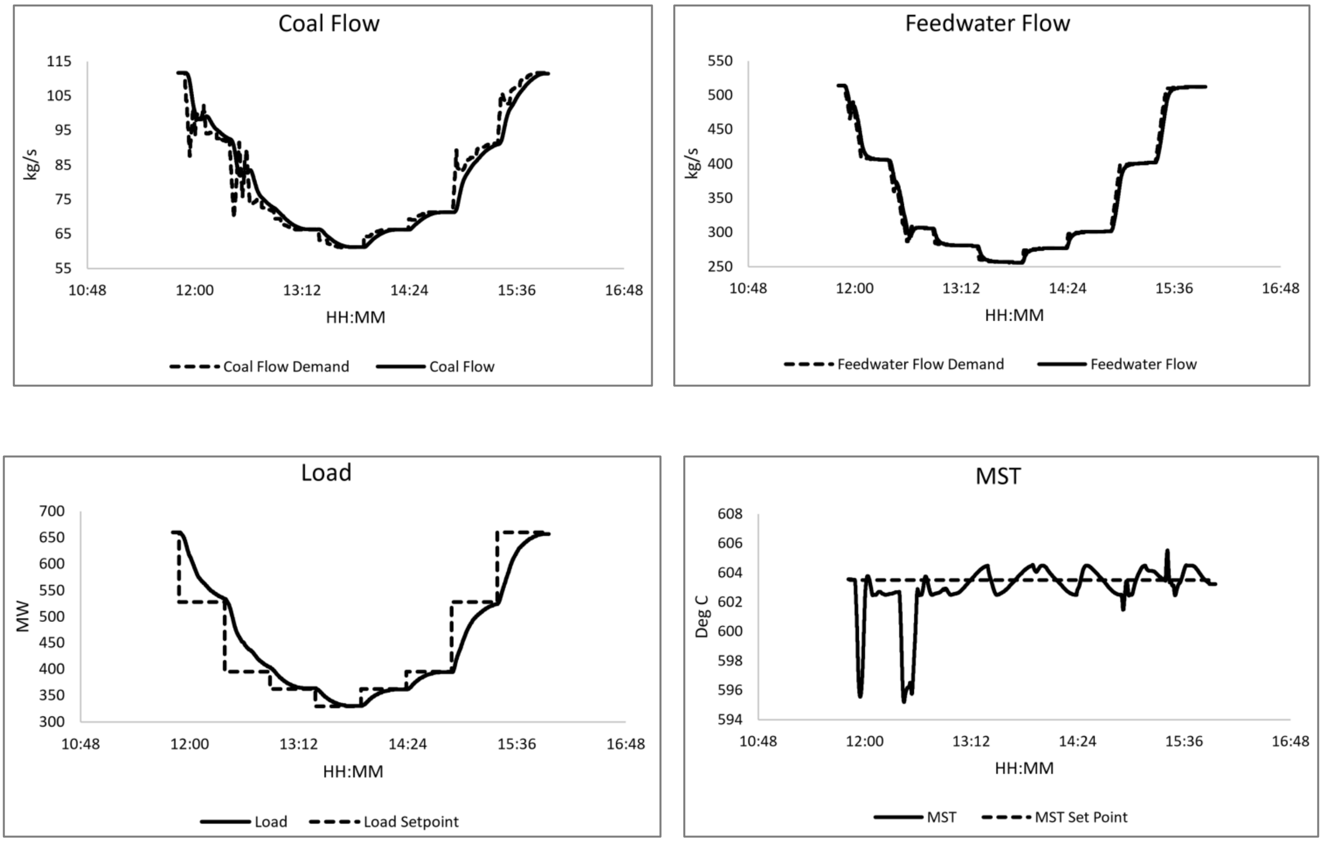


Figure 9*. Closed loop response of system variables.*

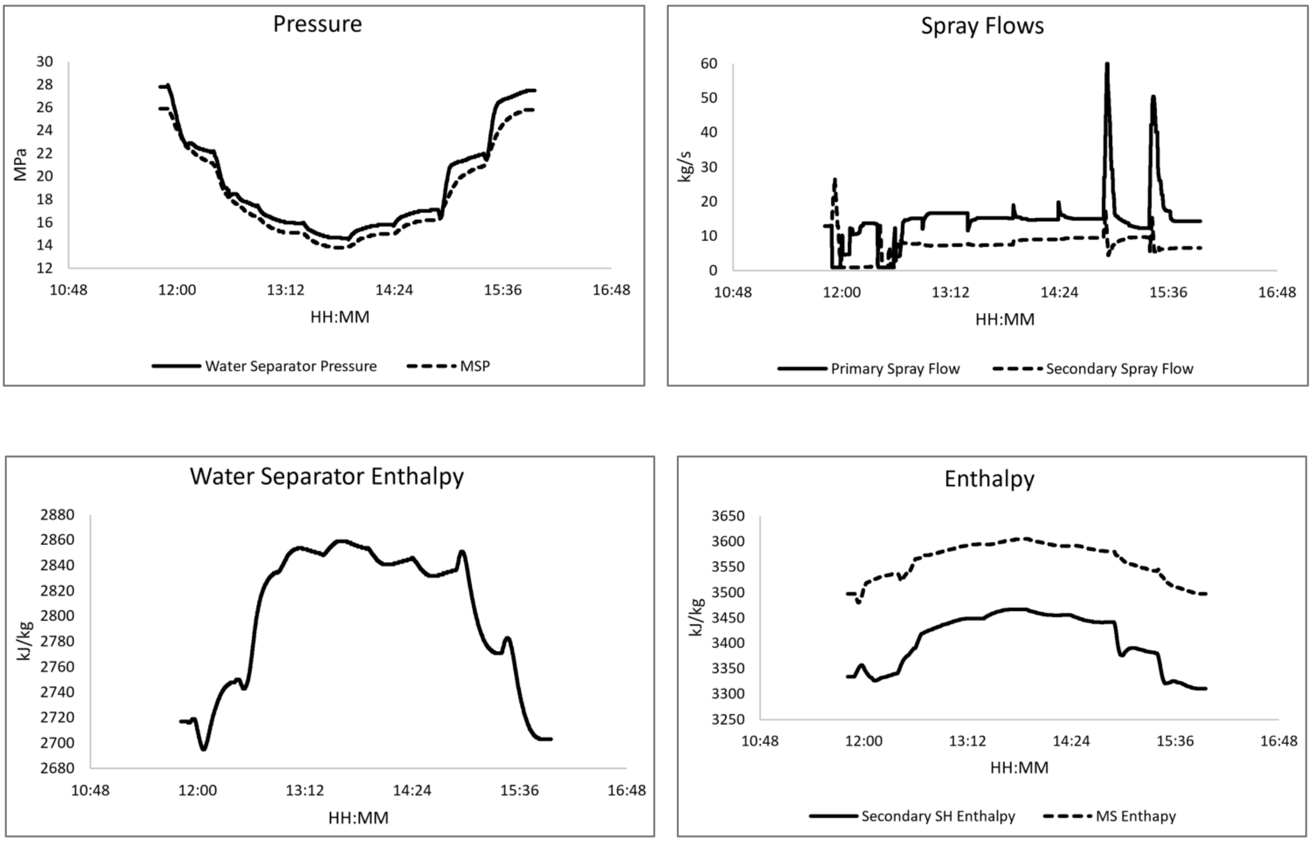


Figure 10. *Closed loop response of system variables.*

The MPC controller demonstrates efficient control action throughout the load profile, effectively tracking the desired trajectory without losing control, even during lower load profiles. These findings highlight the robustness and reliability of the control strategy, underscoring its potential for practical applications in systems requiring precise and reliable control under varying load conditions.

7. Conclusions

In recent decades, research on feedback control strategies for temperature control in coal-fired plants has progressed at an accelerated pace. MPC, due to its inherent ability to handle constraints and multiple-input multiple-output processes, emerges as a feasible option for the boiler-turbine system. In this paper, it is presented a detailed application of model-based predictive control, utilizing the dynamic mathematical model specifically developed for OTB units. The process model after parameter estimation was thoroughly validated through open-loop tests, ensuring its accuracy and reliability. Subsequently, an overview of MPC was provided, followed by a comprehensive explanation of the proposed MPC design specifications. The additional advantage of incorporating coal flow and feedwater flow as manipulated variables, in addition to spray flows, has been firmly established. The effectiveness of the control strategy was assessed through closed-loop simulations, which demonstrated its robustness in handling induced load swings. The MST exhibited only minor deviations from the specified set point, well within the permissible range, even under varying load profiles. The control performance was observed to be consistently smooth, and multiple test cases presented in this study further support the model's efficient control capabilities. Overall, the established MPC design showcases a combination of robust control and optimal performance, affirming its potential for practical implementation in coal-fired plants.

The authors declare that there is no competing financial interest or personal relationship that could have appeared to influence the work reported in this paper.

Nomenclature

u_B	Coal flow command (kg/s)
r_B	Pulverized-coal flow in furnace (kg/s)
c_0	Milling inertia time (s)
p	Steam pressure (MPa)
D	Steam or water mass flow rate (kg/s)
T	Temperature (℃)
h	Specific enthalpy (kJ/kg)
k_{11}	Energy absorbed by steam in economizer, waterwall and low temperature superheater by burning 1 kg coal (kJ/kg)

k_{12}	Energy absorbed by steam in platen superheater by burning 1 kg coal (kJ/kg)
k_{13}	Energy absorbed by steam in high temperature superheater by burning 1 kg coal (kJ/kg)
k_2	Turbine coefficient
u_t	Throttle valve opening
N_e	Unit load (MW)

Subscripts

m	State in separator
fw	Feed water
st	State at throttle war
$sw1$	Primary spray water
$sw2$	Secondary spray water
5	State at output of low temperature superheater
4	State at input of platen superheater
3	State at output of platen superheater
2	State at input of high temperature superheater
sw	Spray water

Abbreviations

OTB: Once-Through Boiler
MPC: Model Predictive Control
MST: Main Steam Temperature
DAE: Differential Algebraic Equations
MIMO: Multi-Input Multi-Output

Conflicts of Interest

The authors declare no conflicts of interest.

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