MULTIVARIBALE CONTROL OF A DRUM TYPE BOILER

BY

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To My Loving Parents

&

Beautiful Niece “Suhaima”

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IN THE NAME OF ALLAH, THE MOST BENEFICIENT, THE MOST MERCIFUL

All praises are due to Allah (SWT), the Cherisher and Sustainer of the worlds, none is worthy of worship but Him. I am sincerely thankful to Him for His kindest blessings on me and all the members of my family. I ask for His blessings, mercy and forgiveness all the time. May the peace and blessings of Allah be upon his dearest prophet, Muhammad (Peace Be upon Him).

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THESIS ABSTRACT

NAME: Syed Minhajullah

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Emission monitoring and control is becoming a crucial subject for process industry. Recently stringent regulations have been enforced to monitor and to keep the emissions to below regulatory levels. Boilers are one of the main sources of emissions of Nitrogen Oxides, commonly known as NO_x. This research work focuses on the control of boiler along with emission control of NO_x. A mathematical model for a drum type boiler is presented that takes into account NO_x development and emission. The Problem formulated considers the steam as a disturbance input as of real industrial situation. Model predictive control (MPC) is developed to control the boiler dynamics including NO_x under constraints and continuous input disturbances. The performance of the controller is compared with the conventional PI controller.

ABSTRACT (ARABIC)

الأسم : سيد منهاج الله

العنوان: التحكم متعدد المتغيرات للغلايه من النوع الاسطواني

التخصص: هندسة نظم

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رصد الانبعاثات والتحكم بها أصبح موضوعا بالغ الأهمية للعمليات الصناعيه. *مؤخرا،تم تطبيق قوانين صارمة لرصد الانبعاثات وللحفاظ عليه في مستويات منخفظه. الغلايات تعتبر واحدة من المصادر الرئيسية للانبعاثات أكاسيد النيتروجين، عاده مثل* NO_x. *هذا البحث يركز على الغلايه جنبا إلى جنب مع التحكم في مقدار الانبعاثات من* NO_x.*سوف يتم تقديم نموذج رياضي للغلايه من النوع الاسطواني بحيث يأخذ في عين الاعتبار نشوء وأنبعاث* NO_x . *لصياغة المشكلة سوف تعتبر البخار كمدخل اضطرابات لتمثل الحالة الصناعيه الحقيقة. طريقة التحكم بالنمودج عن طريق التنبؤي (*MPC*) تم تطويرها للتحكم بالديناميكيات الخاصه بالغلايه بما في ذلك* NO_x *في ظل استمرار القيود المفروضة والاضطرابات. سوف تتم مقارنة أداء وحدة تحكم المصممه مع وحدة تحكم* PI *التقليدية*

CHAPTER 1

INTRODUCTION

In Process Industries and power generation, boilers consume large amounts of fuel and produce considerable amounts of Carbon monoxide and other environmentally damaging gases such as Nitrogen oxides (NO_x). NO_x emission represents a concern as it poses risk to both the environment as well as to the human health. NO_x emission initiates reactions that affect the ozone layer and form acid rain, which could cause health problems, destruction of green land, damage buildings, impairing visibility and many other negative effects. Many efforts are being made worldwide to limit NO_x emission to certain regulatory limits meeting the strict environmental rules on air pollution [1]. Accordingly, emission of NO_x from boilers is considered a major pollutant problem and needs to be carefully monitored and controlled.

On other hand, from process dynamic point of view, boilers are nonlinear, time varying, multi- input multi- output (MIMO) systems. The major problem in controlling such nonlinear devices is that their drum water level dynamics is of integrator type that results in a critically stable behaviour causing the Shrink/Swell phenomena. Particular attention has been given to model drum level dynamics. It has been found in the literature that 30% of the emergency shut downs in pressurized water reactors (PWR) plants are caused by poor level control of the drum water level [2].

Boiler drum level control is critical for both plant protection and equipment safety and applies equally to high and low levels of water within the boiler drum [3-5].The purpose of the drum level controller is to bring the drum up to level at boiler start-up and maintain the level at constant steam load. A dramatic decrease in this level at constant steam load may uncover boiler tubes, allowing them to become overheated and damaged. On the other hand, the drum level may interfere with the process of separating moisture from steam within the drum, thus reducing boiler efficiency and carrying moisture into the process or turbine.

Improving boiler control pays large dividends, in terms of reduced fuel costs, reduced pollution, improved safety and an extended plant life-time. Many efforts in the literature addressed the issue of controlling the drum level. However, rare are those who addressed jointly NO_x emission.

In this work, boiler- NO_x problem has been addressed in three ways.

1) We developed a mathematical model for a drum type boiler that takes into account NO_x *development and emission.*

2) We considered real industrial applications under practical operation constraints and continous input disturbances.

3) We developed Model Predictive Control (MPC) combining control of the boiler dynamics and NO_x emission level.

The block diagram below shows the basic structure of the proposed Model Predictive Controller in the thesis.

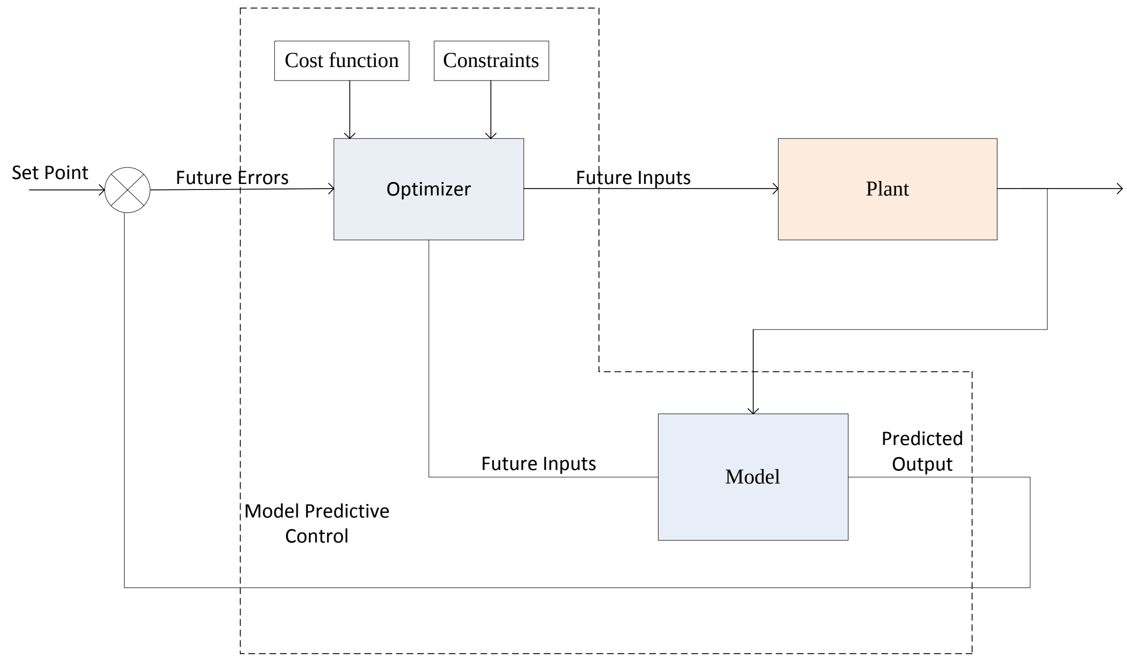

Figure 1.1: Block Diagram Structure of Model Predictive Control

The next chapter provides a detailed literature survey of the work done in the context of boiler modeling and control. NO_x emission monitoring and control and finally model predictive control are also discussed. Chapter 3 highlights the boiler system and its emission. In chapter 4 detailed descriptions of boiler and NO_x model is given and finally an augmented model is developed. In Chapter 5, the proposed controller technique is presented in detail. Chapter 6, describes the MPC formulation of the augmented boiler model along with implementation issues. The results obtained are also presented and the MPC performance is compared with the conventional PI control. Finally, the thesis was rounded up by giving conclusion and recommendations for future work.

CHAPTER 2

LITERATURE SURVEY

In this chapter, some of previous research for boiler modeling, boiler control, NO_x emission monitoring and control and finally model predictive control is discussed.

This chapter is divided into following sections,

i. Review of Modeling of Boilers
ii. Approach to Boiler Control.
iii. Approach to Emission Monitoring and Control.
iv. Model Predictive Control (MPC)

2.1 Review of Modeling of Boilers

The operations of boilers face many challenges stemming from various required safety and control issues as well as economic and regulatory issues. Dynamic simulation models of industrial boilers are essential for the study of plant transient characteristics with the aim to improve the design and control strategies to meet stringent operational requirements. Modeling of boilers has been an ongoing effort for many years. Dynamic models of boiler systems are developed on the basis of laws of conservation of mass, momentum and energy as applied to the various system's components or modules.

To our best knowledge, early work stated by Astrom and Euckland[6], considered a simple non-linear boiler turbine unit. The model was designed in a way such that it can be used as

i. a boiler Turbine model in power system studies
ii. to understand how a boiler behaves under different operating conditions
iii. to synthesize optimal trajectories for large load changes.

The experiments were conducted on the boiler unit P16 and turbine unit G16 at Oresundsverket of Sydsvenka (Sweden) for the purpose of modeling. In the experiment the variables, fuel flow, feed water flow, two attemperator (An apparatus for reducing and controlling the temperature of a superheater vapour or a fluid) flows and the control valve position were considered as inputs. The outputs are drum pressure, generated electric power, drum level, temperatures and pressures in various parts of the system. Different experiments were conducted by changing input variables. One input was changed and others were kept constant. Finally, a simplified model was developed by a combination of data analysis and physical arguments.

A simple non-linear model derived from first principles for a drum boiler was described by Astrom and Bell [7] . The model is characterized by a few physical parameters that are easily obtained from construction data. The models were found to capture the major dynamical behaviour and were validated against experimental data. The models require steam tables for a limited operating range. The model is capable of capturing the essence of the steam generation in the riser pipes.

De Mello [8] has demonstrated the validity of simplified boiler models that have previously been used to represent steam turbine mechanical power response including boiler pressure. Boiler response characteristics derived from the basic energy balance, mass balance and volume balance relations using physical boiler parameters were compared with those obtained from two other simplified models, one which matched both the steady state and transient open loop boiler response characteristics, and a simpler model which matches the initial open loop response. It was shown that both simplified models yield acceptable results of the boiler response including pressure controls.

Astrom and Bell [9] derived from first principles a non-linear model for steam generation processes. Comparison with data from plant experiment indicated that the model derives the behaviour of the system quite well. The predicted pressure swing was large in general. The results showed that increasing the metal mass results in a decrease in the swing of the pressure. Possible modifications to the model include dynamics in the model of circulation flow or making a finer subdivision of the risers.

Peet and Leung [10] discussed the development of a dynamic simulation model and its application in the study and design of drum-type boiler system to meet the operational requirements of fossil fuelled steam plants and to achieve flexible and economic production of steam.

Bell and Astrom [11] derived from first principles a non-linear model for a drum boiler. The model is characterized by a few physical parameters that are easily obtained from construction data and steam tables. Comparisons with data from plant experiments covered a large operating range for a plant at low and high loads. The results of experiments at low and high loads included changes in fuel flow, feed water and steam demand. The agreement of the model results with plant data was good. The pressure dynamics predicted agreed with the plant data. The model captured the major dynamical behaviour of the process which is verified by the extensive comparisons with real plant data presented in the paper.

Control of water circulation in steam generation is also an important problem that must be considered for plant safety and reliability. Poor water circulation may cause tubes burnout resulting in unscheduled boiler shutdown and interrupting plant operation. Poor control may lead to frequent shutdown. Water circulation in natural circulation drum-boilers is one of the critical problems in boiler technology. Such poor circulation may arise from operational-type problems such as PI changes in boiler load causing PI changes in the heat flux as a result of PI changes in fuel flow rates.

Significant modeling of boilers systems did not begin until the 1990's. Still, very little work has been presented to advance the development of modeling and simulation for design.

Adam and Marchetti [12] explored the dynamic simulation of water-in-tube boilers. The model was developed using an algorithm that utilized two non-linear models: one for the evaporation in the vertical tubes and one for the phase separation in the steam drum. Also incorporated was a PI controller for feed-water flow rate while the pressure control loop was open.

A physics based drum boiler model which runs in real-time has been developed by Flynn and O'Malley [13] . Differential equations describing the drum, downcomer and risers were solved and the control parameters were identified using data available from tests carried out on actual plant parameters. The parameters include superheated steam temperature and pressure, feedwater flow rate, fuel flow rate. The model was validated using dynamic data recorded on an actual plant. The model was shown to be useful for predicting performance capability while also modeling critical internal variables such as drum level and steam temperatures which may cause the unit to trip if safety limits are violated.

A non linear dynamic model for natural circulation of drum boilers was presented by Astrom and Bell [14] .The model describes the complicated dynamics of the drum, downcomer, and riser components. It was derived from the first principles and is characterized by a few physical parameters and can be easily scaled to represent any drum power station. The model has four states; two of these accounts for the storage of energy and mass, one for the steam distribution in the risers, and the last for the steam distribution in the drum. The model agrees well with experimental data (shrink and swell). The data obtained from the results for this model were compared to plant data demonstrating the correlation that resulted from the model to the plant data. A strong correlation was proven for both medium and high loads while changing the fuel flow rate, feed water flow rate, and steam valve for both of the loads.

Kim and Choi [15] developed a model for water level dynamics in the drum-riser-downcomer loop of a natural circulation drum-type boiler. The model is based on basic conservation rules of mass, momentum, and energy, together with the constitutional equations. The work provides an investigation of the response of water level dynamics to changes in steam demand and/or heating rate. The results were compared with those of

Astrom and Bell [14]. Likewise Astrom and Bell [14] the assumption of metal temperature being equal to the steam saturation temperature and the linear variation of the steam quality along the riser tubes is employed.

2.2 Approach to Boiler Control

The main control problems that are normally handled are the combustion control and the drum level control. The combustion control is mainly aimed at providing the right energy input to maintain the drum pressure. It is also aimed at controlling the air to fuel ratio to minimize the incomplete combustion and limit the excess air to achieve economic operation at different boiler loads. The objective of the boiler drum level control systems is to maintain the water/steam interface at its optimum level to provide a continuous mass/heat balance by replacing the steam leaving the boiler with feedwater to replace it. The interface level is subjected to several disturbances in the water/steam drum. These are the drum pressure and feedwater temperature.

Particular attention has been given to model drum level dynamics as it has been found in the literature that 30% of the emergency shut downs in pressurised water reactors (PWR) plants are caused by poor level control of the drum water level [2]. The drum-level control is difficult because of the complicated shrink and swells dynamics as stated above. These create a non- minimum phase behaviour, which changes significantly with the operating conditions.

Huang *et al* [4] proposed adaptive control strategy for the drum level of a power plant boiler. The boiler is controlled by three element feed water PI control, Recursive least square (RLS) method is used to identify the plant parameters and Genetic Algorithm (GA) is applied to find the optimum parameters of the controller. Results showed that GA self tuned system is able to have better self adaptation and reduce disturbances compared to the fixed PI system.

Yang *et al* [16] proposed a new approach for water level control in power station based on an internal model control using neural networks. The control system adopted the steam flux signal to the internal model controller. The influence of load changing, which has the ability of feed-forward compensation for steam flux disturbance was considered. The authors indicated that the system also can avoid "false water level" phenomenon.

Pellegrinetti and Bentsman [17], developed a boiler model on the basis of fundamental physical laws with previous efforts in boiler modeling with known physical constants, plant data, and heuristic adjustments The resulting fairly accurate model is non linear and of order four. The model includes inverse response, time delays, measurement noise models, and a load disturbance component. The model can be used for the purpose of model-based control algorithms as well as setting up a real-time simulator for testing of new boiler control systems and operator training.

Pedersen, Hansen and Hangstrup [18] proposed a multivariable controller as optional process optimizing extensions to existing convectional control systems. The basic idea is to consider a conventionally controlled power plant boiler as the process to be optimized. For the purpose it is making use of Linear Quadratic (LQ) controller. The control errors from the conventional controllers are used as inputs to a LQ-controller. The outputs from the LQ controller are added to the outputs from the conventional PI-type controller. The performance has been evaluated on a non linear boiler model.

Kai and Li [19] design fuzzy controlled system to tune the parameters of PI controllers on-line and apply to the drum boiler. Two control variables, fuel flow rate and water feed rate were used as control variables for drum pressure and drum water level. The PI controller and Fuzzy system tuned PI controller were designed. The two controllers were compared, for set point tracking fuzzy controller gave less overshoot and quick convergence. For disturbance rejection also it turned out be effective.

Robert and Lee [20] used Genetic Algorithm (GA) to design PI controller and State feedback controller for a non linear boiler turbine unit. The goal of the GA is to determine the matrix gains to ensure tracking of the reference signal over wide operating range. This controller was compared with that of a LQR system of a linearised model. Step responses showed that GA/PI controller achieved good steady state tracking.

A fuzzy model-based control methodology was proposed by Cheng and Rees [21] for controlling the steam generation in a drum-boiler power plant. The hierarchical control structure consists of three levels; compensator, scheduling and planning layers. The compensator layer includes a set of state feedback compensators, feedforward compensators and state estimators. The scheduling and planning layers were incorporated with the approximate reasoning feature of the fuzzy model to form a fuzzy coordinator.

Elshafei *et al* [22] provides an optimization method of the swing rate for the steam generation units using genetic algorithm. This optimization framework is suggested to provide improved ability of the boilers to respond to fast steam load changes. The optimization technique is able to reduce the firing rate overshoots, drum level fluctuation, feedwater oscillations and maximizing the allowable rate of increase in steam delivery per minute ensuring good performance and good safety.

Wang, Li and Zhang [23] proposed a hybrid classical/fuzzy control methodology to integrate high-level supervision for the steam temperature and water level processes of power plant boiler. To overcome the problem of coordination between two spraying systems they developed decoupling rules based on human experience for primary spraying process and proposed a hybrid intelligent control methodology by adding a extra fuzzy- PI to the existing PI controller for secondary spraying process. For the purpose of water level they proposed a multivariable fuzzy controller which proved to be better than traditional PI control. In industrial applications, it resulted in superiority over the traditional control methods.

Tan, Marquez and Chen [24] proposed a multivariable robust controller design for utility boiler system. The boiler model considered is Syncrude utility plant of SCL (Canada) which has got their simulation package called SYNSIM. The model is simulated using this software. They identified Linear Time Invariant (LTI) model by collecting I/P and O/P data on Synsim and identification tool box of Matlab. For the purpose of control design they adopted H_∞ loop-shaping technique and reduce this controller to multivariable PI controller. The multi loop PI controller presently used in plants, H_∞ controller and its PI approximation both in frequency and time domain were compared and it resulted that designed PI controller outperforms the existing one in both robustness and performance.

Aranda, Frye and Qian [25] developed a dynamic non-linear model for the CPS energy spruce natural circulation drum boiler and also designed a controller for it. Among the model in literature the CPS model closely represented the Astrom and Bell model. The boiler model was simulated on Matlab to study the dynamic behaviour of it, Then an Unscented Kalman Filter (UKF).

(The Unscented Kalman Filter belongs to a bigger class of filters called Sigma-Point Kalman Filters or Linear Regression Kalman Filters, which are using the statistical linearization technique) was applied to the boiler model to estimate the un-measurable states of the model. Two measurable outputs from the model drum pressure and drum water level were fed into the UKF. These estimated states are then compared with the measurable states of the non-linear model. These results tracks the actual outputs, then un-measurable estimation of states gives a clear idea of how much steam is present under the liquid level in the drum. Finally, controller is developed based on linear models that approximate the linear model.

Wen and Ydstie [26] discusses a modeling and control scheme for boiler system. Authors introduced a state space model derived from Astrom and Bell’s boiler model [14] for drum boilers with natural recirculation. The states of this new state space model are total mass and energy inventories. The model shows affine structure in control variables which is beneficial for controller design. The affine structure is build directly from the mass, energy and momentum balance laws. Based on this new model, authors proposed a passivity based inventory controller giving asymptotic stability of the closed loop boiler system.

2.3 Approach to Emission Monitoring and Control

Climate change is one of the greatest problems facing humankind. Pollution is considered the main reason for climate change. Environmental degradation issues due to pollution have gained as significant attention at international and regional levels.

Emissions of Nitrogen oxide NO_x and CO are major global and regional pollutants from industrial boilers, Combustion optimization has recently demonstrated its potential to reduce NO_x emissions. It includes two important and separate steps, i.e. NO_xemission modeling and NO_x emission control (optimization). Due to this there has been research on monitoring and control methods for emission from industries.

Emission monitoring (NO_x) is carried out by different modeling techniques like Computational Fluent dynamics (CFD), Artificial Neural Networks (ANN) and Support Vector Regression (SVR).

Neural network based Soft sensors for monitoring NO_x prediction was addressed by many researchers.

Elshafei, Habib and Dajani [27] developed an inferential soft sensor based on polynomial function network, for emission monitoring of NO_x and O_2 from a water tube boiler. Boiler model was simulated in commercial CFD package FLUENT. Simulation results showed that boiler efficiency increases by 0.25% by decreasing the excess oxygen O_2 from 1% to 5%, in turn saving one ton of fuel daily in a 160 MW boiler. This soft sensor can be used practical application for industrial boilers.

Ahmed [28] proposed soft sensors for NO_x and O_2 prediction from industrial water tube boiler. Soft sensors were based on static neural networks. Different static neural networks like multilayer perceptron and radial basis function were discussed. Particle Swarm Optimization algorithm was used for training multi layer perceptron. A static neural network model was developed using real data from an industrial boiler. Soft sensors were simulated under FLUENT CFD package. Results from different training algorithms were also discussed and compared.

Shakil *et al* [29] developed a soft sensor based on dynamic neural network model for NO_x and O_2 prediction from an industrial boiler. The boiler unit considered here is a water tube boiler equipped with temperature sensors at the superheater tubes and the riser tubes for monitoring their temperature. These temperatures were referred as skin temperatures which are inputs to the model. Data is scaled and then Principal Component Analysis (PCA) is applied for data reduction. The genetic Algorithm (GA) is used to estimate the system's time delays by optimizing a linear time-delay model. Models were validated by real data from a boiler plant. Results demonstrated that the proposed dynamic neural network model performed better than static neural network models.

Dong, McAvoy and Chang [30] proposed a soft –sensor for NOx approximation from an industrial heater. It involves two parts, first one has sensor for data analysis using Non-linear principal component analysis (NLPCA) which has associative neural net with two three-layer neural networks and NLPCA was used for data analysis. The second part involves neural network partial least square (NNPLS). The results showed that the proposed soft sensor approach gives much better results than a linear method.

Qin, Yue and Dunia [31] proposed a self validating inferential sensor for emission monitoring from industrial boilers. Proposed model was based on principal component analysis (PCA). They proposed fault identifications and reconstruction schemes earlier which were used for validation of input sensors. Validated principal components were used to predict the emission from boilers using regressors.

L. Hua, W. Hua and Feng [32] developed a soft-sensor model of NO_x emission based on Least Squares Support vector machines (LSSVM) of Power Station Boilers. Different factors which impact NO_x emission such as boiler load, distribution mode of over-fire air and secondary air, variable coals, burner's swing were studied. 12 data sets were obtained and based on it NO_x emission model was built. This model handles the linear and non-linear properties between the input variables effectively. When compared with ANN, simulation results showed that generalization ability of sample data and the time of its training is shorter.

The primary advantage of NN is the fast and simple model development without a prior detailed knowledge of the process to be identified. One drawback, however, is the long training time to get reasonable results.

Reisnschmidt and Ling [33] developed feedforward Neural network (NN) for the modeling and control of NO_x emissions from coal-fired boilers. NN NOx simulation model and NN controller were trained using real plant data. To restrict the range of controller, Multiple-state neurons are used in NN. For network training purpose a modified propagation algorithm is used. The results showed that neural network NO_x

simulation model and NO_x controller can be used as a real-time advisor for the plant to handle various operating conditions, including faulted conditions.

Ohl, Ayoubi and Kurth [34] proposed a dynamical model of a power plant using static neural network and linear dynamical models. Two different models were presented using radial basis and multilayer perceptron. In the first model, dynamics were introduced at the input of each neuron of multilayer perceptron. In the second case, a dynamical part was used at the output of each neuron in the radial basis neural network. Second order dynamical IIR model was used in each neural network model.

Li and Thompson [35] developed a novel type of neural network, namely a cascade neural network for modeling of NO_x emission from a 300 MW coal fired power generation plant. This cascade neural network has the properties of feed forward network (FFN). The network was shown to have more connection than that found in FNN, and therefore leads to a network with less number of neuron. For training purpose a data set was obtained using DAS system and it was trained using back propagation algorithms with momentum gradient method. Only 3 inner nodes were considered for modeling the NOx emission for a power generation plant. Model was simulated for different time intervals and simulation results showed that the model is capable of predicting NOx to about 7% of error to target ratio.

Li and Thompson [36] presented a mathematical model NO_x emissions for a power plant boiler. The model is developed from the extended Zeldovich mechanism and needs only few physical parameters from experiments. The boiler with oil firing unit was used for experiments. For the sake of modeling NO_x different parameters were obtained from experiments. The model can be used for combustion control and optimizing boiler operation as well. Finally, responses of NO_x to changes in fuel flow rate, fuel air ratio and burner tilt are shown.

Li**,** Thompson and Peng [37] proposed a NO_x emissions modeling for real-time operation and control of a 200 MW coal-fired power generation plant. The fundamentals governing the NO_x formation mechanisms and a system identification technique is used to develop a grey-box model. This approach extracted a collection of fundamental non-linear functions from the NO_x formation equations. Based on operation plant data used for modeling and validation, a linear Auto Regressive (ARX) model and a non-linear ARX model (NARX) are built. Although the three models were similar in terms of short-prediction performance, the developed grey-box model is able to consistently produce better overall long-term production than other two models. When compared with CFD models if only NO_x emission information is required than the proposed model gives the better prediction.

Hao, Kefa and Jianbo [38] introduced a way of optimizing the NO_x using neural network and Genetic algorithm (GA) for pulverized coal combustion of 600 MW capacity tangentially fired boiler operated under different operating conditions. Several tests were conducted by changing the boiler parameters like boiler load, secondary air distribution pattern, coal quality, etc. to analyse the NO_x emission characteristics of the boiler. Based on experimental data, a neural network based model was developed and was trained using Back Propagation (BP) algorithm, and GA was applied to find the optimum operating parameters to decrease the NO_x emission. ANN model proved to be more convenient and direct and less time consuming comparatively to CFD.

Hao, Kefa and Fan [39] introduced an approach to predict the NO_x emission characteristics of a large capacity pulverized coal fired boiler with artificial neural networks (ANN). The NO_x emission and carbon burnout characteristics were investigated through parametric field experiments. The effects of over-fire-air (OFA) flow rates, coal properties, boiler load, air distribution scheme and nozzle tilt were studied. On the basis of the experimental results, an ANN was used to model the NO_x emission characteristics and the carbon burnout characteristics. Compared with the other modeling techniques, such as computational fluid dynamics (CFD) approach, the ANN approach is more convenient and direct, and can achieve good prediction effects under various operating conditions. For optimization, a modified genetic algorithm (GA) using the micro-GA technique was employed to perform a search to determine the optimum solution of the ANN model, determining the optimal set points for the current operating conditions, which can suggest operators' correct actions to decrease NO_x emission.

Ahmad *et al* [40] developed a model based on ANN for monitoring and control of emission from the palm oil mill. The different pollutants (CO, NO_x and SO) data has been collected by using a gas analyzer. ANN model is combined with genetic algorithm (GA) to find the optimal operating value. Initially GA writes the selected input parameters in the text file. The text file is then read by the ANN and received as a new input parameter. Then, ANN will predict the output value, this generated value is compared with the pollutant limit. If the value exceeds the limit, GA generates new input parameters from the GA operator. It is repeated until the optimal input values of fuel are found.

Zhang *et al* [41] developed a hybrid ANN model to predict the boiler efficiency and pollutant emissions of a 360MW W-flame coal fired boiler. As boiler efficiency and NOx emissions have strong relationship with furnace temperature, it was selected as intermediate variable in the hybrid model, hence the predictive precision of hybrid model was improved. Based on the neural network and optimal objects GA was employed to seek real-time solution for every 30 seconds. Optimum manipulated variables were obtained under different operating conditions. This algorithm was interconnected with DCS gave the supervisory control and achieved real-time coordination optimization control of utility boiler.

Zheng *et al* [42] developed a new technique for modeling NO_x emission rather than by NN. Support Vector Regression (SVR) was introduced to model the relationship between NO_x emissions and operating parameters of a 300 MW coal-fired utility boiler, in which 19 operating parameters of the boiler was chosen as inputs, the NO_x emission as output. Experiments were conducted under different conditions. The training and testing data for SVR modeling were obtained from the DCS and CEMS equipped on the boiler.SVR parameters were determined by the grid search method and GA. To search for or to regulate the (optimizing) the optimal inputs of SVR model so as to achieve low NOx emissions Ant Colony Optimization (ACO) is used. The predicted NO_x emissions from the SVR model showed better agreement than that of ANN and ACO proved to be better optimizing tool than GA. Combination of SVR and ACO showed that it reduces NOx emission by about 18.69% (65ppm) and moreover, a time period of less than 6 min was required for NOx emissions modeling and 2 min for run of optimization under a PC system which are suitable for the online application of the actual power plants.

Zhao and Wang [43] proposed a hybrid model by combining SVR with simplified boiler efficiency model to obtain relationship between operational parameters and both NOx emission and boiler efficiency of 600 MW pulverised coal fired utility boiler. The experimental data was recorded by DCS and CEMS. In hybrid model, three SVR models were employed for relationship purpose. Grid search method and 5-fold cross validation method were combined to find the SVR parameters. For optimizing purpose, CenterPSO was introduced rather than traditional PSO. The results showed that prediction of NO_x emission and boiler efficiency by the hybrid model reduces by about 13.83mg/Nm 3 % and increases efficiency by 2.1 %. When compared with the BPNN model, it showed to be more promising than BPNN.

Zhou, Zheng and Cen [44] most recently introduced SVR based NO_x emission model and used ACO for solving low NO_x emission from a 300 MW coal-fired utility boiler. It showed that ACO has better performance than Gain terms of quality of solutions and convergence speed. However, its computational efficiency is yet to be improved (about 2min computational time). For that purpose Particle Swarm Optimization (PSO) was employed as an optimizing tool in order to improve time efficiency and so as to reduce NOx emission. The proposed approach were compared with GA and ACO under different conditions and showed that the mean optimization results derived from PSO, ACO and GA were 32.67%, 32.27% and 26.37% NO_x reduction respectively. The computational time of PSO was less than 25 sec under a PC system, was about one fifth of those required for ACO.

2.4 Model predictive Control (MPC)

The working of MPC is well-known in the literature and will be discussed in detail in Chapter 5. In the literature, different MPC structures and slightly varying algorithms are abundantly found. The typical way to present these is to apply the algorithm to a challenging problem/application and observe the results.

Hogg and El-Rabaie [45] presented an application of Generalised Predictive control (GPC) to superheat steam pressure of a 200 MW drum boiler. They initially used a, single loop PI controllers, but performance of such controllers is limited since they do not account for variations in the system parameters. Then they used a practical motivation for considering adaptive or self-tuning control. The results showed that improvements in control can be achieved with GPC. Steam pressure variations were reduced, without offsets or overshoot, and with less controller activity. In addition, due to interactions between control loops, there was a reduction in variations of steam temperatures and other outputs.

Molloy and Ringwood [46] showed that a linear model based controller is multivariable and computationally efficient than a conventional PI controller. They employed a general predictive control strategy which attempts to achieve its objective by finding the controller action which minimises an appropriate cost function .The controller was fuzzified to operate well over the full operating range of the plant.

Sbarbaro and Jones [47] applied a nonlinear predictive controller incorporating a nonlinear model-based observer within the MPC framework for the control of a paper machine headbox. The proposed approach was shown to handle deterministic disturbances, constraints in the manipulated variables and mismatch between model and process. Under very restrictive assumptions the algorithm can be interpreted as a linearizing controller.

Parker, Doyle and Pappas [48] applied MPC to control the level of blood glucose in Type I diabetic patients. A nonlinear model of the diabetic patient is developed using compartmental modeling theory and literature data. The constraint handling and prediction capabilities of MPC provide an excellent framework for the glucose control problem. Linear MPC proved to be sufficient for controlling blood glucose, but it results in glucose concentrations near the output lower bound. Therefore, Linear MPC with state estimation, utilizing a Kalman filter and a more accurate Internal Model (IMC), yields improved control when compared to the linear MPC scheme and a discretized IMC controller from literature.

Tan, Chen and Marquez [49] employed MPC on SYNCRUDE utility boiler plant for boiler firing rate control. Initially, the system is equipped with PI control, to control firing rate with ease and simplicity, but due to large (load) disturbances, primarily due to firing rate limit constraints, causes unstability, so a Derivative term in the existing PI controller is introduced and re-tune the resultant PI controller for firing rate control. Later they used MPC to overcome the poor performance of PI controller for small load disturbances. Simulation results showed that both PI and MPC controllers can improve plant stability and performance due to sudden change in steam demand for firing rate control of an industrial boiler, but MPC was recommended as it gives superior performance and stability and handles controller constraints effectively.

MPC is also applied to glass melting process [50] and mechanical pulp bleaching process [51].

Xu, Shaoyuan and Cai [52] proposed a cascade model predictive control scheme for boiler drum level control. This algorithm had been implemented to control a 75-MW boiler plant, and the results showed an improvement over conventional (PI) control scheme. The system has two loops, the inner loop (feedwater flow-valve position) used an adaptive model based predictive controller, to overcome the disturbances, while the outer loop (drum level water flow system) used a GPC controller to restrain the error from nonlinear identification of the generalized system. Simulation results showed that cascade GPC performed better than the well tuned cascade PI controller, and the performance of the system was very good.

Vladimir and Findejs [53] showed application of model predictive control for advanced combustion control (ACC). Their main emphasis was to control boiler pressure while simultaneous keeping combustion (air-fuel ratio) optimization coordination. They also came up with the actual plant results and operational experience with ACC and it showed substantial improvement in boiler efficiency and reduction in NOx production.

Majanne [54] demonstrated the use of MPC to control the pressure in a multilevel steam network in a simulator environment. Three steam pressures controlled were steam pressure in the high pressure (HP) header, pressures in the intermediate pressure (IP) and low pressure (LP) headers. He compared operation of MPC with conventional PI controller. Results showed that MPC can stabilize pressures in IP and LP headers better than PI controller, and pressure response in the HP header were almost equal. He also demonstrated MPC as a tool for process design.

Liu and Lin [55] presented MPC method which combines integral control and constraint handling proposed for mechatronic system. They designed state observer using pole placement for output feedback control. They applied the proposed controller to the piezo-actuated system. Different controller design parameters, (Prediction horizon, control horizon, weighting parameters) that effects control design were analyzed.

CHAPTER 3

BOILER SYSTEM AND EMISSION FORMATION

3.1 Boilers in Brief

Boiler system is briefly introduced in this section since it is the plant under study in this thesis.

The term "boiler" applies to a device for generating (1) steam for power, processing or heating purposes; or (2) hot water for heating purposes or water supply [56]. Boilers are designed to transmit heat by convection and radiation from combustion of fuel. Heating mechanism is provided through a firebox or a furnace. The purpose of this firebox is to burn the fuel to provide heat for the convection process. Boiler operation is a complex operation [27], hot water or steam must be delivered to couples system or turbine at a fixed rate, pressure and temperature for reliable operation. It is also desired to keep the pollutants minimum while maintaining optimal efficiency of the boiler. Simplified dynamic models for steam and water side for drum boilers were proposed in [7]. These models have been developed to be used to guide power plant operations or to design simulators and control systems. Nonlinear model for boiler dynamics were proposed by Pellegrinetti and Bentsman [17] and NO_x emission by Li and Thompson [36].

A common classification of boilers is based on whether the gas flows inside or outside the tubes. In fire tube boilers, the flue gases flow inside the tubes, whereas in water tube boilers, the gas flows outside the tubes. The features of each type are discussed below.

3.1.1 Fire tube boilers

Fire tube boilers consist of a series of straight tubes that are housed inside a water-filled outer shell [57]. The tubes are arranged so that hot combustion gases flow through the tubes. As the hot gases flow through the tubes, they heat the water surrounding the tubes. The water is confined by the outer shell of boiler. To avoid the need for a thick outer shell fire tube boilers are used for lower pressure applications. Generally, the heat input capacities for fire tube boilers are limited to 50 mbtu per hour or less, but in recent years the size of fire tube boilers has increased. Most modern fire tube boilers have cylindrical outer shells with a small round combustion chamber located inside the bottom of the shell. Depending on the construction details, these boilers have tubes configured in one, two, three, or four pass arrangements. Because the design of fire tube boilers is simple, they are easy to construct in a shop and can be shipped fully assembled as a package unit.

These boilers contain long steel tubes through which the hot gases from the furnace pass and around which the hot gases from the furnace pass and around which the water circulates. Fire tube boilers typically have a lower initial cost, are more fuel efficient and are easier to operate.

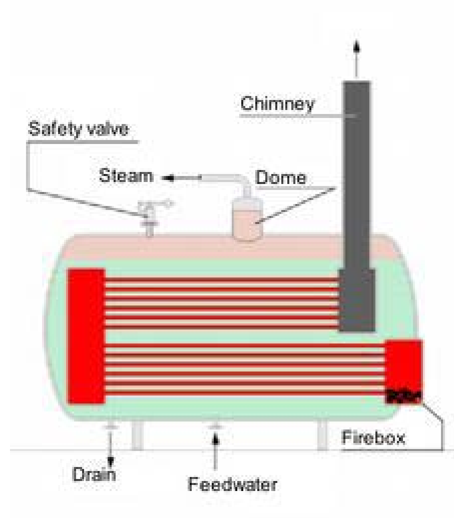

Figure 3.1: A fire tube boiler diagram

3.1.2 Water tube boilers

In this type, the water tubes are arranged inside a furnace in a number of possible configurations: often the water tubes connect large drums, the lower ones containing water and the upper ones, steam and water; in other cases, such as a mono tube boiler, water is circulated by a pump through a succession of coils. This type generally gives high steam production rates, but less storage capacity than the above. Water tube boilers can be designed to exploit any heat source and are generally preferred in high pressure applications since the high pressure water/steam is contained within small diameter pipes which can withstand the pressure with a thinner wall.

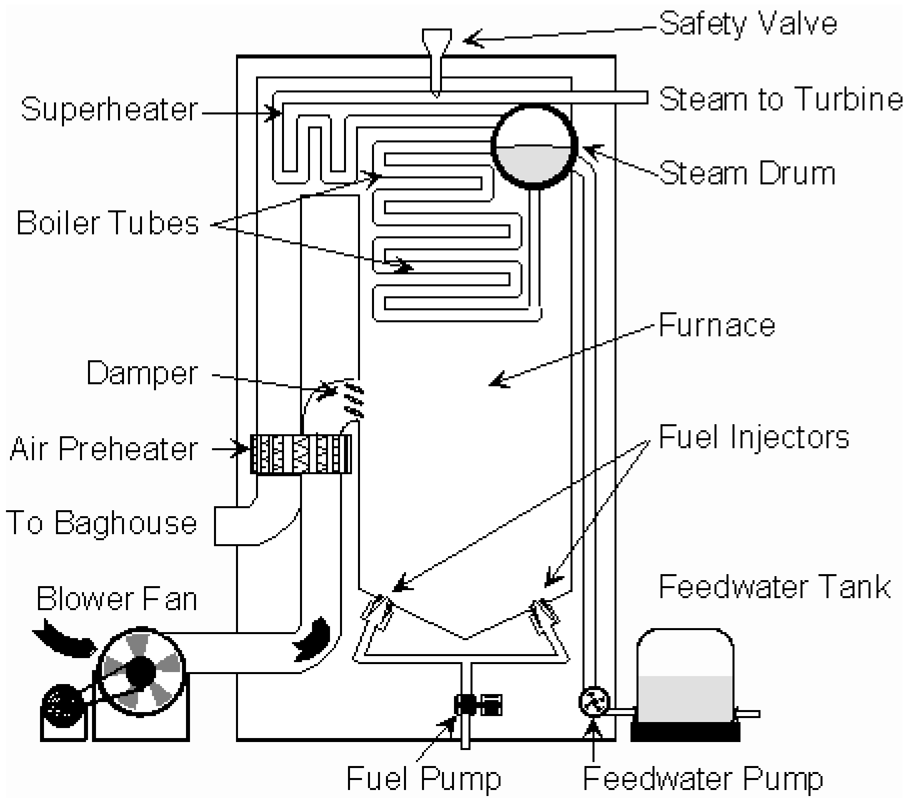

Figure 3.2: Schematic of the water tube boiler

3.2 Main components of a Boiler:

Riser:

Heat collecting surfaces constructed from tubing and conveying boiler circulating water upwards to the steam drum are generally called risers. The risers may originate from either the water wall header at the base of the furnace, or from the mud drum. Boiler circulating water absorbs primarily radiant energy from the furnace fireball while resident in risers jacketing the furnace.

Downcomer

Water is carried down from the boiler drum to the mud drum or to the water wall feedwater header through tubes called downcomers. The downcomers are not heated and are located outside of the furnace cavity.

Drum:

Figure 3.3 is a representation of a drum-type boiler. The steam drum and mud drum are mounted in a furnace and are interconnected with watertubes called risers and downcomers. The furnace includes one or more burners for the combustion of an air and fuel mixture. The heat of combustion is transferred to the watertubes to generate steam. Steam bubbles form in the tubes (risers) closest to the burner and rise to the steam drum where they are separated from the water.

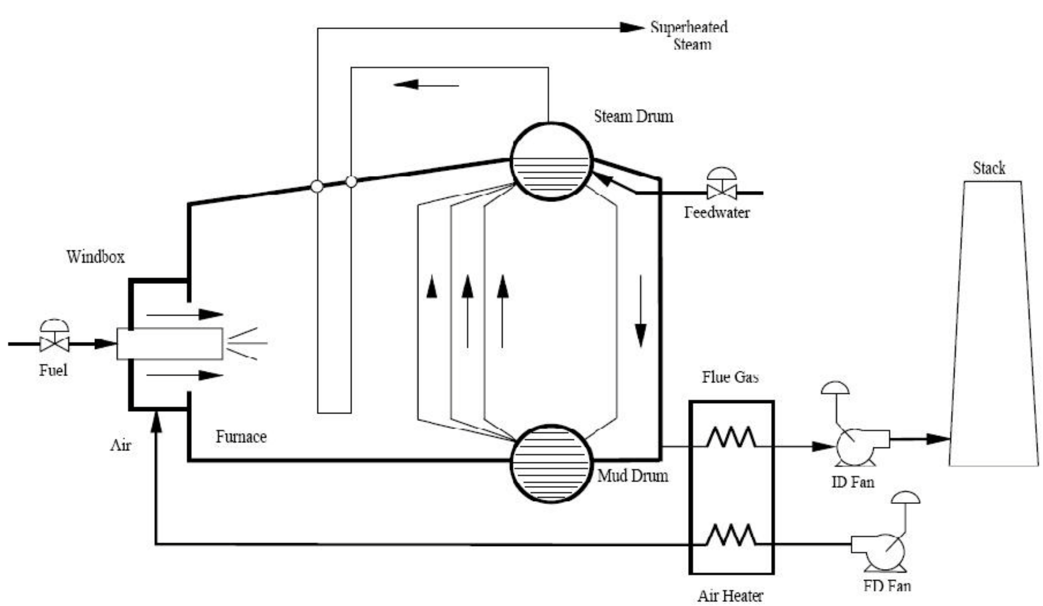

Figure 3.3: Structure of a drum boiler

The steam in the risers is replaced by water in the downcomers to provide natural circulation in the watertubes. A continuous supply of feedwater is necessary to replace the steam leaving the boiler. In most cases, the saturated steam leaving the steam drum is returned to the furnace for superheating.

Superheater

The superheater is a flue gas to steam heat exchanger. Heat from the flue gases is added to the saturated steam from the drum.

Burner

The burner is used to introduce fuel and air to the furnace at the required velocities, turbulence, and concentration to maintain ignition and combustion of the fuel within the furnace.

Forced Draft Fan

A forced draft (FD) fan provides combustion air to the wind box from which it is delivered to the burners.

Economizer

Feedwater from the condensate-feedwater system enters the economizer located in the furnace flue gas ductwork. Waste heat from the flue gas is absorbed by the feedwater in order to improve efficiency.

Induced Draft Fan

An induced draft (ID) fan draws the flue gases from the furnace and drives them up the stack. Heat from the flue gas is used to preheat the combustion air to improve efficiency.

Air pre-heater

The steam-generator air heater improves boiler efficiency by transferring heat to incoming combustion air from the flue gases before they pass to the atmosphere. The heat is transferred to the air from the flue gas through a regenerative heat-transfer surface in a rotor that turns continuously through the gas and airstreams.

3.3 Theory of NOx Formation

This section gives a brief introduction to the fundamental theory of NO_x formation. Nitrogen oxides are of environmental concern because they initiate reactions that result in the formation of ozone and acid rain, which can cause health problems, damage buildings, and reduce visibility. The allowable NO_x emissions from boilers vary depending on local regulations but are gradually edging toward single-digit values in parts per million (ppm) due to advances in combustion and pollution control technology. The principal nitrogen pollutants generated by boilers, gas turbines, and engines and other combustion equipment are Nitric Oxide (NO) and Nitrogen Dioxide (NO_2) collectively referred to as NO_x and reported as NO_2. Once released into the atmosphere, NO reacts to form NO_2,which reacts with other pollutants to form ozone (O_3). Oxides of nitrogen are produced during the combustion of fossil fuels through the oxidation of atmospheric nitrogen and fuel-bound nitrogen.

These sources produce three kinds of NO_x: fuel NO_x, prompt NO_x, and thermal NO_x.

3.3.1 Fuel NO_x

Fuel NO_x is generated when nitrogen in fuel combines with oxygen in combustion air. Gaseous fuels have little fuel-bound nitrogen, whereas coal and oil contain significant amounts. Fuel-bound nitrogen can account for about 50% of total NO_x emissions from coal and oil combustion. Most NO_x control technologies for industrial boilers reduce thermal NO_x and have little impact on fuelNO_x, which is economically reduced by fuel treatment methods or by switching to cleaner fuels. Fuel NO_x is relatively insensitive to flame temperature but is influenced by oxygen availability [58].

3.2.2 Prompt NO_x

Prompt NO_x results when fuel hydrocarbons break down and recombine with nitrogen in air. Prompt NO_x is chemically produced by the reactions that occur during burning; specifically, it forms when intermediate hydrocarbon species react with nitrogen in air instead of oxygen. PromptNO_x, so called because the reaction takes place ahead of the flame tip, accounts for about 15–20 ppm of the NO_x formed in the combustion process and is a concern only in low temperature situations.

3.2.3 ThermalNO_x

Thermal NO_x forms when atmospheric nitrogen combines with oxygen under intense heat. This rate of formation increases exponentially with an increase in temperature and is directly proportional to oxygen concentration. Its formation is well understood and straightforward to control. Keeping the flame temperature low reduces it. Below a certain temperature, thermal NO_x is nonexistent. Combustion temperature, residence time, turbulence, and excess air are the other factors that affect the formation of thermal NO_x. Most NO_x is formed in this manner in gas turbines, industrial boilers, and heaters fuelled by natural gas, propane, butane, and light fuel oils. The thermal NO_x is due to the direct oxidation of molecular nitrogen N_2 in hot flames and can be described as

$$
\begin{aligned}
&N_2 + O \rightleftarrows NO + N \\
&N + O_2 \rightleftarrows NO + O \\
&N + OH \rightleftarrows NO + H
\end{aligned}
\tag{3.1}
$$

CHAPTER 4

MATHEMATICAL MODEL FOR DRUM BOILER AND NOx (AUGMENTED SYSTEM)

4.1 Drum Boiler Model

The model has been adapted from the work of Astrom and Bell [14]. The considered boiler is 160MW oil fired boiler unit in Sweden. In this model, much of the system behaviour is captured by considering the mass and energy balance for total system so that a fourth order non-linear state space model can be obtained.

The model describes the complicated dynamics of the drum, downcomer, and riser components. It is derived from the first principles and is characterized by a few physical parameters and can be easily scaled to represent any drum power station.

The basic schematic of a boiler is given in the following figure as shown by Astrom and Bell.

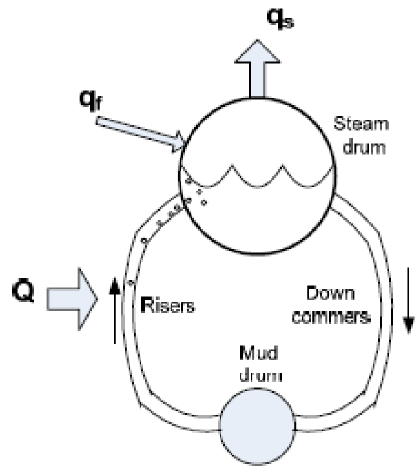

Figure 4.1: Schematic picture of a drum boiler

In the above figure [22], Q is the heat applied on the riser tubes. This applied heat causes the water in the drum to boil. The applied heat also causes saturated steam to rise in riser-drum-downcomer loop. Feedwater, q_f, is the flow rate of water being supplied to the boiler. Saturated steam, q_s, is the flow rate of the steam which is fed to the superheaters and the turbine.

4.1.1 Governing Equations of Drum Boiler

A simple model of the drum boiler, that captures the pressure dynamics very well is a second order model based on the global mass and energy balances [14].

Three inputs to the model are $q_{s,} q_{f,} Q$ and two measurable outputs are drum pressure, p and the drum water level, l .

Standard notations used to write the balance equations are: V denotes volume, ρ denotes specific density, u specific internal energy, h specific enthalpy, t temperature and q mass flow rate. Also the subscripts, Also, the subscripts, s , w, f and m refer to steam, water, feedwater and metal, respectively. The double subscripts, t, d and r denoting the total system, drum and the riser are used for clarification of the system components. The total mass of the metal tubes and the drum is m_t and the specific heat of the metal is C_p.

The global mass balance is:

$$\frac{d}{dt}[\rho_s V_{st} + \rho_w V_{wt}] = q_f - q_s \tag{4.1}$$

The global energy balance is:

$$\frac{d}{dt}[\rho_s u_s V_{st} + \rho_w u_w V_{wt} + m_t C_p t_m] = Q + q_f h_f - q_s h_s \tag{4.2}$$

Since the internal energy is $u = h - P/\rho$, the global energy balance can be written as

$$\frac{d}{dt}[\rho_s u_s V_{st} + \rho_w h_w V_{wt} - p\ V_{wt} + m_t C_p t_m] = Q + q_f h_f - q_s h_s \tag{4.3}$$

The total volume of the drum, downcomer, and risers is:

$$V_t = V_{st} + V_{wt} \tag{4.4}$$

These equations along with saturated steam tables capture the gross behaviour of a simple boiler and describe the drum pressure responses due to input q_f and q_s fluctuations. The second order model which follows describes the total water in the system but does not capture the drum water level dynamics because the distribution of steam and water are not included. The state variables for the state model are p and V_{wt}.

$$e_{11}\frac{dV_{wt}}{dt} + e_{12}\frac{dp}{dt} = q_f - q_s$$

$$e_{21}\frac{dV_{wt}}{dt} + e_{22}\frac{dp}{dt} = Q + q_f h_f - q_s h_s \tag{4.5}$$

Where,

$$e_{11} = \rho_w - \rho_s$$

$$e_{12} = V_{st}\frac{\partial \rho_s}{\partial \rho} + V_{wt}\frac{\partial \rho_w}{\partial \rho}$$

$$e_{21} = \rho_w h_w - \rho_s h_s$$

$$e_{22} = V_{st}(h_s\frac{\partial \rho_s}{\partial \rho} + \rho_s\frac{\partial h_s}{\partial \rho}) + V_{wt}(h_w\frac{\partial \rho_w}{\partial \rho} + \rho_w\frac{\partial h_w}{\partial \rho}) - V_t + m_t C_p\frac{\partial t}{\partial s} \tag{4.6}$$

But the serious deficiency in this simple model lies in its failure to model drum water level. Although it does determine the total amount of water in the system it does not take into account the steam in the risers and below the water surface level in the drum. To do this separate mass and energy balances must be written for the risers and the drum.

Riser dynamics:

The global mass balance for the riser is:

$$\frac{d}{dt}(\rho_s\bar{\alpha}_v V_r + \rho_w(1-\bar{\alpha}_v)V_r) = q_{dc} - q_r \tag{4.7}$$

where $\bar{\alpha}_v$ is the average volume fraction in the risers, q_r is the total mass flow rate out of the risers and q_{dc} is the total mass flow rate into the risers.

The global energy balance of the riser section is

$$\frac{d}{dt}(\rho_s h_s \bar{\alpha}_v V_r + \rho_w h_w (1-\bar{\alpha}_v) V_r - pV_r + m_r C_p t_s) = Q + q_{dc} h_w - (\alpha_r h_c + h_w) q_r \tag{4.8}$$

Eliminating the flow rate out of the risers, q_r, multiplying Eq.(4.7) by $-(h_w + \alpha_r h_c)$ and adding to Eq.(4.8) gives,

$$\begin{aligned}
&\frac{d}{dt}(\rho_s h_s \bar{\alpha}_v V_r) - (h_w + \alpha_r h_c)\frac{d}{dt}(\rho_s \bar{\alpha}_v V_r) \\
&\quad + \frac{d}{dt}(\rho_w h_w (1-\bar{\alpha}_v) V_r) \\
&\quad - (h_w + \alpha_r h_c)\frac{d}{dt}(\rho_w (1-\bar{\alpha}_v) V_r) \\
&\quad - V_r \frac{dp}{dt} + m_r C_p \frac{dt_s}{dt}) = Q - \alpha_r h_c q_{dc}
\end{aligned}$$

This can be simplified to

$$\begin{aligned}
&h_c(1-\alpha_r)\frac{d}{dt}(\rho_s \bar{\alpha}_v V_r) + \rho_w (1-\bar{\alpha}_v) V_r \frac{dh_w}{dt} \\
&\quad - \alpha_r h_c)\frac{d}{dt}(\rho_w (1-\bar{\alpha}_v) V_r) + \rho_s \bar{\alpha}_v V_r \frac{dh_s}{dt} \\
&\quad - V_r \frac{dp}{dt} + m_r C_p \frac{dt_s}{dt}) = Q - \alpha_r h_c q_{dc}
\end{aligned} \tag{4.9}$$

Drum Dynamics:

The dynamics for the steam in the drum is:

$$\rho_s \frac{dV_{sd}}{dt} + V_{sd}\frac{d\rho_s}{dt} + \frac{1}{h_c}\Big(\rho_s V_{sd}\frac{dh_s}{dt} + \rho_w V_{wd}\frac{dh_w}{dt}$$
$$-(V_{sd} + V_{wd})\frac{dp}{dt} + m_d C_p \frac{dt_s}{dt}\Big)$$
$$+\alpha_r(1+\beta)V_r\frac{d}{dt}(1-\bar{\alpha}_v)\rho_w + \bar{\alpha}_v\rho_s)$$
$$= \frac{\rho_s}{T_d}(V_{sd}^0 - V_{sd}) + \frac{h_f - h_w}{h_c}q_f \tag{4.10}$$

Astrom and Bell conveniently chose four state variables with good physical interpretation that describe the storage of mass, energy and momentum. These state variables capture the pressure, water, riser, and drum dynamics. The state variable for the drum pressure, p represents the total energy. The state variable for the total water volume V_{wt} represents the accumulation of water. The state variable for the steam mass fraction or quality in the riser outlet α_r represents the distribution of steam and water. Finally, the state variable for the steam volume under the liquid level inside the drum is represented by V_{sd}. The time derivatives of these state equations can be rewritten as:

$$e_{11}\frac{dV_{wt}}{dt} + e_{12}\frac{dp}{dt} = q_f - q_s$$

$$e_{21}\frac{dV_{wt}}{dt} + e_{22}\frac{dp}{dt} = Q + q_f h_f - q_s h_s$$

$$e_{32}\frac{dp}{dt} + e_{33}\frac{d\alpha_r}{dt} = Q - \alpha_r h_c q_{dc}$$

$$e_{42}\frac{dp}{dt} + e_{43}\frac{d\alpha_r}{dt} + e_{44}\frac{dV_{sd}}{dt} = \frac{\rho_s}{T_d}(V_{sd}^0 - V_{sd}) + \frac{h_f - h_w}{h_c}q_f \tag{4.11}$$

The outputs are chosen as the drum-level l and the drum pressure p .

$$l = \frac{V_{sd} + V_{wd}}{A_d} \tag{4.12}$$

where

$$V_{wd} = V_{wt} - V_{dc} - (1 - \bar{\alpha}_v)V_r \tag{4.13}$$

Steam tables are required to calculate

$h_s, h_w, \rho_s, \rho_w, t_s, \frac{\partial h_s}{\partial p}, \frac{\partial h_w}{\partial p}, \frac{\partial p_s}{\partial p}, \frac{\partial p_w}{\partial p}$ and $\frac{\partial t_s}{\partial p}$ at the pressure p

Steam table was interpolated with a function using MATLAB, the drum boiler dynamic model of Astrom and Bell is based on physical parameters.

The set of nonlinear differential equations Eq. (4.11) representing the time dependence of the state variables can be presented in a matrix form as follows:

$$\begin{bmatrix} e_{11} & e_{12} & 0 & 0 \\ e_{21} & e_{21} & 0 & 0 \\ 0 & e_{32} & e_{33} & 0 \\ 0 & e_{42} & e_{43} & e_{44} \end{bmatrix} \begin{bmatrix} dV_{wt}/dt \\ dp/dt \\ d\alpha_r/dt \\ dV_{sd}/dt \end{bmatrix} = \begin{bmatrix} q_f - q_s \\ Q + q_f h_f - q_s h_s \\ Q - \alpha_r h_c q_{dc} \\ \frac{\rho_s}{T_d}(V_{sd}^0 - V_{sd}) + \frac{h_f - h_w}{h_c} q_f \end{bmatrix}$$

Where,

$$e_{11} = \rho_w - \rho_s$$

$$e_{12} = V_{st}\frac{\partial \rho_s}{\partial \rho} + V_{wt}\frac{\partial \rho_w}{\partial \rho}$$

$$e_{21} = \rho_w h_w - \rho_s h_s$$

$$e_{22} = V_{st}(h_s \frac{\partial \rho_s}{\partial \rho} + \rho_s \frac{\partial h_s}{\partial \rho}) + V_{wt}(h_w \frac{\partial \rho_w}{\partial \rho} + \rho_w \frac{\partial h_w}{\partial \rho}) - V_t + m_t C_p \frac{\partial t}{\partial s}$$

$$e_{32} = \left(\rho_w \frac{\partial h_w}{\partial p} - \alpha_r h_c \frac{\partial \rho_w}{\partial \rho}\right)(1 - \bar{\alpha}_V)V_r$$

$$e_{33} = ((1-\alpha_r)\rho_s + \alpha_r \rho_w)h_c V_r \frac{\partial \bar{\alpha}_v}{\partial \alpha_r}$$

$$e_{42} = V_{sd}\frac{\partial \rho_S}{\partial p} + \frac{1}{h_c}\Big(\rho_s V_{sd}\frac{\partial h_S}{\partial \rho} + \rho_w V_{wd}\frac{\partial h_w}{\partial \rho} - V_{sd}$$
$$- V_{wd} + m_d C_p \frac{\partial t_s}{\partial p}\Big) + \alpha_r(1+\beta)V_r\Big(\bar{\alpha}_V \frac{\partial \rho_S}{\partial p} + (1-\bar{\alpha}_V)\frac{\partial h_w}{\partial \rho} + (\rho_s - \rho_w)\frac{\partial \bar{\alpha}_v}{\partial p}\Big)$$

(4.14)

4.1.2 Linearisation of Drum Boiler Model

Non-linear drum boiler model can be expressed by $\dot{x} = f(x,u)$ *and* $y = g(x,u)$

Since most control system techniques require a linear model, the non-linear model is linearised.

The resulting linear model is expressed by following state space equation

$$\begin{aligned}\partial\dot{x} &= A\partial x + B\partial u \\ \partial\dot{y} &= C\partial x + D\partial u\end{aligned} \qquad (4.1.2.1)$$

The operating point around which the plant is linearised is

$x^o = [56.28\ 8500\ 0.0346\ 4.1432]$

$u^o = [50\ 50\ 86.121]$

Mass flow rate of Steam (q_s) = 50 kg/s

Mass flow rate of Water (q_f) =50 kg/s

Fuel flow rate (W_f) = 86.121 MW

Volume of water in the drum = 56.28 m^3

Drum pressure = 8500 kPa

Steam mass fraction in riser = 0.0346

Volume of steam in the drum = 4.14 m^3

at these values, system matrices are given by

$$A = \begin{bmatrix} 0 & 0 & -5.269e-016 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -0.1546 & 0 \\ 0 & 0 & -16.9454 & -0.0833 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.002045 & 0.001418 & 3.64e-007 \\ -0.4655 & -0.06679 & 0.0003091 \\ 4.757e-005 & 6.824e-006 & 3.058e-008 \\ 0.01203 & -0.003133 & -1.176e-006 \end{bmatrix}$$

$$C = \begin{bmatrix} 1/2 & 00 & 0 & 0 \\ 0 & 1/20 & 0 & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{4.1.2.2}$$

4.2 NOx Emission Model

The model considered is 300MW oil fired drum boiler of a Kilroot power station in Northern Ireland [59] The boiler was designed to supply its turbine with steam at a temperature of $540^0 c$ and up to pressure of 162 bar. It has got one burner box on each corner. Each burner box contains nine separate sections. The fuel used is crude oil.

Three inputs to the model are Fuel flow rate W_f, Burner tilt position ξ, and Fuel air ratio λ and the output is NO_x.

Thermal NO_x is the principal source of nitrogen oxide emissions at Kilroot. The formation of thermal NO_x is determined by a set of chemical reactions known as extended Zeldovich mechanism.

The principal reactions are:

$$
\begin{aligned}
&N_2 + O \underset{k_{-1}}{\overset{k_1}{\rightleftarrows}} NO + N \\
&N + O_2 \underset{k_{-2}}{\overset{k_2}{\rightleftarrows}} NO + O \\
&N + OH \underset{k_{-3}}{\overset{k_3}{\rightleftarrows}} NO + H
\end{aligned}
\tag{4.2.1}
$$

The rate coefficients for the forward reactions (4.21)-(4.23) are K_1, K_2, K_3, and for the corresponding backward reactions are K_{-1}, K_{-2}, K_{-3} Invoking the steady-state approximation for the N-atom concentration, that is $\frac{d(N)}{dt} \cong 0$, and assuming the partial equilibrium for the reaction

$$O + OH \Leftrightarrow O_2 + H$$

NO formation rate may be expressed

$$\frac{d(NO)}{dt} = \frac{2[O](K_1 K_2 [O_2][N_2] - K_{-1} K_{-2} [NO]^2)}{K_2 [O_2] + K_{-1} [NO]} \tag{4.2.2}$$

Considering the initial concentrations of NO and OH are low and only the forward reaction rates are significant, therefore the NOx formation rate can be expressed as

$$\frac{d(NO)}{dt} = 2K_1 (O)(N_2)$$

In this equation, the O can be related to the O_2 from the assumed equilibrium condition of reaction

$$0.5O_2 \Leftrightarrow O$$

$$K_o = (O)/(O_2)^{\frac{1}{2}}$$

And equation …becomes

$$\frac{d(NO)}{dt} = 2K_1K_0(O_2)^{\frac{1}{2}}(N_2)$$

Oxygen Volume flow rate:

$$V_{f\,o_2} = (1.87C + 0.70S + 5.6H)W_f = \beta W_f \tag{4.2.3}$$

$W_f = Fuel\,mass\ flow\,rate$

C, S and H are Carbon, Sulphur, and Hydrogen weight percentage in the fuel.

Stoichiometric air mass flow

$$W_{a,st} = \frac{V_{f\,o_2}}{0.21v_a} = \frac{\beta W_f}{0.21v_a} \tag{4.2.4}$$

v_a = is the specific volume of air (m3/kg)

$\lambda_{st} = \frac{W_f}{W_{a,st}} = \frac{0.21v_a}{\beta}$ = stoichiometric Fuel-to-Air ratio

Let $\dot{V}_a, W_a$ be the Air volume flow rate, and Air mass flow rate respectively.

Then $\dot{V}_a = v_a W_a$ and let the actual Fuel-to-Air ratio be $\lambda_{\frac{f}{a}} = \frac{W_f}{W_a}$

Theoretical Oxygen concentration in the exhaust (after burning)

We usually define the air-to fuel ratio,

$$\lambda_e = \frac{W_a}{W_{a,st}} \qquad (4.2.5)$$

The concentration for Oxygen in the exhaust is given by

$$O_2 = \frac{\beta}{v_a}(\lambda_{st} - \lambda) \qquad (4.2.6)$$

Therefore, equation (4.34) can be written as

$$\begin{aligned} \frac{d(NO)}{dt} &= 2K_1K_0(N_2)(\beta / v_a)^{1/2}(\lambda_{st} - \lambda)^{1/2} \\ &= \alpha(\lambda_{st} - \lambda)^{1/2} \end{aligned} \qquad (4.2.7)$$

λ is the fuel to air ratio and λ_{st} is the stoichiometric Fuel-to-Air ratio

Assuming that

$$\alpha = f(W_{f,}\xi) = \alpha_0 W_f^r (1 + \alpha_1 \frac{\xi - 55}{90}) \qquad (4.2.8)$$

Equation (4.3.9) gives NO formation rate

$$\frac{d(NO)}{dt} = \alpha_0 W_f^r (1 + \alpha_1 \frac{\xi - 55}{90})(\lambda_{st} - \lambda)^{1/2} \qquad (4.2.9)$$

For physical parameter estimation experiments were conducted on the boiler unit [59] Thus corresponding parameters $\alpha_0, \alpha_1, and\ r$ were obtained as 1806, 0.438 and 0.25 respectively.

$$\frac{dY_{NO}(t)}{dt} = 1806 W_f^{0.25}(1 + 0.438 \frac{\xi - 55}{90})(\lambda_{st} - \lambda)^{1/2} - Y_{NO}(t) \qquad (4.2.10)$$

4.2.1. Linearisation of NOx Model

Considering the equation

$$\frac{dY_{NO}(t)}{dt} = 1806 W_f^{0.25}(1 + 0.438\frac{\xi - 55}{90})(\lambda_{st} - \lambda)^{1/2} - Y_{NO}$$

The NO_x non linear model can be expressed as

$$\dot{x}_{NO} = f(x,u)$$

$$u = (W_f, \xi, \lambda)$$

The resulting linear model is expressed by following state equation

$$\partial\dot{x} = A_{NOx}\partial x + B_{NOx}\partial u \qquad (4.2.1.1)$$

Where

$$A_{NOx} = \frac{\partial f(x^0, u^0)}{\partial x}; B_{NOx} = \frac{\partial f(x^0, u^0)}{\partial u} \qquad (4.2.1.2)$$

The operating point around which the NO_x non linear model is linearised is

$$x^0 = 232.4\, ppm$$

$$u^0 = [2.13 \;\; 55 \;\; 0.0679] = [W_{f_0}, \xi_{0,} \lambda_0]$$

Therefore, $\dot{x}_{NO} = f(x_0, u_0)$

Differentiating 4.2.12 with respect to W_f

$$\left(\frac{\partial f}{\partial W_f}\right)\Delta W_f =$$

$$451.5 * W_{f_0}{}^{-0.75}[1+0.438\frac{(\xi_0-55)}{90}]*[\lambda_{st}-\lambda_0]^{1/2} \tag{4.2.1.3}$$

$$= 451.5 * 0.56 * 0.0824 \ = 20.83$$

Differentiating 4.2.12 with respect to ξ

$$\left(\frac{\partial f}{\partial \xi}\right)\Delta \xi \quad =$$

$$1806 * W_{f_0}{}^{0.25} * [0.438/90] * [\lambda_{st}-\lambda_0]^{1/2} \tag{4.2.1.4}$$

$$= 1806 * 1.2 * 4.866e - 003 * 0.0824 \ = 0.86$$

Differentiating 4.2.12 with respect to ξ

$$\left(\frac{\partial f}{\partial \lambda}\right)\Delta \lambda \ =$$

$$-903 * W_{f_0}{}^{0.25}[1+0.438\frac{(\xi_0-55)}{90}]*[\lambda_{st}-\lambda_0]^{-1/2} \tag{4.2.1.5}$$

$$= -903 * 1.2 * 12.126 = 13139.7$$

Therefore, Linearised model is:

$$\dot{x}_{NO} = -x_{NO} + 20.83 W_f + 0.86\xi - 13139.7\lambda \tag{4.2.1.6}$$

Equation, 4.2.16 will be appended as 5th state in the augmented model

$$\dot{x}_{NO} = -x_{NO} + 20.83 W_f + 0.86\xi - 13139.7\lambda$$

$$\dot{x}_{NO} = -1[x_{NO}] + [20.83 + 0.86 - 13139.7]\begin{bmatrix} W_f \\ \xi \\ \lambda \end{bmatrix} \tag{4.2.1.7}$$

4.3 Need of Augmented Model

Boiler drum level control is critical for both plant protection and equipment safety and applies equally to high and low levels of water within the boiler drum. The purpose of the drum level controller is to bring the drum up to level at boiler start-up and maintain the level at constant steam load. A dramatic decrease in this level at constant steam load may uncover boiler tubes, allowing them to become overheated and damaged. An increase in this level may interfere with the process of separating moisture from steam within the drum, thus reducing boiler efficiency and carrying moisture into the process or turbine.

Pollution of environment from industrial processes has been blamed for causing climate changes. Climate changes in recent time have increased the frequency of natural disasters. The concerns over the global warming and environmental degradation have led to the enforcements of stringent constraints. These constraints are nowadays among the most important factors impacting on plant performance and profitability. These new regulations have already led to the close down of some production sites. These regulations have changed, and will keep on changing the rule of the game in many industrial sectors. Many of the international agreements are imposing limits on emissions of CO, $NO_x$and other gases. Due to the new regulation, measures have been taken to limit the emission up to regulatory level.

4.3.1. Linear Augmented Model

The augmented model is developed by considering the linear model of drum boiler shown in section 4.12 and NO_x model mentioned in section 4.21. A Schematic of the augmented model is shown below

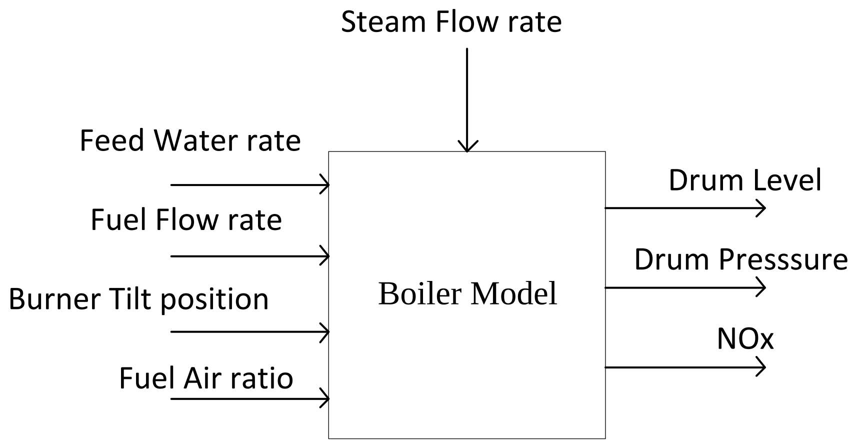

Figure 4.2: Augmented model of Boiler and NOx

Model Formulation

The augmented model has 5 inputs and 3 outputs as mentioned below:

Inputs:

Mass flow rate of Steam (q_s) (kg/s)

Mass flow rate of Water (q_f) (kg/s)

Fuel flow rate (W_f) (kg/s)

Burner Tilt Position (ξ),

Fuel Air Ratio (λ)

Outputs:

Drum Level (l) (mts)

Drum Pressure (p) (kPa)

NO_x (NO) (ppm)

Referring to the linear model developed in section 4.12, we need to add a fifth state to account for NOx, as developed in equation 42.1.6.

The operating point around which the augmented model is linearised is:

$x^0 = [56.28 \; 8500 \; 0.0346 \; 4.41432 \; 232.4]$

$u^0 = [50 \; 50 \; 2.13 \; 55 \; 0.0679]$

State space augmented model linearization is given by:

$$\begin{aligned} \dot{x} &= A_{aug}x + B_{aug}u, \\ y &= C_{aug}x + D_{aug}u \end{aligned} \tag{4.3.1}$$

Before coming up with the augmented model, we need to scale the units of Fuel flow rate(u_3) of linear boiler model from MW to kg/s

$Q = W_f * HHV$

$Q =$ Flow rate (MW);

$W_f =$ Fuel flow rate (Kg/s)

HHV = High Heating Value of Fuel (KJ/Kg)

HHV of Crude oil=40360 KJ/Kg [60]

Therefore, system matrices are

$$A_{aug} = \begin{bmatrix} 0 & 0 & \text{-5.269e-016} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -0.1546 & 0 & 0 \\ 0 & 0 & -16.9454 & -0.0833 & 0 \\ 0 & 0 & 0 & 0 & -1 \end{bmatrix}$$

$$B_{aug} = \begin{bmatrix} -0.002045 & 0.001418 & 0.0147 & 0 & 0 \\ -0.4655 & -0.06679 & 12.475 & 0 & 0 \\ \text{4.757e-005} & \text{6.824e-006} & 0.0012 & 0 & 0 \\ 0.01203 & -0.003133 & -0.0024 & 0 & 0 \\ 0 & 0 & 20.83 & 0.86 & -13139.7 \end{bmatrix}$$

$$C_{aug} = [1/2 \quad 00 \quad 0 \quad 0 \quad 0$$
$$0 \quad 1/2 \quad 00 \quad 0 \quad 0$$
$$0 \quad 0 \quad 0 \quad 0 \quad 1]$$

$$D_{aug} = [0 \quad 0 \quad 0 \quad 0 \quad 0$$
$$0 \quad 0 \quad 0 \quad 0 \quad 0$$
$$0 \quad 0 \quad 0 \quad 0 \quad 0] \qquad (4.3.2)$$

CHAPTER 5

MODEL PREDICTIVE CONTROL

5.2 Overview

Model Predictive Control (MPC), is an advanced control theory and method, that is primarily based on prediction and optimization [61]. MPC has numerous applications especially within the process industry. MPC originated from the industry and was developed and practiced for nearly 20 years before the academic world got its eyes on it. So, for a long time MPC was used without even having been proven stable.

One of the big advantages of MPC compared to other control theories is its ability to handle constraints, both in the process variables, that are to be controlled and in the manipulated variables that are the calculated output of the MPC and are used to control the plant. Many industrial processes benefit from operating close to or at their limits, to improve production effectiveness and consequently maximize the profit, at the same time manage to stay within safety or environmental restraints. MPC is well suited for multivariable systems but even smaller feedback systems can be rendered more effective with the use of MPC, especially if the application contains deadtimes. Since MPC algorithms are more computationally demanding than simpler control algorithms, such as

PI control, the advantage of MPC keeps growing due to the ever-increasing computational speed of modern computers.

5.1 The Predictive Controller Concept (MPC Strategy)

Model Predictive Control refers to a class of algorithms that compute a sequence of signals (manipulated variable adjustments) in order to optimize the future behaviour of a plant. The optimal sequence is generated by utilizing a model of the process. The model of the system is any entity that describes the input and output relations and any type of model can be used. We will utilize the state-space modeling technique to describe our processes. Naturally, these models can be linear or non-linear. Also, if the process is subjected to disturbances, noise or variations, these can be incorporated to the process models in the form of disturbance or noise models. This will allow the effect of disturbances on the predicted process to be taken into account. MPC also incorporates process constraints in the prediction. All of these qualities constitute the Model Predictive Controller Concept [61].

The strategy of MPC can be well understood from Figure 5.1

At the present time n, the future outputs (*y(n+k) for k=1.... P)* of the system over a prediction horizon (P or H_p), are predicted at each instant by using the model of the process, knowing values up to instant n (past inputs and outputs) and future inputs (*u(n), u(n+1),..., u(n+k) for k=1…*) over the control horizon (C or H_c)

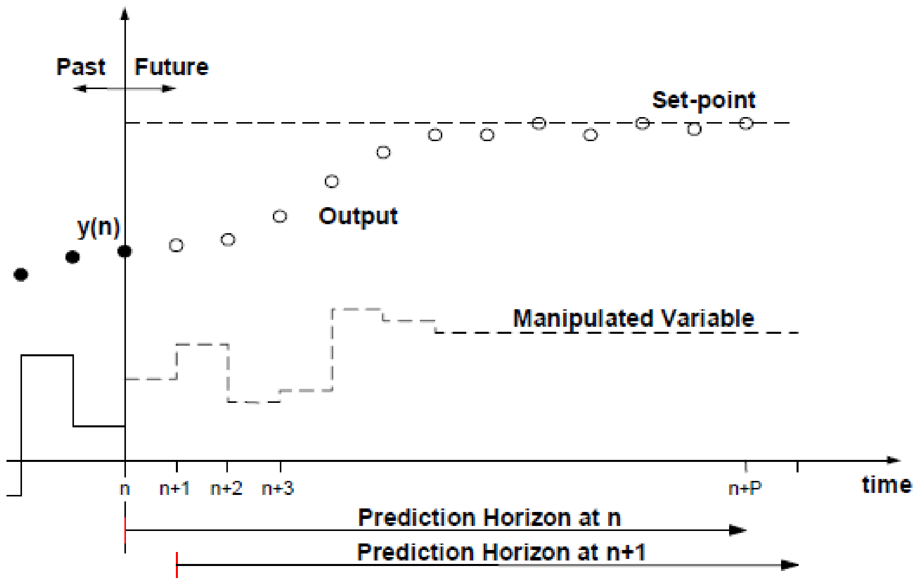

Figure 5.1:Strategy of MPC

Thus we can define the parameters as

$$u = [u(n), u(n+1), \ldots\ldots\ldots\ldots u(n + H_p - 1)]^T$$

$$\hat{y} = [\hat{y}(n), \hat{y}(n+1), \ldots\ldots\ldots\ldots \hat{y}(n + H_p - 1)]^T$$

$$r = [r(n), r(n+1), \ldots\ldots\ldots\ldots r(n + H_p - 1)]^T$$

In Figure 5.1, the past inputs *(u(n-k) for k=1...* C *-1*) are expressed by solid lines and the future inputs *(u(n+k) for k=1...* H_c *)* are shown by dashed lines. The set of future inputs which minimize an objective function are applied to the system. Only the first element of the future input is applied to the process since a new measurement of the output can be present at the next sampling instant. This procedure is repeated for next sampling time with addition of the new measurements, this is called receding strategy.

A model is used in order to predict the future outputs based on past inputs and outputs of the system. A comparison is made between the predicted output of the plant and the reference trajectory of it and the future errors of the plant are calculated at each time step. The optimizer calculates the best future inputs considering the objective function and the constraints. Only the first element of this optimal set is applied to the plant and the same procedure repeated at the next sampling time.

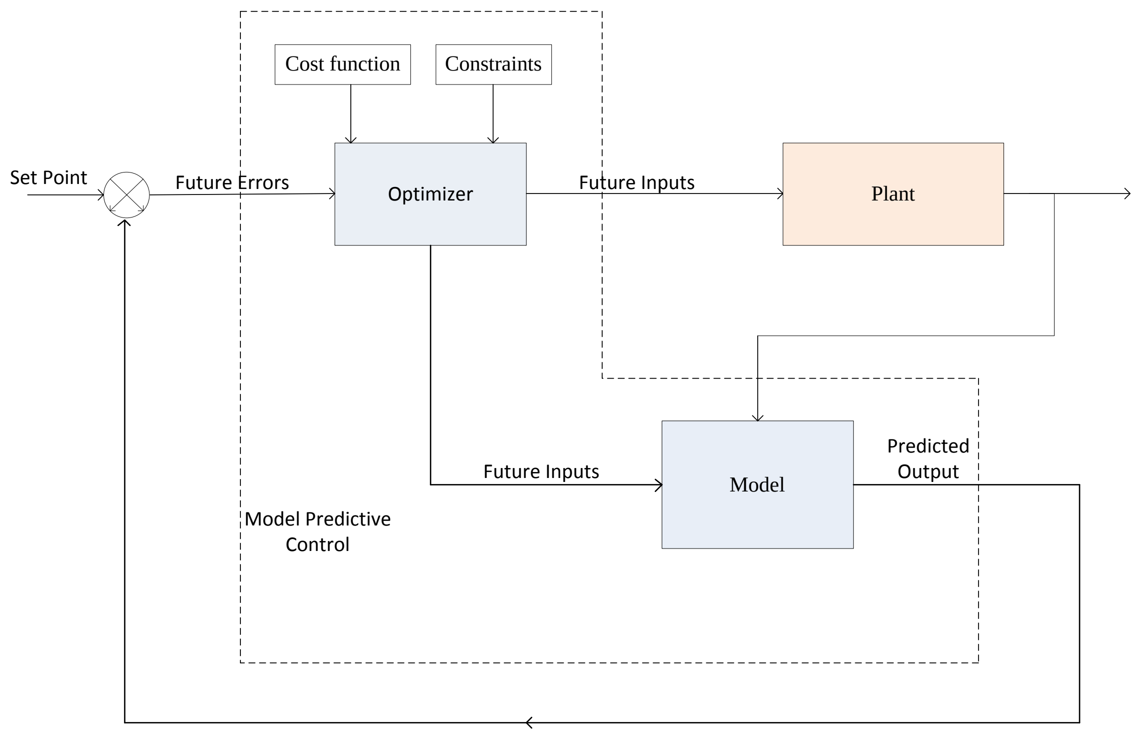

Figure 5.2: Basic structure of MPC

5.2 Summary of Model Predictive Control Algorithm

The Model Predictive Control algorithm can be briefly described to have the following three general steps [61].

1. Explicit use of a model to predict the process output along a future time horizon (Prediction Horizon, H_p).
2. Calculation of a control sequence along a future time horizon (Control Horizon, H_c), to optimize a performance index.
3. A receding horizon strategy, so that at each instant the horizon is moved towards the future which involves the application of the first control signal of the sequence calculated at each step.

5.3 Elements of MPC models

In this section the components that build up a model predictive control are discussed.

5.3.1 Process Model

The process model is the heart of the model predictive control concept. Explicitly, MPCs use a model of the plant to be controlled to determine the future. Many different types of models exist for MPC algorithm. Process models can be linear as well as non-linear.

Historically, the models of choice in early industrial MPC applications were time domain, input/output, step or impulse response models due to the ease of understanding provided by these models. The linear models can be developed relatively easy and also provide acceptable results when the plant is operated in the neighbourhood of the operating point. Thus linear model have been emphasized and worked upon in this thesis.

Linear State Space Model:

State space model is the common technique of model representation. It have several advantages including easy generalization to multi-variable systems, ease of analysis of closed loop properties, and on-line computation. Every linear lumped system with p inputs, q outputs and n state variables can be described by a set of equations of the form [thesis40]:

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx\end{aligned} \tag{5.4.1.1}$$

The size of the constant matrices, A, B, C, and D are:

- $A = n \times n$
- $B = n \times p$
- $C = q \times n$
- $D = q \times p$

While in the equations 5.4.1.1, x are the states, $\dot{x}$ represents the derivative of the states, u is the input and y is the output of the process.

Other Models

Other dynamic models of the systems that can be used with Linear MPC as follows:

1. Impulse Response Model
2. Step Response Model
3. Transfer Function Model

5.3.2 Cost function

In order to determine the health of the tracking (predicted process output, $\hat{y}(n)$ tracking the reference trajectory, $r(n)$), a criterion function or cost function is used. Typically, such a function is a function of $\hat{y}$, r and u . A simple criterion function is given in the Equation 5.4.2.1 and it is,

$$J = \sum_{i=1}^{H_p} [\hat{y}(n+i) - r(n+i)]^2 \tag{5.4.2.1}$$

In this criterion, there is no involvement of u. Other criterion functions can be obtained by augmenting different penalty terms to this criterion function. These penalties usually involve the input, u and the rate of change of the input, Δu . These quantities are penalized by weighting matrices when they exceed a certain desired threshold. A more comprehensive criterion function is

$$J = \sum_{i=1}^{H_p} e(n+i)^T Q e(n+i) + \sum_{i=1}^{H_c} \Delta u(n+i)^T R \Delta u(n+i) + \sum_{i=1}^{H_p} u(n+i)^T S \ (\boldsymbol{n}+i) \tag{5.4.2.2}$$

Q, R and S are the weighting matrices, H_c is the control horizon and e is the error between the desired output and the predicted output. i.e.,

$$e = r(n) - \hat{y}(n)$$

Now minimization of J with respect to u over the prediction horizon gives the controller output sequence u_{opt} i.e.,

$$u_{opt} = \arg\{\min_u J\}$$

Then, u_{opt} is the optimal with respect to the criterion function that is minimized. As a result, the future tracking error is minimized. If there is no disturbance or constraints and the model is exactly identical to the process, the process will track the reference trajectory exactly on each of the sampling instants.

5.3.3 Constraints

In practice, all industrial processes are subject to constraints. These constraints are discussed here before moving on to the discussion of the proposed MPC controller. For constrained model predictive control of a physical system, some criteria must be satisfied along with the minimization of the quadratic cost function. These conditions/criteria are known as *constraints*. The most common constraints are constraints on the manipulated (input to the process) and/or state variables. These constraints can make even a linear system nonlinear. Most commonly these constraints are in the form of saturation characteristics: valves with a finite range of adjustment, flow rates with maximum values due to fixed pipe diameters, or control surfaces with limited deflection angles. Input constraints also appear in the form of rate constraints: valves and other actuators with limited slew rates. These constraints, especially of the saturation type, are also often active, when a process is running at its most profitable condition.

Constraints can also be used to represent the performance objectives of the controllers. Although most control constraints should be respected throughout the operation as hard constraints, sometimes, especially during the case when the system is subjected to unexpected disturbances, it may be unavoidable to exceed some state constraints i.e. soft constraints. Hard constraints are usually imposed on the input to the process while soft constraints are usually implemented on the output of the process.

Obviously, it is preferable (intended) to avoid violations of the soft constraints as well to ensure optimal or safe plant operation.

5.4 MPC Characteristics

MPC has remarkable features, some of which are as follows:

1. It is relatively easy to tune and can handle non-minimal phase and unstable processes.
2. It handles structural changes and it can be easily extended to multiple input-multiple output (MIMO) systems.
3. It is robust to modeling errors to some extent.
4. It allows operation closer to constraints, hence increased profit.
5. It can take account of actuator limitations.
6. Predictive control can canter for process constraints during the controller design itself. It is the most attractive feature of MPC.
7. Process model can be finite impulse response (FIR), step response, transfer function, state space or even non-linear. This is the contrast with respect to linear quadratic (LQ) or pole-placement control.
8. Known and unknown disturbances can also be catered for in the design process.
9. Because MPC is predictive in nature, if the reference set-point trajectory is known in advance (e.g. Drum Level and Pressure), it too can be used in the controller design by “looking ahead” for the trajectory.

CHAPTER 6

MPC FORMULATION OF THE AUGMENTED BOILER MODEL

6.1 Problem Formulation

The goal of the thesis is to develop an MPC controller for the augmented boiler model to keep the drum level and drum pressure at the desired reference despite variations in the quantity of steam demanded, and also to limit the emission of NOx to the lowest value.

In this chapter, formulation of MPC for the linear augmented model developed in Chapter 4 is shown. Initially elements of MPC like cost function and constraints are described then followed by MPC with Observer and MPC with Integral action controller for the augmented boiler model. Finally the performance of the proposed MPC controller is compared with that of conventional PI control.

6.2 Cost function

The objective is to minimize the deviation from the desired drum level and drum pressure and *reduce NO_x to certain level without controlling it,* in the presence of measured disturbance. The cost function will have the following appearance.

$$J = \sum_{i=1}^{H_p} \left[Q_{level} \, |[Y_{level,i} - Y_{level,ref,i}]|^2 + Q_{pressure} \, |[Y_{pressure,i} - Y_{pressure,ref,i}]|^2 \right]$$
$$+ \sum_{i=1}^{H_c} \left[R_{fuel} \, |(u_{fuel,i})|^2 + R_{feedwater} \, |(u_{feedwater,i})|^2 + R_{tiltposi} \, |(u_{tiltposition,i})|^2 + R_{fuelairratio} \, |(u_{fuelairratio,i})|^2 \right]$$

The weighting matrices of output Q_{level} and $Q_{pressure}$ are kept as 1, while the weights for the change in inputs R_{fuel}, $R_{feedwater}$, $R_{burnertiltpostion}$, $R_{fuelairratio}$ are kept as 0.1.

6.3 Constraints

In our design, Prediction Horizon (H_p) is chosen to be 4 and control horizon (H_c) as 2 and the model is constrained under following limits.

$$u_{\min} = \begin{bmatrix} -20 \\ -4 \\ -10 \\ 0 \end{bmatrix} \leq \begin{bmatrix} Feedwaterrate \\ Fuelflowrate \\ TiltPosition \\ Fuelairratio \end{bmatrix} \leq \begin{bmatrix} 20 \\ 10 \\ 10 \\ 0.04 \end{bmatrix} = u_{\max}$$

6.4 State Observer design

State observer can be described as a copy of the system with a feedback from the measured output with an observer gain to get a better value of the estimated state. MPC with state estimation has advantage over standard MPC. The increased amount of information provided to the controller yields tighter control. Thus, we estimate the all states of boiler along with NO_x.

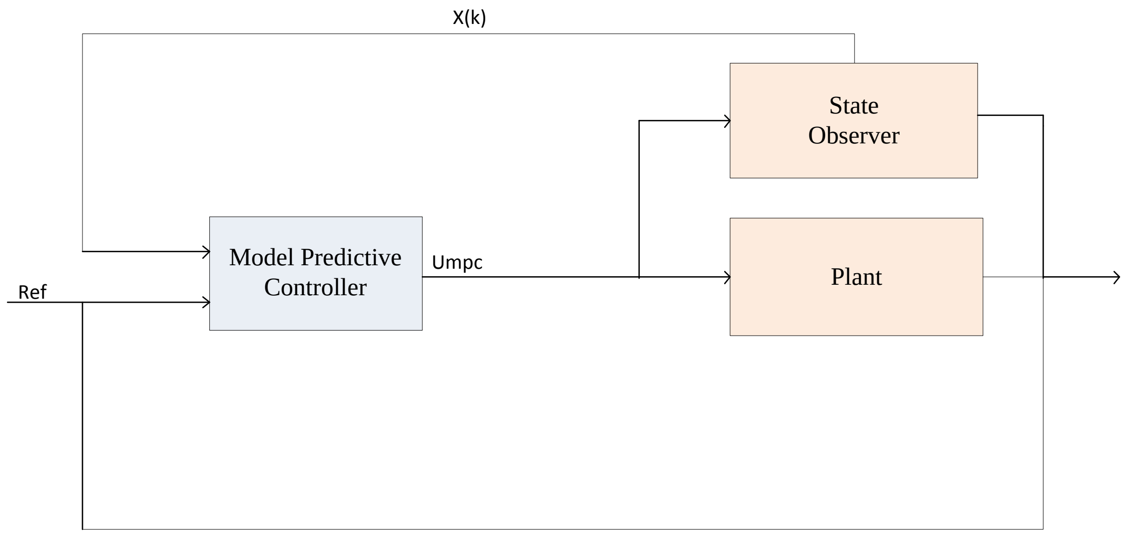

Figure 6.1: MPC structure with State Observer

Designing of observer for estimation of states can be done by several approaches. For example, a common technique is pole-placement or well known is Kalman filter. In our study, pole placement technique is used. An advantage of this approach is that stability of the closed-loop system is guaranteed by placing the poles in the stable region. Let the state vector of the observer be $\hat{x}$ and the state estimation error be $e = x - \hat{x}$

By constructing and subtracting the observer dynamics from the original system dynamics the estimation error dynamics becomes $\dot{e} = (A - LC)e$, where L is the observer gain, which has to be designed such that it assures stability by having all the eigen values of $(A - LC)$ to the left half plane (stable region) in the s-plane.

The observer dynamic equation can be summarized as follows:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y})$$

or

$$\dot{\hat{x}} = (A - LC)\hat{x} + Bu + Ly$$

The observer gain L is determined by assigning a set of pole locations and using the Matlab command *place* which is shown below

desEigvalue = [-0.5 -1.2 -0.75 -0.6 -1];

L=place (A', C', [desEigvalue]');

Using the above code we find that,

$$L = \begin{bmatrix} 936.4 & 1934.5 & 0 \\ 0 & 0.9 & 0 \\ 2.4 & 6.2 & 0 \\ -888.5 & -1899.7 & 0 \\ 0 & 0 & 0.5 \end{bmatrix}$$

However, the gain matrice L determined by manually assigning pole locations provide satisfactory control.

Thus, the response of the system under 10 kg/s (20% increase of nominal value) of step change in steam flow rate is shown for MPC with observer system, there was a steady state offset error in drum level as shown in figure 6.2.

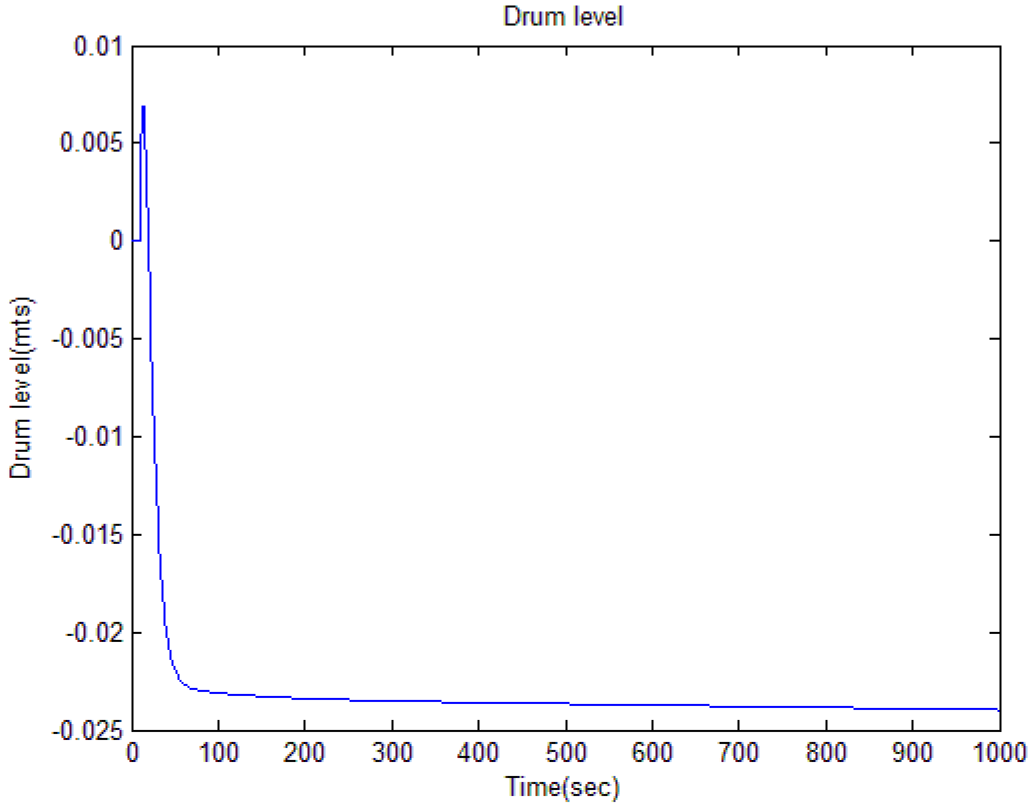

Figure 6.2 : Response of drum level for MPC with Observer

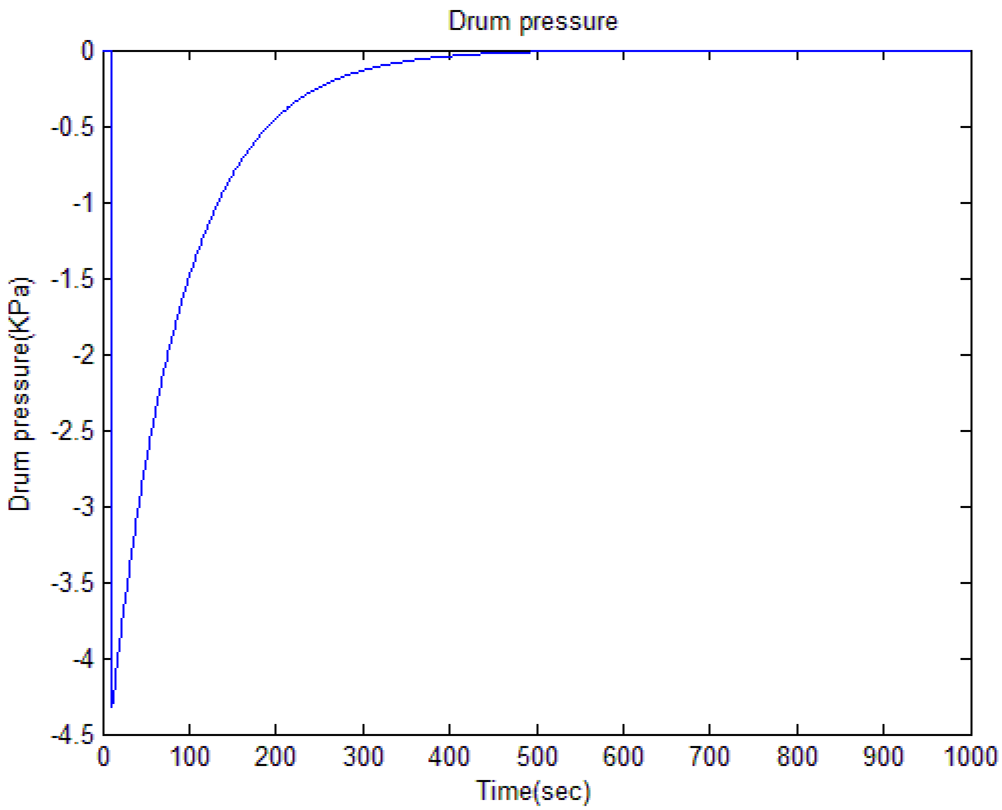

Figure 6.3: Response of drum pressure for MPC with observer

6.5 MPC with Integral Control

In order to overcome the steady state offset error in drum level, an integrator was added. The MPC control structure with state estimation and integral control is shown in figure below.

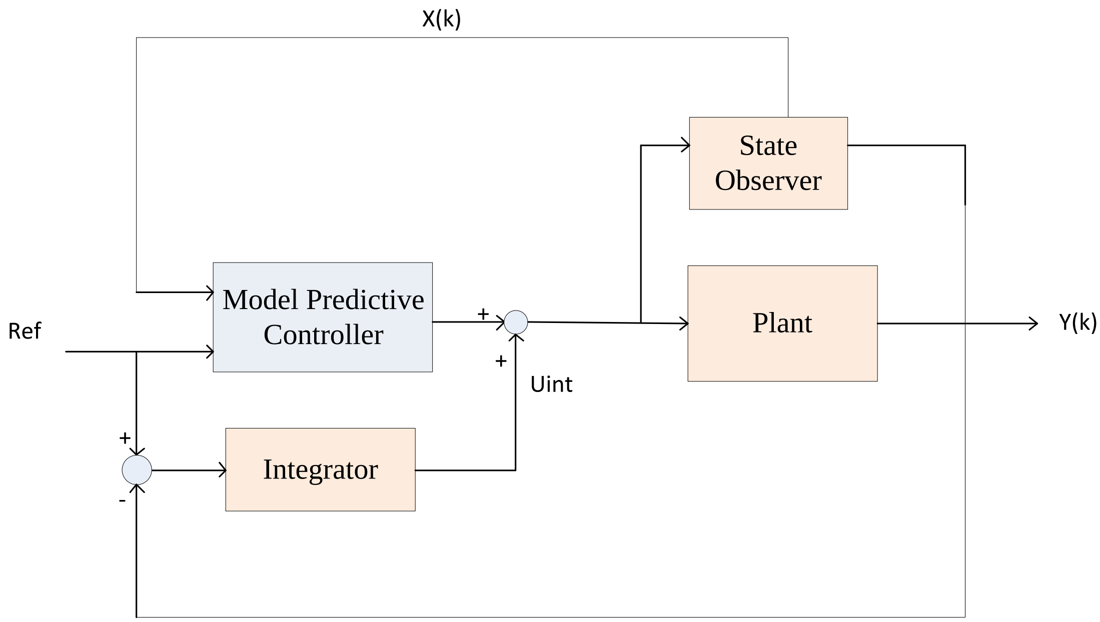

Figure 6.4: MPC structure with state estimator and integral control

Before implementing the above structure, Muske and Badgwell approach for elimination of steady-state offset error using MPC was applied. Their approach involves augmenting the system model to include a constant step disturbance which as shown below:

$$\begin{bmatrix} \dot{x} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} A & G_d \\ 0 & I \end{bmatrix} \begin{bmatrix} x \\ q \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u$$

$$\dot{y} = [C \;\; 0] \begin{bmatrix} x \\ q \end{bmatrix}$$

where $q \in R^{s_d}$, s_d is the number of augmented disturbance states, G_d determines the effect of the disturbance. The model was augmented by steam flow rate, but the results did not show significant improvement. The conditions to use such formalism as presented in [62] appeared to be stringent and less practical for the current problem.

Thus the technique of inserting the integral action in the MPC is implemented by integration of the output vector as

$$\dot{q} = q - y$$

After adding the integrator and system dynamics together the augmented system is represented as:

$$\dot{x} = \overline{A}x + \overline{B}u$$

$$Y = \dot{C}\,\dot{x}$$

$$\begin{bmatrix} \dot{x} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} A & 0 \\ -C & I \end{bmatrix} \begin{bmatrix} x \\ q \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u$$

$$\dot{y} = [C \;\; 0] \begin{bmatrix} x \\ q \end{bmatrix}$$

$$\dot{x} = \begin{bmatrix} x \\ q \end{bmatrix} \overline{A} = \begin{bmatrix} A & 0 \\ -C & I \end{bmatrix} \overline{B} = \begin{bmatrix} B \\ 0 \end{bmatrix} \overline{C} = [C \;\; 0]$$

6.6 Simulation Results and Discussion

Response of the system under 10 kg/s of step change in steam flow rate for MPC with integral system is shown. Due to the variation in the steam flow rate, causes an increase in the fuel flow rate from 0 kg/s at 20 sec to 0.46 kg/s at 25 sec. At 26sec, reduction form 0.46 kg/s to 0.425 and remains constant as shown in figure 6.5.

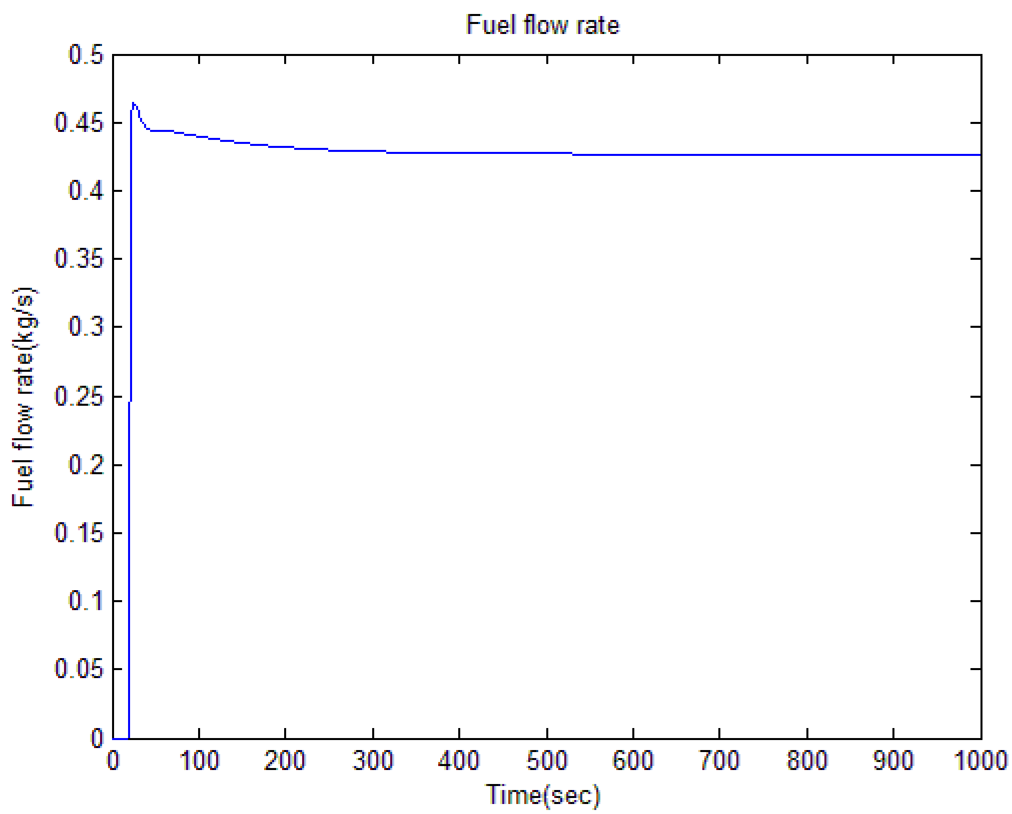

Figure 6.5: Response of Fuel Flow rate for MPC with Integral

For every pound of steam that leaves the drum we must add a pound of water in order to maintain the desired level. In our study 10kg/s of steam is leaving so we need to add 10 kg/s of water which was achieved as shown in figure below.

Thus the feedwater rate follows similar trend to that of steam flow rate but with a slight larger oscillation before it settle down.

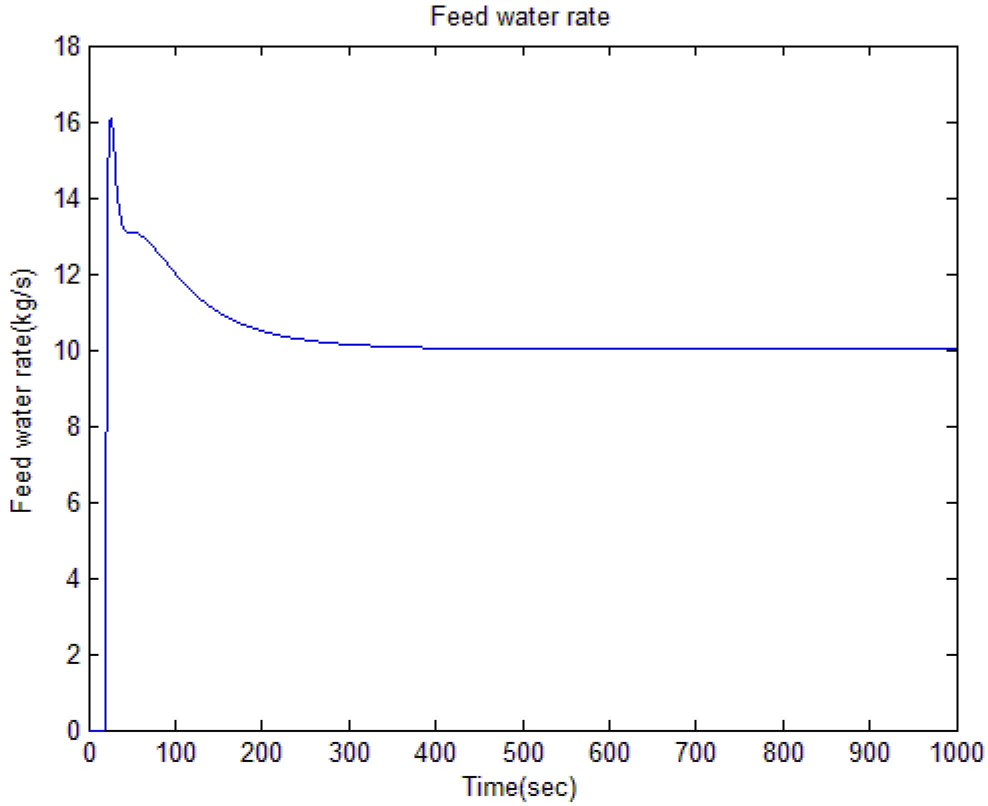

Figure 6.6: Response of Feed Water rate for MPC with Integral

The corresponding response of drum pressure is shown in figure 6.7. At 20 sec, the pressure starts dropping from 0 kPa to -4.43 kPa at 21 sec, then increases to -3.55 kPa at 40 sec, again decreases to -4.56 kPa at 102 sec.

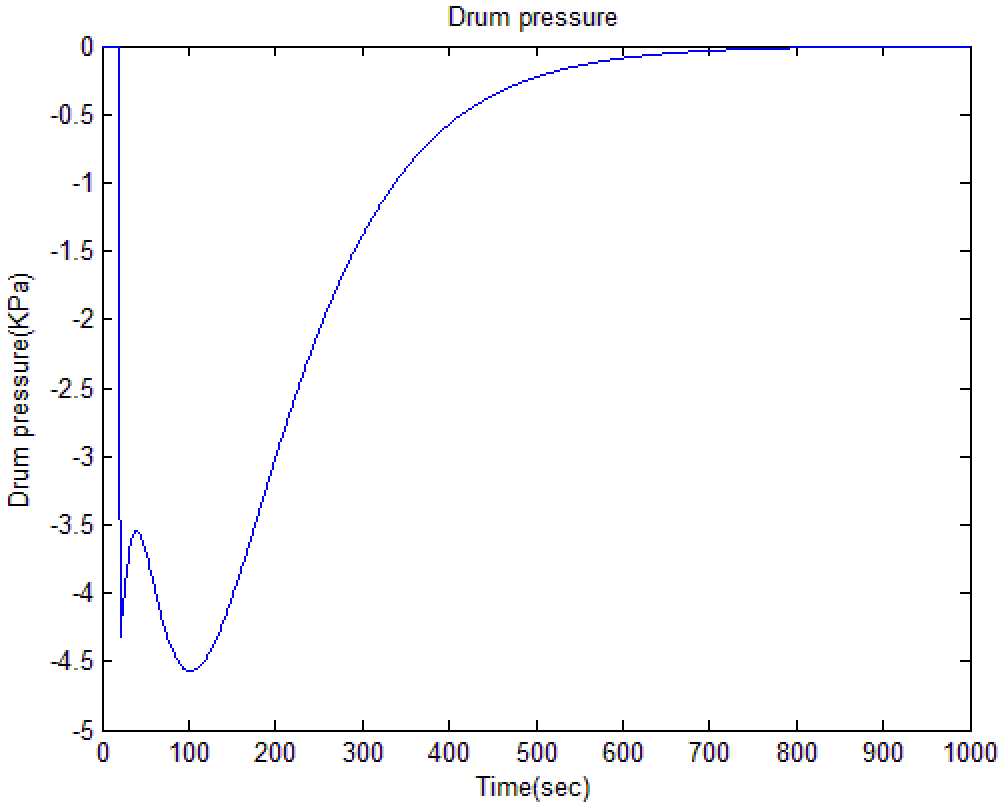

Figure 6.7: Response of Drum Pressure for MPC with Integral

Figure 6.8 shows the variation of drum level and exhibits the allowable limits of the low and high level.

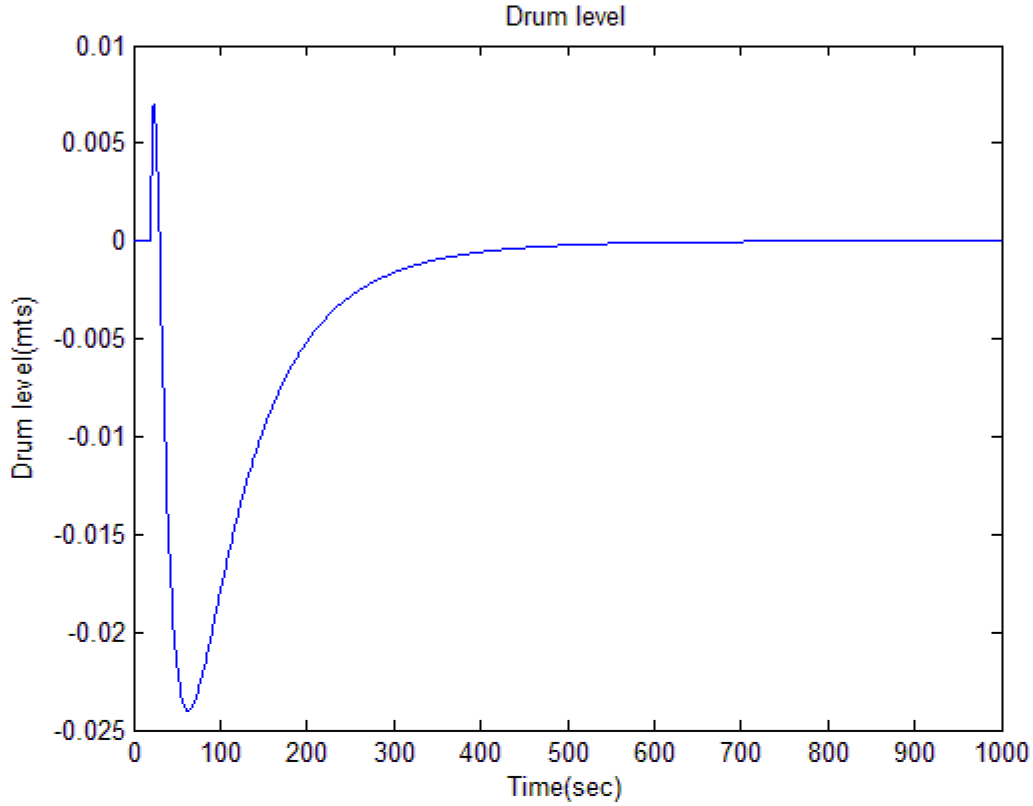

Figure 6.8: Response of Drum Level for MPC with Integral

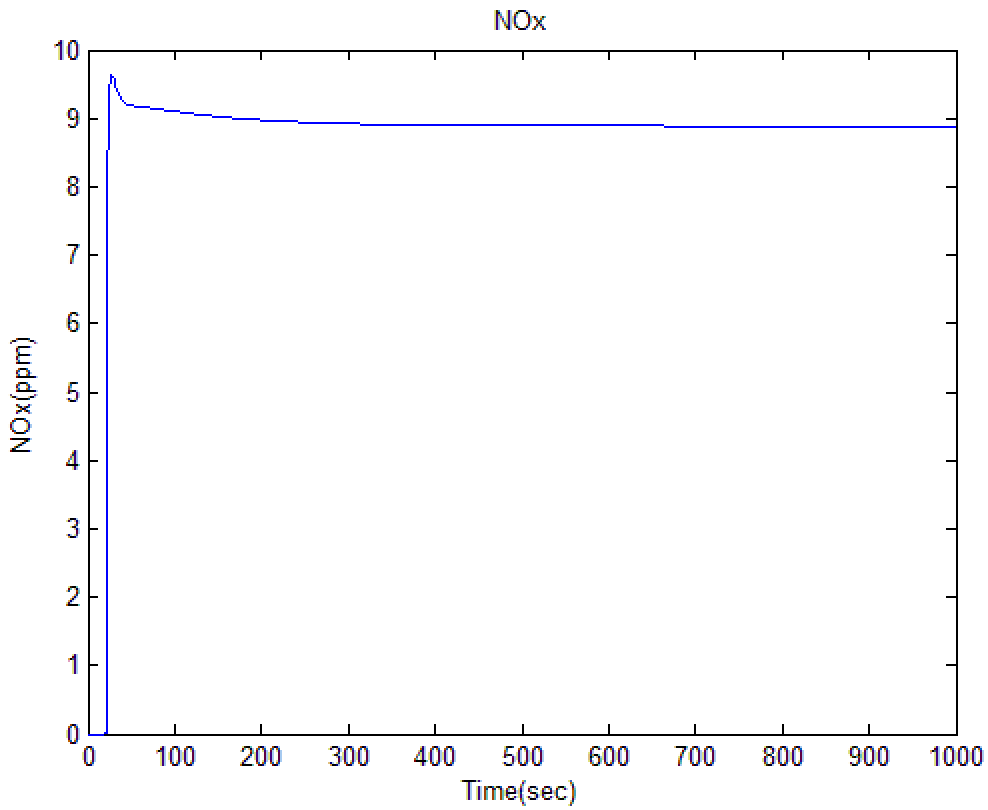

Figure 6.9: Response of NOx for MPC with Integral

6.6.1 Comparison of MPC and PI Controller

Results show that response of MPC with constraints is much better that conventional control. The graph clearly shows that the oscillatory behaviour of drum level has been decreased and with MPC it settles to steady state value very quickly at 1000 sec in response to PI and also drop in drum pressure has been reduced significantly. The controller reduces the oscillations in fuel flow rate and eliminates feed water oscillations which causes frequent failure of the water feed pumps and it reduces overshoot of NO_x thus releasing less amount of NO_x to the environment.

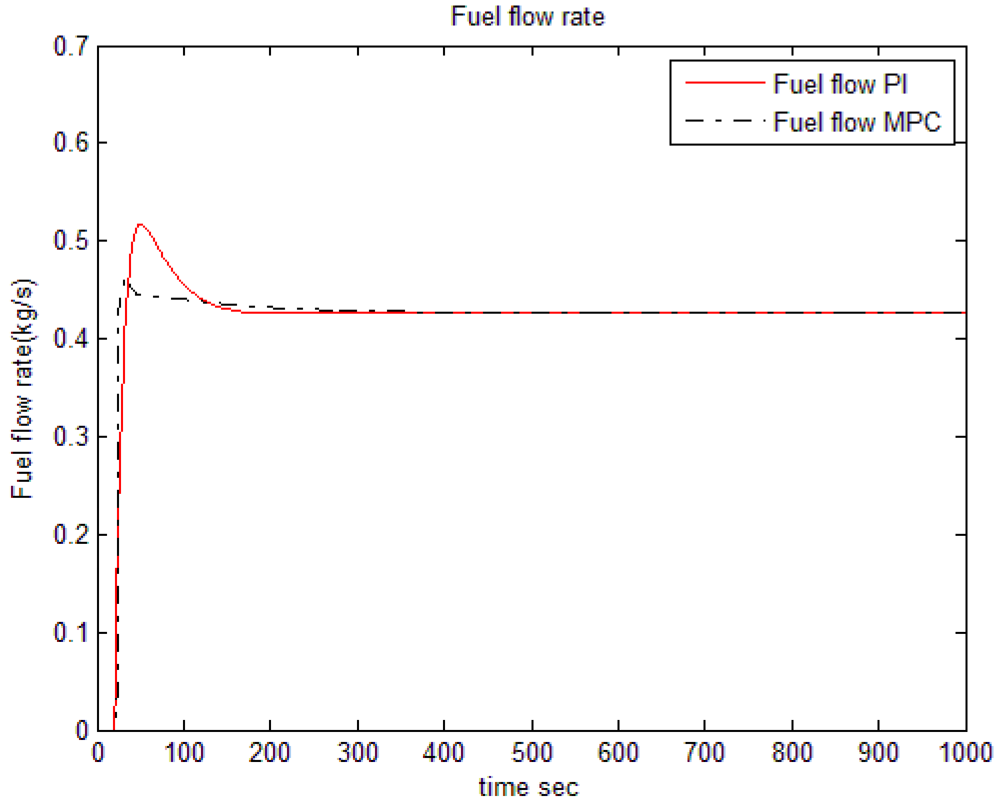

Figure 6.10: Comparison of Fuel Flow rate

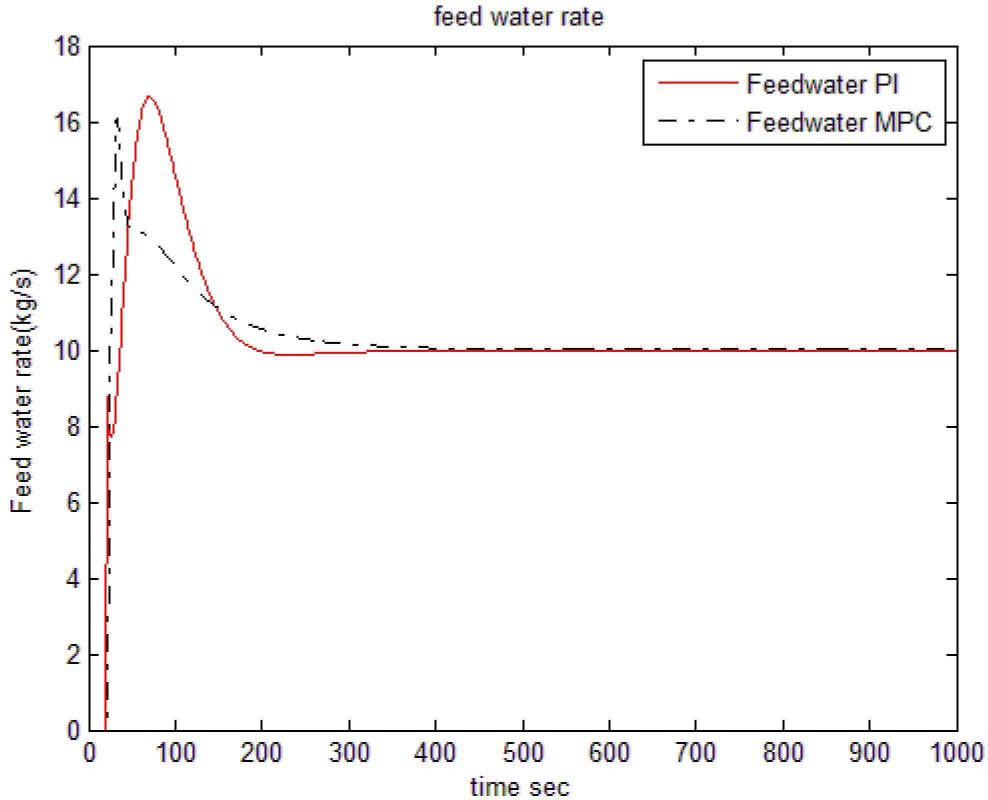

Figure 6.11: Comparison of Feed Water rate

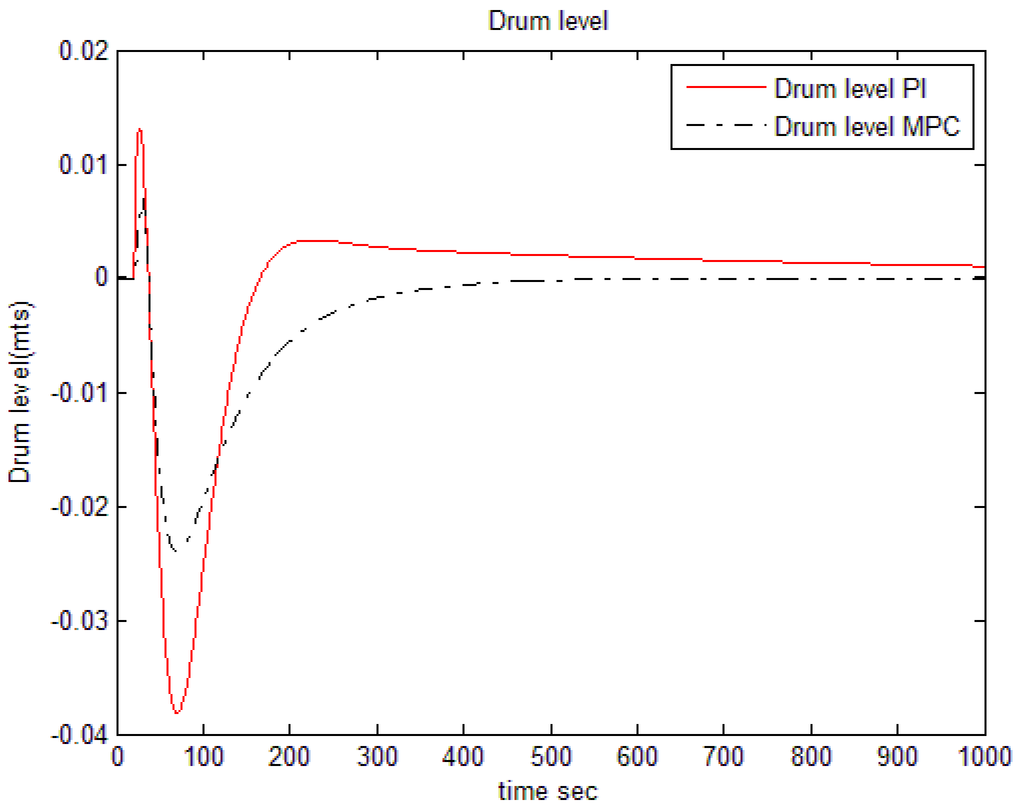

Figure 6.12: Comparison of Drum Level

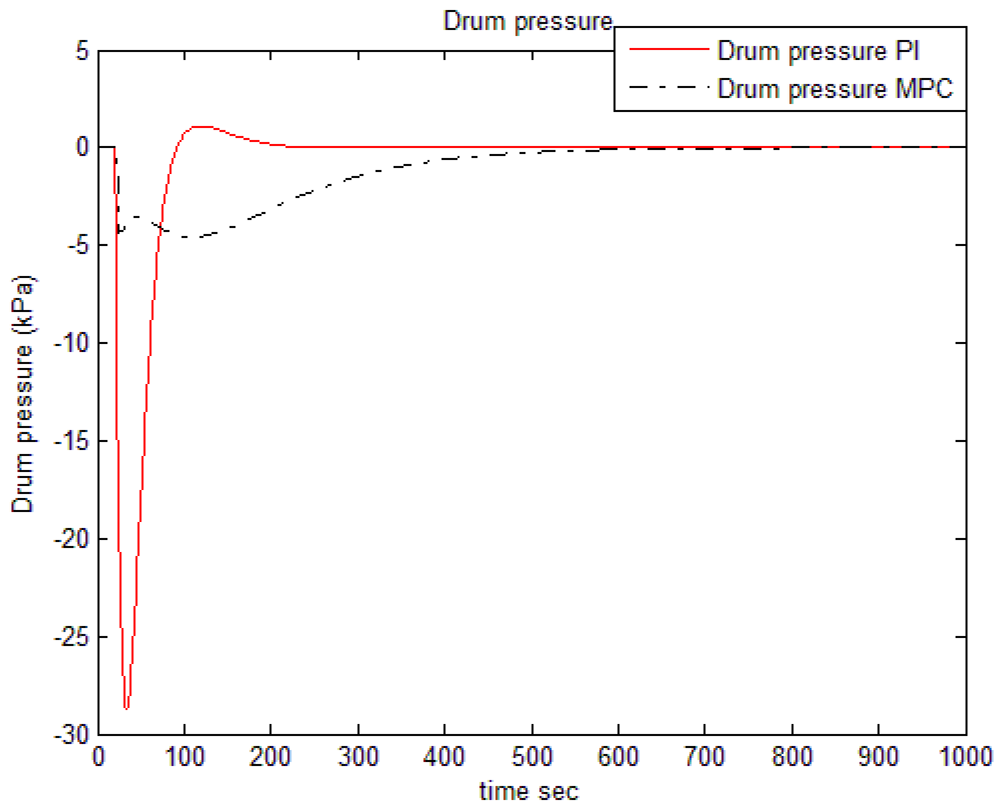

Figure 6.13: Comparison of Drum Pressure

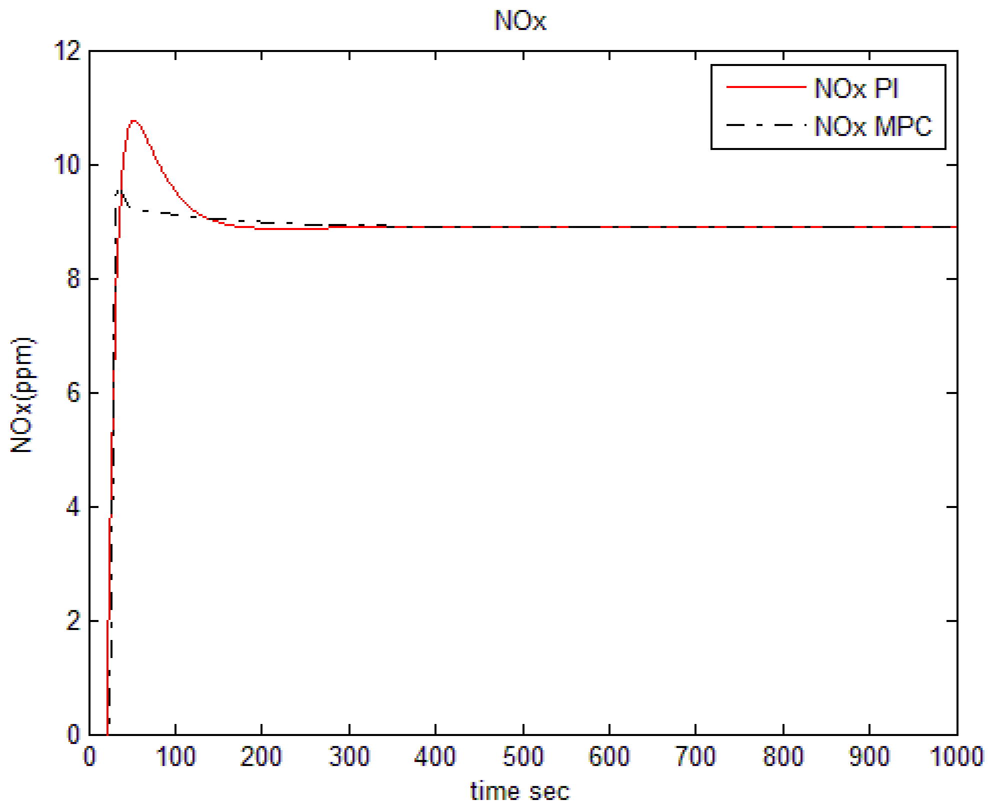

Figure 6.14: Comparison of NOx

6.6.2 Controlling NOx with drum dynamics

As we have stated in the previous cost function that we are controlling drum dynamics without NO_x control, i.e. not including the NO_x in cost function. So, in order to control NO_x to steady state level with drum dynamics we made analysis which is shown below.

Cost function

The objective is to minimize the deviation from the desired drum level and drum pressure and also *reduce NO_x to steady state level by controlling it,* in presence of measured disturbance. The cost function will have the following appearance

$$J = \sum_{i=1}^{H_p}\left[Q_{level}\,|[Y_{level,i} - Y_{level,ref,i}]|^2 + Q_{pressure}\,|[Y_{pressure,i} - Y_{pressure,ref,i}]|^2 + Q_{NOx}\,|[Y_{NOx,i} - Y_{NOx,ref,i}]|^2\right]$$
$$+ \sum_{i=1}^{H_c}\left[R_{fuel}\,|(u_{fuel,i})|^2 + R_{feedwater}\,|(u_{feedwater,i})|^2 + R_{tiltposi}\,|(u_{tiltposition,i})|^2 + R_{fuelairratio}\,|(u_{fuelairratio,i})|^2\right]$$

In our design, Prediction Horizon (H_p) is chosen to be 4 and control horizon (H_c) as 2 and the model is constrained under same limits as mentioned earlier. With the above cost function implementation, the system response remains same for drum level, drum pressure and we are able to reduce NO_x back to steady state level. Thus, the following figures show the response of drum level, drum pressure and NO_x respectively

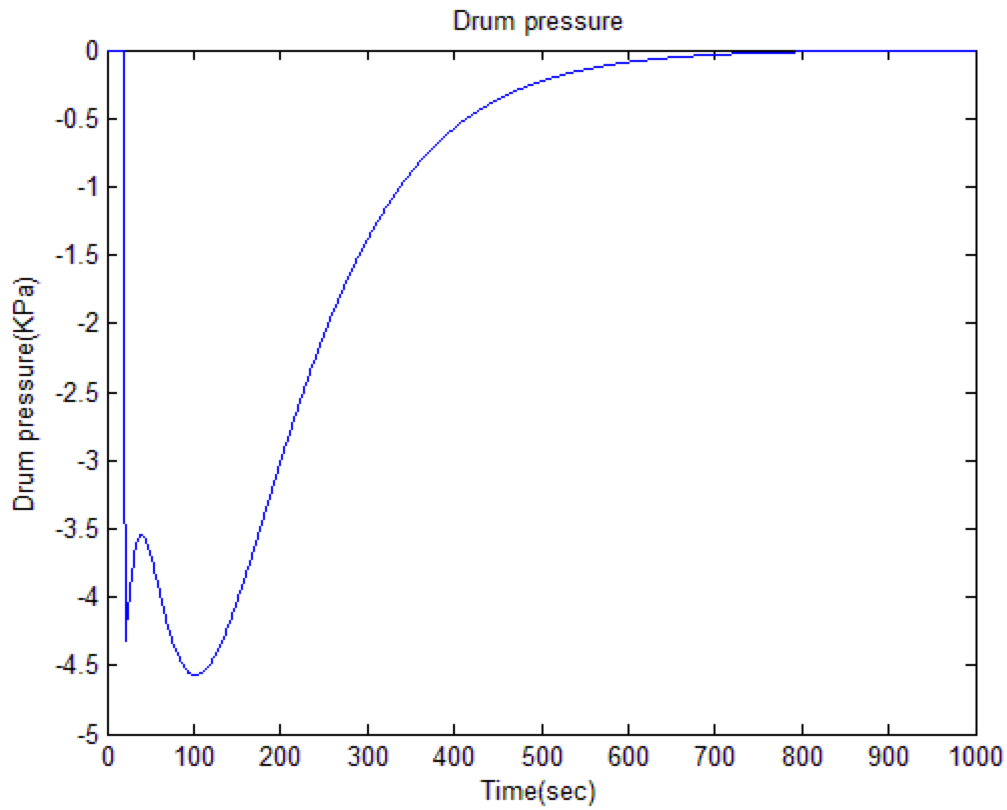

Figure 6.15: Response of Drum Pressure with NOx Control

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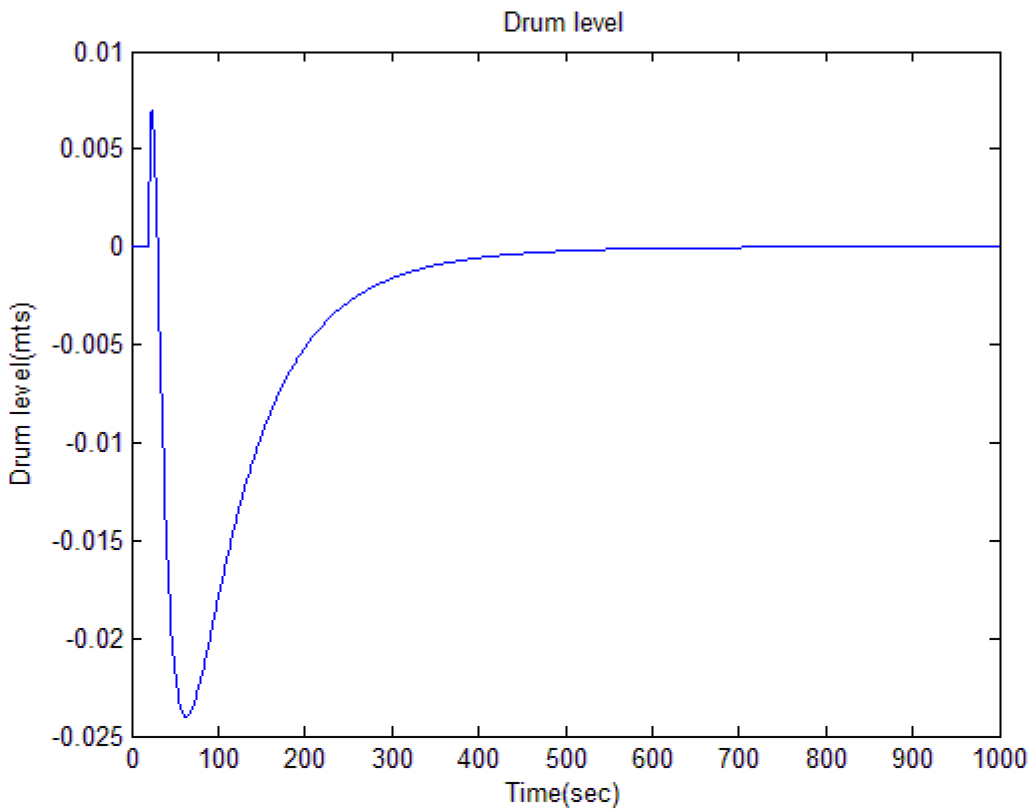

Figure 6.16: Response of Drum Level with NOx Control

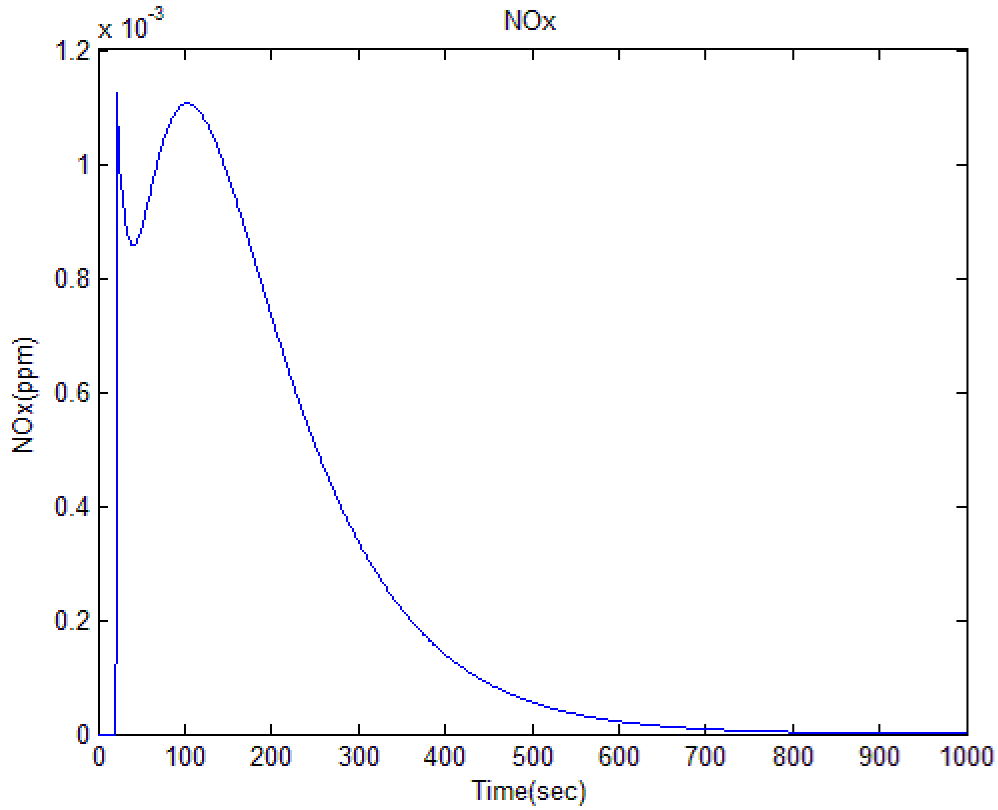

Figure 6.17: Response of NOx under control

SPECIAL CASE:

Comparison of PI and MPC for a disturbance of 20kg/s steam flow rate

We have seen in the previous section that the proposed MPC controller performs well in all aspects compared to PI control, especially drum pressure as the pressure drop has been reduced to -5kPA from -28kPA. But for the case of drum level, there is not much improvement as the variation difference is only 1.4 centimetres, which is a minor difference. So, to have a better evaluation of the performance, we analysed the response of boiler for disturbance of 20kg/s of steam demand. We are able to have a much better performance in drum level and also other responses which are shown below.

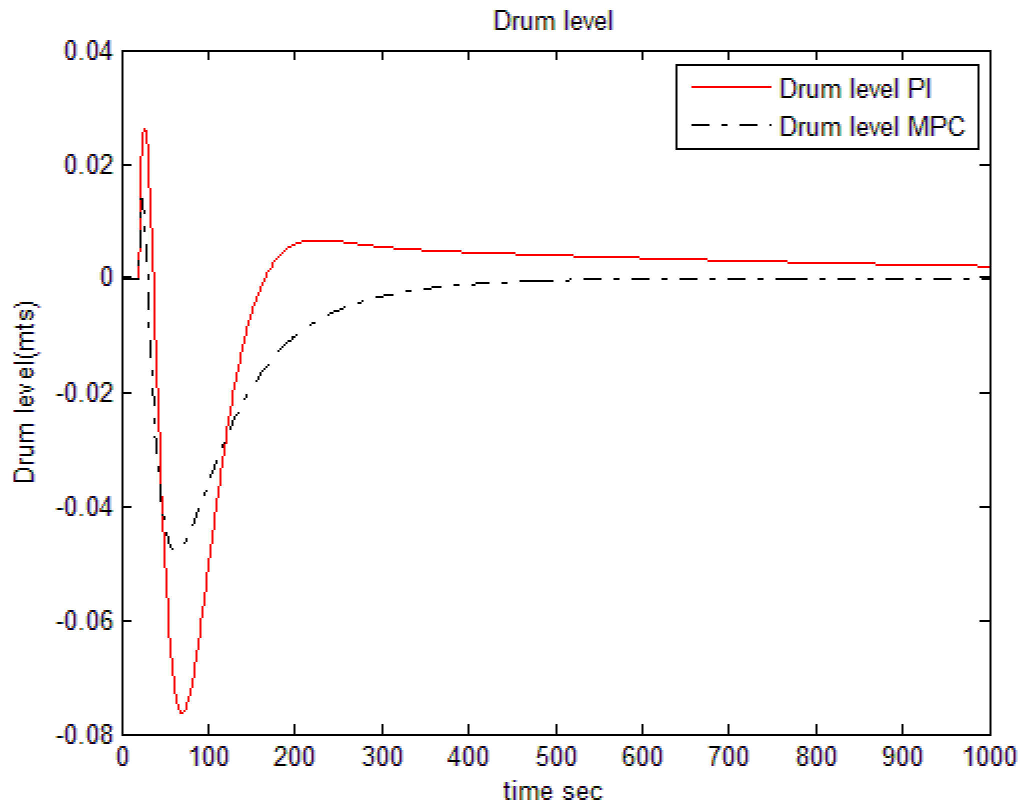

Figure 6.16: Comparison of Drum Level for 20 kg/s disturbance

When a step change of 20 kg/s in steam demand is made, the proposed controller is keeping the drum level under allowable limits, i.e. 4.4 centimetres while the PI controller keeps the level to 7.8 centimetres which may trip the boiler.

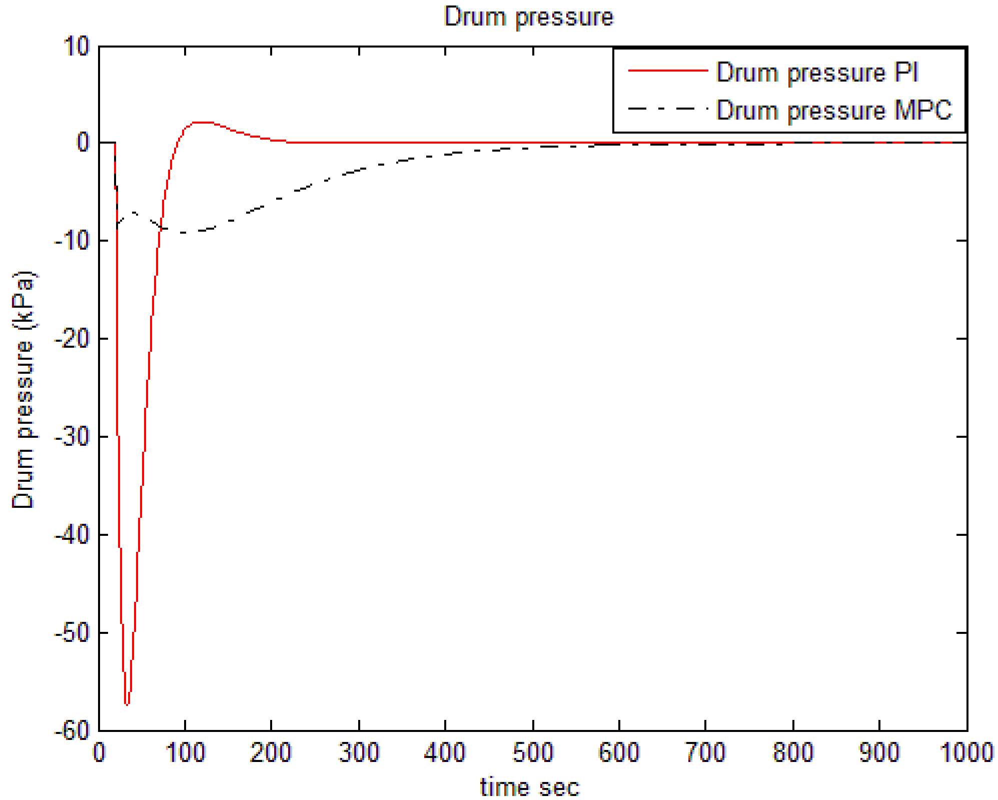

Figure 6.17: Comparison of Drum Pressure for 20kg/s disturbance

The drum pressure drop has been reduced significantly even in presence of 20kg/s step change in steam demand, which is much better than PI controller. Also, there is reduction in overshoot of NOx which can be seen in the figure below.

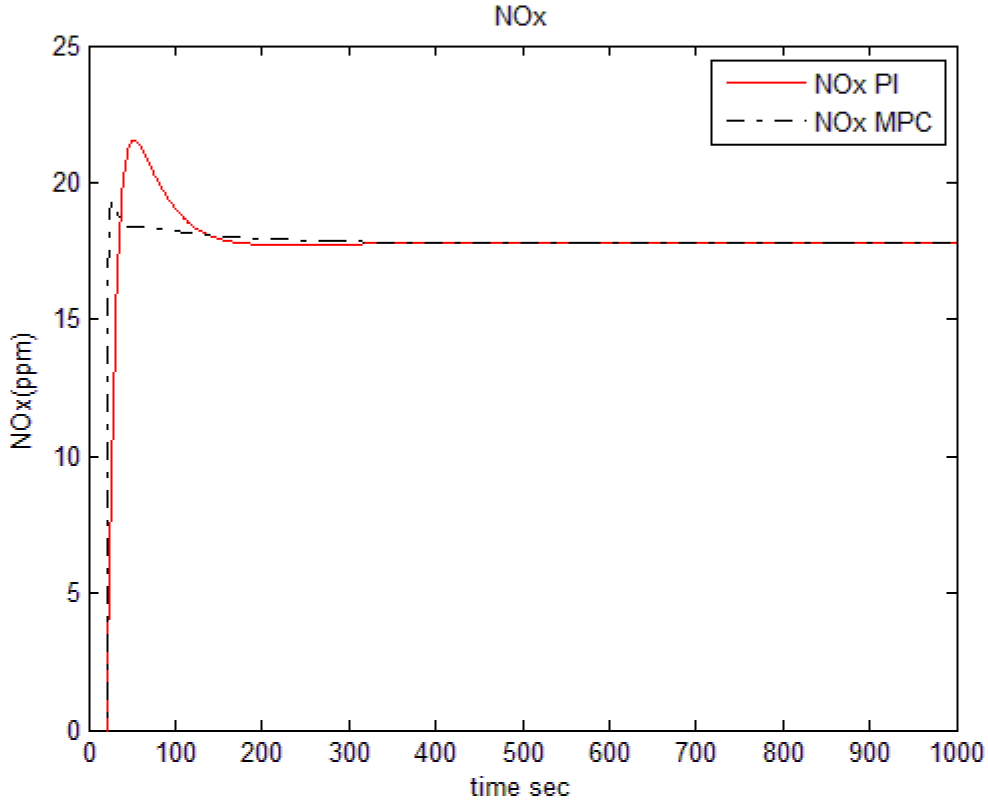

Figure 6.18: Comparison of NOx for 20kg/s disturbance

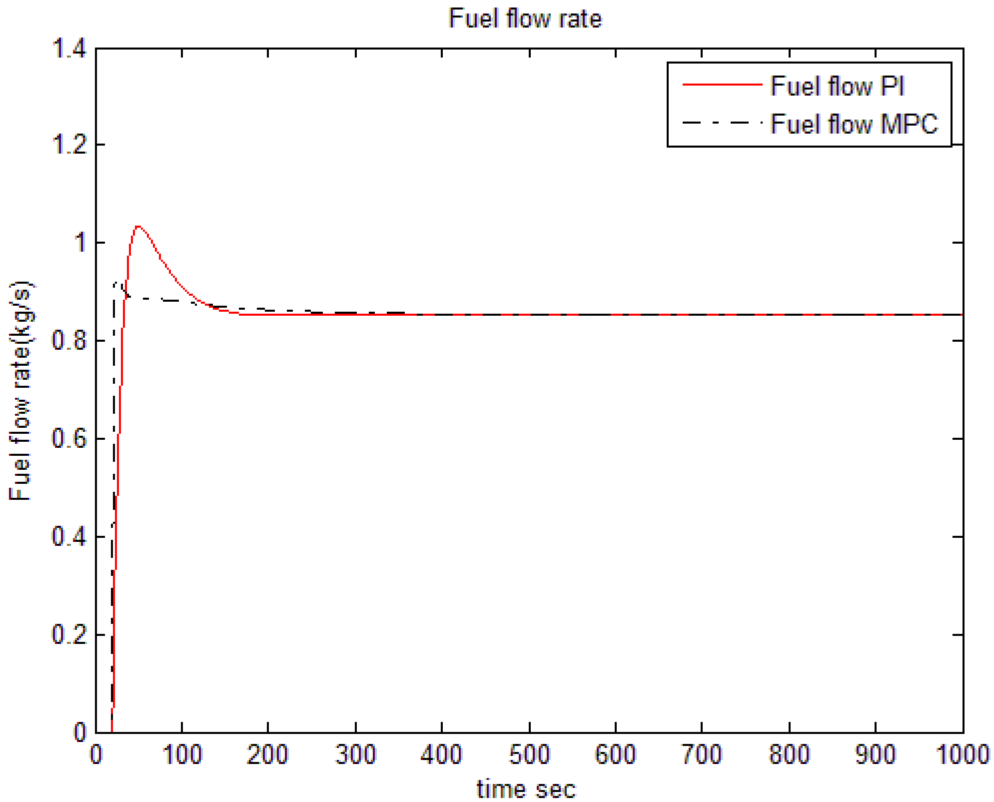

Figure 6.19: Comparison of Fuel flow rate for 20kg/s disturbance

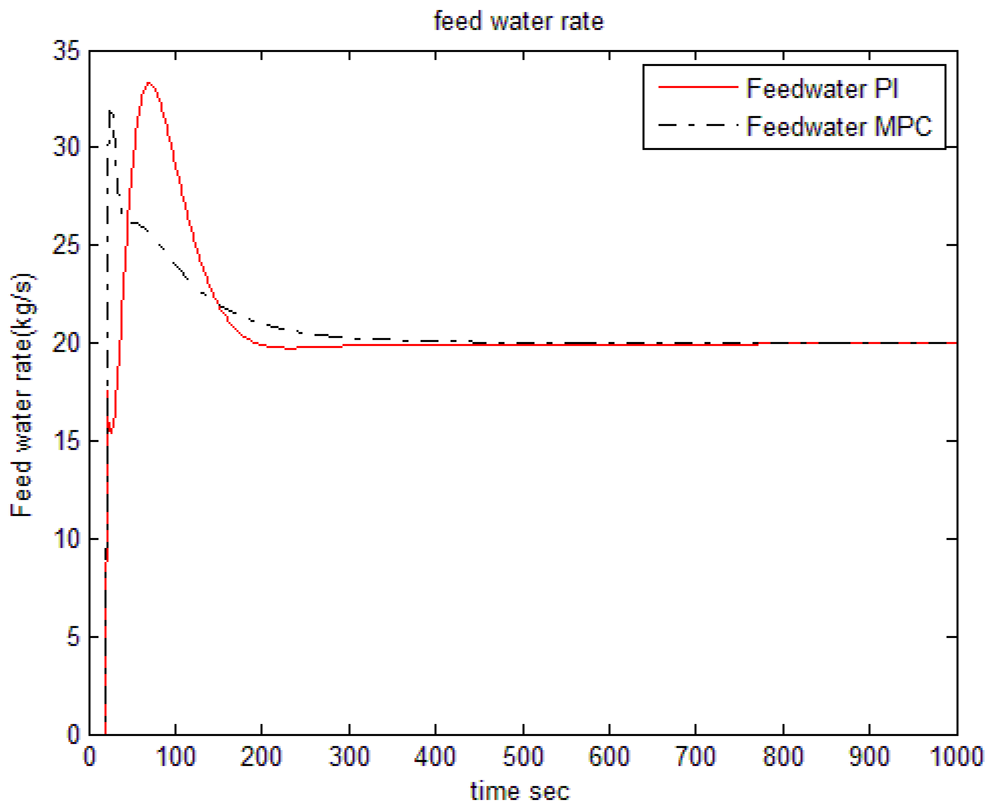

Figure 6.20: Comparison of Feed flow rate for 20kg/s disturbance

CHAPTER 7

CONCLUSIONS AND FUTURE RESEARCH

7.1 Conclusion

The work presented in this thesis focuses upon the problem of controlling a drum type boiler operation as well as its NO_x emission level in presence of variations of the steam demanded. For that purpose an augmented model integrating both boiler and NO_x models has been developed. The augmented model was developed from the knowledge of Astrom and Bell drum boiler model and Li and Thompson NO_x emission model. Before coming up with augmented model, scaling of Astrom model was done in order match with NO_x model. Model Predictive Control (MPC) technique has been implemented for controlling the system. Conventional PI controller was also implemented. Results shown in Chapter 6 demonstrated that the performance of the proposed controller improves the performance and plant stability under sudden changes in steam demand better than PI controller.

7.2 Recommendations

In the present work, we developed a linear simulation model of boiler which considers NO_x formation and also controlling the emission of NO_x is carried out, but still some of the other areas in terms of modeling is to be explored. Following are some of the recommendations for future research

a) Firstly, the present work considers the dynamics of the plant to be linear, thus we can develop a non liner boiler model considering NO_x.

b) We can also consider other emission pollutants like CO and O_2 for modeling purpose.

c) Adaptive control with combination of MPC may also provide better results. Very few work on adaptive-MPC approach is reported in literature for this area of research.

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APPENDIX

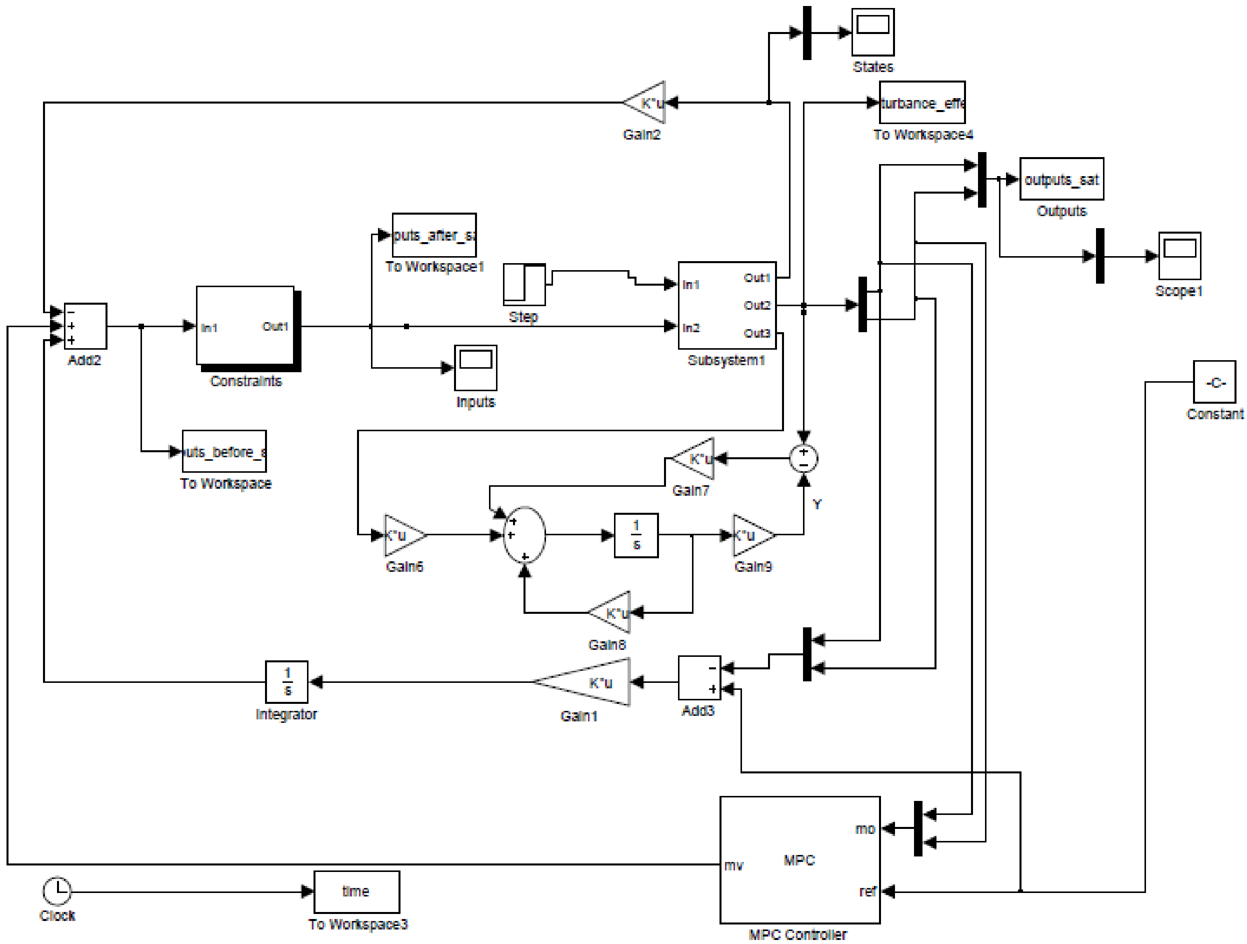
i. Matlab code for MPC with Obsever and Integral

```
%.........Code for boiler obsv with integral...%

Clear all;
close all;
load MPC1

global Ad1hat Bd1hat Cd1hat Dd1hat Khat z;

umin=[-20;-4; -10;   0.0; -20;-4; -10 ;0.0]';
umax=[20 ;10;  10;  0.04; 20;10 ;  10; 0.04]';
z=[ 0 0 0 0 0 0 ];%[ qs state-vector]
X0=[0 0 0 0 0]';
Y0=[ 0 0 0]';
U=[0 0 0 0 0]';

 A=[0  0     -5.269e-016    0          0;...
    0  0         0          0          0;...
    0  0      -0.1546       0          0;...
    0  0     -16.9454   -0.0833        0;...
    0  0         0          0         -1];
HHV=40360; kJ/Kg
b13=(3.64e-7)*HHV;

b23=0.0003091*HHV;
b33=(3.058e-8)*HHV;
```

```
b34=(-1.176e-006)*HHV;

B=[-0.002045    0.001418     b13     0      0;...

  -0.4655      -0.06679     b23     0      0;...

   4.757e-005   6.824e-006    b33     0      0;...

   0.01203     -0.003133     b34     0      0;...

      0          0        20.83   0.86   -13139.73];

Ad=20;

C= [1/Ad 0 0 1/Ad 0;

   0 1 0 0 0];

  D=zeros(2,5);

Khat=place(A,B(:,2:5),[-0.5 -1.2 -0.75 -0.6 -1]/5);

L=place(A',C',[-0.5 -1.2 -0.075 -0.06 -1])';

tfinal=1000;

sim('boiler_withoutNOxcontrol_integral');
 figure(1);
plot(outputs(:,2));

xlabel('Time(sec)');ylabel('Drum level(mts)');

title('Drum level');

 figure(2);

plot(outputs(:,3));

xlabel('Time(sec)');ylabel('Drum pressure(KPa)');

title('Drum pressure');

 figure(3);

plot(NOx(:,2));

xlabel('Time(sec)');ylabel('NOx(ppm)');

title('NOx');

figure(4);
```

```
plot(inputs(:,2));
xlabel('Time(sec)');ylabel('Feed water rate(kg/s)');
title('Feed water rate');
 figure(5);
plot(inputs(:,3));
xlabel('Time(sec)');ylabel('Fuel flow rate(kg/s)');
title('Fuel flow rate');
```

ii. Simulink Model for MPC + Observer + Integral



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