



UNIVERSITY OF
BIRMINGHAM

Study of Energy Efficient Supercritical Coal-Fired Power Plant Dynamic Responses and Control Strategies

By

OMAR R. IBRAHIM MOHAMED

A Thesis Submitted To

The University Of Birmingham

For The Degree Of

DOCTOR OF PHILOSOPHY

School Of Electronic, Electrical

& Computer Engineering

College Of Engineering & Physical Science

The University Of Birmingham, UK

August 2012

UNIVERSITY OF
BIRMINGHAM

University of Birmingham Research Archive

e-theses repository

This unpublished thesis/dissertation is copyright of the author and/or third parties. The intellectual property rights of the author or third parties in respect of this work are as defined by The Copyright Designs and Patents Act 1988 or as modified by any successor legislation.

Any use made of information contained in this thesis/dissertation must be in accordance with that legislation and must be properly acknowledged. Further distribution or reproduction in any format is prohibited without the permission of the copyright holder.

ABSTRACT

The world is facing the challenge of global warming and environment protection. On the other hand, the demand of electricity is growing fast due to economic growth and increase in population. With the consideration of environmental issues and sustainable development in energy, ideally, renewable energy such as wind, solar, and tidal wave should be only resources to be explored. Since the growth in demand is also a heavy factor in energy equations, then the renewable energy alone is not able to generate enough electricity to fill the gap within a short time of period. Therefore, fossil fuel such as coal fired power plants cannot be ruled out immediately due to their generation capacity and flexibility in load following. However, any new coal fired stations should be cleaner compared with traditional power plants. Supercritical (SC) power plants are one of the most suitable choices for environmental enhancement and higher efficiency. However, there has been an issue of whether or not to adopt this technology in the UK because it is not clear whether the dynamic response and performance for SC plants can satisfy the British Grid Code requirement.

This thesis reports a study of dynamic responses of SC power plants through mathematical modeling, identification, and simulation. It also presents a new control strategy based on an alternative configuration of generalized predictive control for enhancement of the SC plant responses.

In the process of modeling development, Genetic Algorithms are used for parameter identification and model response optimization. The model has also been verified for certain operation conditions with the different sets of data obtained from 600MW SC

power plant. A Genetic Algorithm offers a more reliable and simpler identification method than conventional optimization techniques adopted in the previously published literature.

The control strategy is based on generalized predictive control scheme which is widely used for power plant control. Model predictive control is a well recognized technology for control of industrial systems. The control philosophy behind the work presented in the paper is to develop a control strategy to achieve prediction of the future demand for fuel input and implement control actions at the earliest possible time. Any control actions taking for the milling process will take a long time to show their influences onto the boiler, turbine and generator responses as the whole process experiences coal transmission, grinding, drying and blowing to the furnace. The signals of the controller are used to adjust the reference of the plant local controllers instead of directly applying the control signal. Also, under the complete process structure with its associated predictive control strategy, the influences of milling conditions are reported. It has been proved that the milling response improvements play an important role in improving the plant output responses and satisfaction of the GB Grid Code. Three schemes have been tested in the thesis: generalized predictive control, predictive control using three augmented models, and model predictive control in parallel with dynamic compensator. The 1st scheme is designed for small load changes around nominal conditions while the others are used to conduct large load changes and partial load rejection simulation study.

DEDICATION

This work is dedicated to my wife

ACKNOWLEDGEMENTS

I would like to express my thanks firstly to Allah (God) for supporting me and providing me blessings to complete this work.

I would like to express my gratitude to my supervisor Prof. Jihong Wang who guided me during my research, and I appreciate her patience and advices. Her encouragement and support were really great motivation for me. I really have benefited from each minute of discussion with Prof. Jihong Wang. The suggestions, criticisms and the guidance I received from her were valuable which made this thesis possible. Also, I would like to thank my co-supervisor Dr. Bushra Al-Duri for her patience, advices, and discussions.

I would like to thank Dr. David Goodall and Dr. Joe Wood for devoting part of their valuable time to read and exam my thesis.

Thank to my wife for her great patience and unlimited love and care. Thanks to my parents for their patience and support throughout all of my life.

Table of content

Chapter 1 Introduction	1
1.1 Background and Motivation	2
1.2 Description of Research Methodology	5
1.3 Research Objectives	13
1.4 Coal as Fuel of Power Stations	14
1.5 Advances in Clean Coal Technologies	17
1.6 Carbon Capture and Storage	21
1.7 Major Contribution of the Thesis	23
1.8 Thesis Organization	26
Chapter 2 Overview of Coal Fired Power Plant Processes and Progress in Research	29
2.1 introduction	29
2.2 Coal Fired Power Generation Process	30
2.3 Rankine Cycle	32
2.4 Supercritical Boiler Technology	34
2.5 Types of Supercritical Boilers	37
2.6 Main Parts of Supercritical Boiler	40
2.6.1 Evaporator Surface	40
2.6.2 Superheaters and Reheaters (SH & RH)	41
2.6.3 Evaporator Surface	42
2.7 Subcritical vs. Supercritical Boilers	42
2.8 Summary for the features of Supercritical Boilers	46
2.9 Overview of Research in SC Power Plant Modeling and Control	48
2.9.1 Mathematical Modeling of SC Power Plant Process	48
2.9.2 Unknown Parameter Identification for Modeling	52
2.9.3 Research Progress in Control of SCPP	53
2.10 Power Plant Simulation Tools	56
2.11 Summary	57
Chapter 3 Mathematical Modeling of s Supercritical Coal Fired Power Generation Processes	59
3.1 introduction	59

3.2 A historical Review	60
3.3 The Boiler-Turbine Process Description	61
3.4 Thermodynamic Principles for Modeling	62
3.5 The Boiler Heat Exchanger Modeling	66
3.5.1 Economizer Model	75
3.5.2 Waterwall Model or Furnace inner tubes Model	75
3.5.3 Superheater Model and Throttle Pressure Model	76
3.6 Heat Transfer in the Boiler	77
3.7 Mass Flow Rates	79
3.7.1 Intermediate Mass Flow Rates	79
3.7.2 Outlet Mass Flow Rates	79
3.8 Turbine Model	80
3.8.1 Reheater Model	82
3.9 The Synchronous Generator Model	82
3.9.1 The Turbine Generator Interactions	84
3.10 Summary of the Whole Systems and The Proposed Simulation Tool	86
Chapter 4 Parameter Identification for Modelling	90
4.1 introduction	90
4.2 A Review	91
4.3 Genetic Algorithms	93
4.4 Rosenbrock's Function	97
4.5 Justification of Using GA	99
4.6 Model Parameter Identification	101
4.6.1 Data Analysis and Description	101
4.6.2 Parameter Identification Using GA	104
4.7 Summary	111
Chapter 5 A Complete Power Plant Process Model	112
5.1 introduction	112
5.2 Simulation Study Using Different Sets of Data and Results Analysis	113
5.3 Comparison of Static Performances with the Results Obtained Using	

Thermolib Model	122
5.4 Coal Mill Model for Normal Grinding Process	126
5.5 Summary	132
Chapter 6 Model Predictive Control theory and its Applications to SCPP	133
6.1 introduction	133
6.2 Historical Development in SCPP	135
6.3 Introduction to Receding Horizon Principle	138
6.4 Prediction	142
6.5 Optimization of Control Signals	145
6.5.1 Active Set Method	148
6.5.2 Interior Point Method	149
6.6 Illustration Example	150
6.6.2 Controller design and Application on Paper Machine Nonlinear Model as a Plant	153
6.7 Summary	159
Chapter 7 MPC Control of Supercritical Power Plant and Simulation Study	160
7.1 introduction	160
7.2 Configuration of the Control Strategy	161
7.3 1 st Scheme of Control: Model based Predictive Control Strategy	163
7.3.1 Results Analysis and Discussions 1	171
7.4 2 nd Scheme of Control: Multi-Model based Predictive Control Strategy	173
7.4.1 Results Analysis and Discussions 2	179
7.5 3 rd Scheme of Control: Multivariable Optimal Controller	180
7.6 Summary	192
Chapter 8 Conclusion and Suggested Future Research	193
8.1 Conclusions	193
8.2 Recommendations for Future Research	197
Reference	200
APPENDIX	209
A.1	212

A.2	214
A.3	217

List of figures

Fig 1.1 Main Components of Supercritical Coal Fired Power Plant	6
Fig 1.2 Parameter Identification Problem Formulation	8
Fig 1.3 Controlled Reference or Adjusted Reference Values	13
Fig 1.4 Controlled Action or Adjusted Action Values	14
Fig 1.5 Modes of FBC	18
Fig 1.6 Simplified Schematic View for Coal Fired Supercritical Boiler Process	20
Fig 1.7 Carbon Capture methods	22
Fig 2.1 Simplified Diagram for Typical Coal Fired Power Plant	31
Fig 2.2 Four Process Cycle For Steam Power Plant	33
Fig 2.3 Steam Power Plant Operating on a Rankine Cycle	34
Fig 2.4 Temperature Volume Diagram for a Substance Such as Water	36
Fig 2.5 Pressure Temperature Diagram for a Substance Such as Water	37
Fig 2.6 Tower-Type SC boiler	39
Fig 2.7 Tow-Pass SC boiler	39
Fig 2.8 Down-Shot SC boiler	40
Fig 2.9 Typical Design Arrangement for SH or RH	42
Fig 2.10 Subcritical Drum-Type Plant Cycle	43
Fig 2.11 Supercritical Once-through Plant Cycle	44
Fig 2.12 T-S Diagram of Steam and Water	45
Fig 2.13 T-S Diagram for Sub- and Supercritical Boilers	46
Fig 2.14 Simulation results as an example from previous research (Suzuki <i>et al.</i> 1979)	51
Fig 3.1 Once-through Unit Schematic Diagram	62
Fig 3.2 Illustration of the Concept of Control Volume	64
Fig 3.3 Diagram of the Heat Exchanger to be Modelled	67
Fig 3.4 the Spray water in the real power plant and in the model	77
Fig 3.5 A simplified Single Reheat Turbine Model	82
Fig 3.6 The ith mass Spring System	85
Fig 3.7 Blocks Description of the Boiler Turbine Generator System	87
Fig 4.1The flow Diagram of Genetic Algorithms	94

Fig 4.2 Genetic Algorithm Tool	96
Fig 4.3 2-Dimensional Rosenbrock's Function	98
Fig 4.4 The GA performance for Optimization	99
Fig 4.5 A set of data with indicated operating conditions	103
Fig 4.6 Identification Procedures of Boiler Turbine Generator System	105
Fig 4.7 Measured and simulated frequency deviation	108
Fig 4.8 Measured and Simulated Electrical Power	108
Fig 4.9 Measured and simulated steam flow rate	109
Fig 4.10 Measured and simulated main steam temperature	109
Fig 4.11 Measured and simulated main steam Pressure	110
Fig 5.1 Measured and simulated frequency deviation for data set.2	113
Fig 5.2 Measured and simulated electrical power for data set.2	114
Fig 5.3 Measured and simulated main steam temperature for data set.2	114
Fig 5.4 Measured and simulated main steam pressure for data set.2	115
Fig 5.5 Measured and simulated main steam flow for data set.2	115
Fig 5.6 Measured and simulated frequency deviation for data set.3	116
Fig 5.7 Measured and simulated electrical power for data set.3	116
Fig 5.8 Measured and simulated main steam temperature for data set.3	117
Fig 5.9 Measured and simulated main steam pressure for data set.3	117
Fig 5.10 Measured and simulated main steam flow for data set.3	118
Fig 5.11 Measured and simulated frequency deviation for data set.4	118
Fig 5.12 Measured and simulated electrical power for data set.4	119
Fig 5.13 Measured and simulated main steam temperature for data set.4	119
Fig 5.14 Measured and simulated main steam pressure for data set.4	120
Fig 5.15 Measured and simulated main steam flow for data set.4	120
Fig 5.16 The SC plant cycle's component used in thermolib model	123
Fig 5.17 Clipped view of the extended MS excel file for Chemical Data of Thermolib	124
Fig 5.18 Cross sectional View of Typical Vertical Spindle Mill	127
Fig 5.19 SC Coal Fired Power Plant response to simulatenous 20% step change in 2min fo fuel flow, feedwater flow, valve position	131
Fig 6.1 The basic Idea of receding horizon Predictive Control	139

Fig 6.2 Paper Machine Headbox	150
Fig 6.3 The impact of 1 st input on all system outputs	152
Fig 6.4 The impact of 2 nd input on all system outputs	152
Fig 6.5 Model based predictive control applied on paper machine nonlinear model	154
Fig 6.6 Manipulated inputs for set-point [0 0 0] disturbance size=1	155
Fig 6.7 Output Variables for set-point [0 0 0] disturbance size=1	155
Fig 6.8 Manipulated inputs for set-point [0.1 0 0.02] disturbance size=1	156
Fig 6.9 Output Variables for set-point [0.1 0 0.02] disturbance size=1	156
Fig 6.10 Manipulated inputs for set-point [0 0 0] disturbance size=4	157
Fig 6.11 Output Variables for set-point [0 0 0] disturbance size=4	157
Fig 6.12 Manipulated inputs for set-point [1 1 1] disturbance size=9	158
Fig 6.13 Output Variables for set-point [1 1 1] disturbance size=9	158
Fig 7.1 Schematic diagram for the predictive control and the SCPP process	162
Fig 7.2 Main steam Pressure response	164
Fig 7.3 Electrical Power Response	165
Fig 7.4 Controlled Variables of the Plant	166
Fig 7.5 Frequency	167
Fig 7.6 Manipulated inputs to the plant	167
Fig 7.7 Major variables of one mill	168
Fig 7.8 Manipulated inputs	169
Fig 7.9 Frequency	170
Fig 7.10 Controlled Variables of the Plant	170
Fig 7.11 Major variables of one mill	171
Fig 7.12 Multi- model Predictive controller scheme	173
Fig 7.13 Manipulated inputs	174
Fig 7.14 Controlled variable of the plant	175
Fig 7.15 Mill major variables	176
Fig 7.16 Manipulated variables	177
Fig 7.17 Controlled variables	178
Fig 7.18 Variables per mill in service	179

Fig 7.19 Parallel Cooperative Controller of MPC and MIMO compensator	182
Fig 7.20 SCPP responses to 33% partial load rejection (output variables)	185
Fig 7.21 SCPP responses to 33% partial load rejection (input variables)	186
Fig 7.22 Mill responses	187
Fig 7.20 SCPP responses to 66% partial load rejection (output variables)	189
Fig 7.21 SCPP responses to 66% partial load rejection (input variables)	190
Fig 7.22 Mill responses	191

LIST OF SYMBOLS

D	Damping factor
E	Energy (MJ).
e	Generator internal voltage(p.u.)
ff	Fitness function.
g	Acceleration due to gravity
U	Internal Energy
u	Input vector of subsystem, or internal energy per unit mass.
J	Moment of Inertia.
KE	Kinetic Energy (MJ)
M	Inertia constant.
M	Mass (Kg)
v	Fluid velocity (m/s)
V	Terminal voltage (p.u)
V	Volume (m ³).
v	Specific volume (m ³ /Kg)
P	Power
P	Pressure (MPa)
PE	Potential Energy (MJ)
Q	Heat flow (MJ/s)
θ	Mechanical angle
r	Reference vector
R	Input weight matrix.
T	Temperature (C°).
t	Time or time constant (s)
F_s	Feeder speed (mm/s)
u	Input vector
M	Mass (Kg)
w	Mass flow (Kg/s)
x	Reactance (p.u).
x	State variables vector
y	Output variable vector
y	Output vector of subsystem
H	Enthalpy (MJ)
h	Enthalpy (MJ/ Kg).
Q	Output weight matrix
W	Work flow (MJ/s)
δ	Rotor angle of the generator (p.u)
ρ	Density (Kg/m ³)
ω	Speed (p.u)
Γ	Torque (p.u)

Subscripts

a	Accelerating
air	Air
CV	Control Volume
e	Electrical
fw	Feedwater
hp	High pressure turbine
hx	Heat Exchanger
i	Input

<i>mech</i>	Mechanical
<i>mpd</i>	Mill product pressure.
<i>o</i>	Output
<i>out</i>	Outlet
<i>pa</i>	Primary air
<i>rh</i>	Reheater
<i>d</i>	Direct axis
<i>econ</i>	Economizer
<i>in</i>	Inlet
<i>ms</i>	Main steam
<i>p</i>	Plant
<i>q</i>	Quadrature axis
<i>sh</i>	Superheater
<i>ww</i>	Waterwall

List of Abbreviations

ACSL	Advanced Continuous Simulation Language
AH	Air Heater
ARMA	Auto-Regressive Moving Average
ASTM	American Society of Testing and Materials
BMCR	Boiler maximum continuous rate
CCS	Carbone Capture and Storage
CCGT	Combined Cycle Gas-Turbine
DEH	Digital-Electro-Hydraulic
DMC	Dynamic Matrix Control
DRNN	Diagonal Re-current Neural Network
ECON	Economizer
EMF	Electromotive Force
FC	Fixed Carbone
FBC	Fluidized-bed combustion
FSH	Final Superheater
GA	Genetic algorithm
GB	Great Britain
GBGC	Great Britain Grid Code
GCV	Gross Calorific Value
HP	High pressure

HRH	High temperature Reheater
HX	Heat exchanger
IP	Intermediate pressure
KKT	Kraush-Kuhn-Tucker
LP	Low pressure
LQR	Linear Quadratic Regulator
LRH	Low temperature Reheater
LSH	Low temperature Superheater
MIMO	Multi-Input Multi-Output
MMS	Modular Modeling System
MPC	Model Predictive Control
MS	Main steam
NCV	Net Calorific Value
NN	Neural Network
NMPC	Nonlinear Model Predictive Control
OOM	Object Oriented Modeling
PC	Pulverized Coal
PSH	Platen Superheater
QP	Quadratic Programming
RH	Reheater
SC	Supercritical
SCPP	Supercritical Power Plant

SH	Superheater
SISO	Single-Input Single-Output
UK	United Kingdom
USC	Ultra-Supercritical
VM	Volatile Matter
WW	Waterwall

Chapter 1

Introduction

Power Plant Engineering is a sub-area of power system analysis that deals with the performance of power generation plants and their processes of energy conversions. Supercritical coal fired power station technology is considered to be one of the most advanced technologies which are expected to have good contributions into power generation and environment improvements. Supercritical power plants have a higher thermal efficiency, higher generation capacities, and lower environmental damage compared with the subcritical boiler technology. The challenge addressed in the thesis is to study the dynamic response of a supercritical power plant and investigating the possible ways to enhance its responses. However, the dynamic responses of supercritical power plants are not extensively studied as those as subcritical power plants and therefore their responses are still not clear enough as subcritical plants.

Modeling and simulation supercritical plants is needed to conduct the necessary study of the supercritical power plant responses and investigate the feasible strategies to enhance its responses. This chapter is an introductory to the thesis. The next section presents the motivation of this research followed by the problem formulation. Three sections are dedicated to discussions the coal as fuel to power stations, clean coal technologies, and carbon capture and storage. Finally the major thesis contributions and thesis organization are reported.

1.1 Background and Motivation

By 2030, 48 GW of generation capacity in the UK must be replaced, based on projected economic growth and projected life expectancy of a number of existing power plants. To get the government targets for reducing undesired carbon emissions by 20% by 2020 and 80% by 2050, while keeping the energy reliable and economical is essential to long term economic competitiveness. There is presently a particularly wide variety of renewable energy technologies being considered. Nuclear power generation is supposed have a long time from set-up to operation and it is not a sustainable energy source. About 40% of recent electrical power is produced by oil/gas in the UK, but the price of gas/oil encounters a huge vacillation and uncertainty (Nowadays, there are fewer oil power stations, and power generation is mainly gas and CCGT based power generation). Renewable energy resources alone are not able of producing enough electrical energy to the big gap of load capacity. Apart from renewable energy, it is likely that coal remains a dominant fuel for electricity generation for many years to come. To achieve the various goals in load demand, environment, economics and performance, coal fired power stations are really in need, actually the realistic choice, for compensation the gap of generation (Wang. 2009).

Coal is the world's the most widely used fuel for electricity generation. The major attraction of coal is abundance. Significant deposits can be found in most parts of the world, from the USA to South Africa, across Europe, and in many parts of Asia and Australia. Exceptions exist, such as Japan and Taiwan, where resources are limited; these countries import vast quantities of coal. Among the continents, only South America and South Africa- outside South Africa- have limited reserves. Coal is the cheapest of fossil fuels. This is another reason why it is attractive; however, it is also the dirtiest of fossil

fuels, producing large quantities of ash, nitrogen oxides (NO_x) and carbon dioxide (CO₂) (Breeze. 2005). As a result the combustion of coal has been responsible for some of the world's environmental damage, barring accidents, created by heavy industry anywhere in the world (Breeze. 2005).

Coal fired power generation must be cleaner. Power plants which are based on conventional pulverized coal (PC) combustion technologies, and subcritical steam conditions, have net 33-39% net efficiency, implying significant flue gas emissions, generated by coal combustion. To improve the efficiency cycle it is necessary to increase the steam pressure and temperature without jeopardising the environmental impact. Supercritical power plant (SCPP) does just that; leading to higher efficiency due to supercritical steam generation and reduced toxic gas emissions per unit of electricity generation. Indeed, power plants using supercritical boilers have higher energy efficiency up to 46% which is approximately 10% above conventional subcritical coal fired power plants. On the other hand, this technology costs less than other clean coal technologies (e.g. coal gasification) due to a simpler process design, and can be fully integrated with appropriate CO₂ capture technology in a timely manner (Wang. 2009). In addition to higher energy efficiency, lower emission levels for supercritical power plants are achieved by better conversion of fuel, lower energy losses from circulating SC steam due to using 'sliding pressure' operation, in which the throttle pressure set-point is made as function of unit load demand rather than constant value (Kundur. 1994) and using well-proven emission control technologies.

Despite the numerous advantages, the SC power plant still faces reservations. The most significant issue is that there is no energy storage unit in the boiler as in drum-type units. Energy storage is necessary for operational flexibility and rapid frequency responses

in power generation. Currently, in a subcritical boiler, this is achieved by a drum where the energy stored is released in order to regulate the opening of the turbine expansion valves opening and produce the necessary primary responses. Though operating at high pressure increases cycle efficiency, the stored energy is reduced. The adoption of SC power plant technology is still a challenging issue faced by the power industry worldwide and it is far more challenging to adopt this technology in the UK; mainly, for compliance with the GB Grid Code (GBGC). The UK grid code is far more demanding than other European countries due to the relatively small scale of the UK electricity network. As a result, it is unsure whether a SC power plant is able to produce the necessary 10% frequency response fast enough to satisfy the requirement in the grid code. That is, the supercritical power plant system may have difficulties to provide/release the 10% increase in load required, primarily, within:

- 10~30 seconds;
- Regeneration time of 20min;

which is required by the national grid code NGC. Ensuring NGC compliance for supercritical boiler power generation is an important pre-requisite for gaining acceptance in the UK for this highly promising clean coal technology. It is not clear what is the best dynamic response can be achieved by supercritical power plants. So there is an urgent demand to conduct the whole process modelling and simulation study to get clearer picture of the dynamic response of supercritical coal fired power plant and to study the feasible control strategy to improve the dynamic responses.

Currently, no supercritical or ultra-supercritical boilers operate in the UK so no measured power plant data could be obtained, which make it difficult for UK researchers alone to

conduct the research tasks. There are more than 400 units worldwide, with China operating 24 of them and there are more to be built. Therefore, there is possibility for international collaboration in this area of research through communication with industrial experts in China (Wang. 2009). Thus, the research aims to study/investigate the dynamic response of SCPP and issues related to improving its responses.

1.2 Description of Research Methodology

The main target of the thesis is studying the dynamic response of supercritical coal fired power plants before their actual operation in the UK. It is well known that this study needs some results expectation before actual adoption and realization. So it is important to have a mathematical model that describes the main characteristics of such power stations. Then, the first task is to derive a mathematical model that represents the main features of a real supercritical coal fired power plant. The difficult issue is to find supercritical boiler model with detailed information and a full set of parameters. The components can be described in Fig1.1 that shows the linked components of a SCPP which are: the coal mill, the supercritical boiler, the turbine outside view, and the synchronous generator view. Of course the associated process can be more complicated and contain many other devices, but this sequence formulates the main dynamical characteristics of a coal fired supercritical power plant. Though the more frequent components, to be considered for modeling, in the literature are the boiler-turbine units, the consideration of milling process, from the fuel side, and electric generator, from the infinite bus side, offers longer process model and more targeted to meet the research requirement. The difficulty to be first experienced then is to derive a simplified trustable model to simulate the SCPP responses over a wide operating range as best as we can.

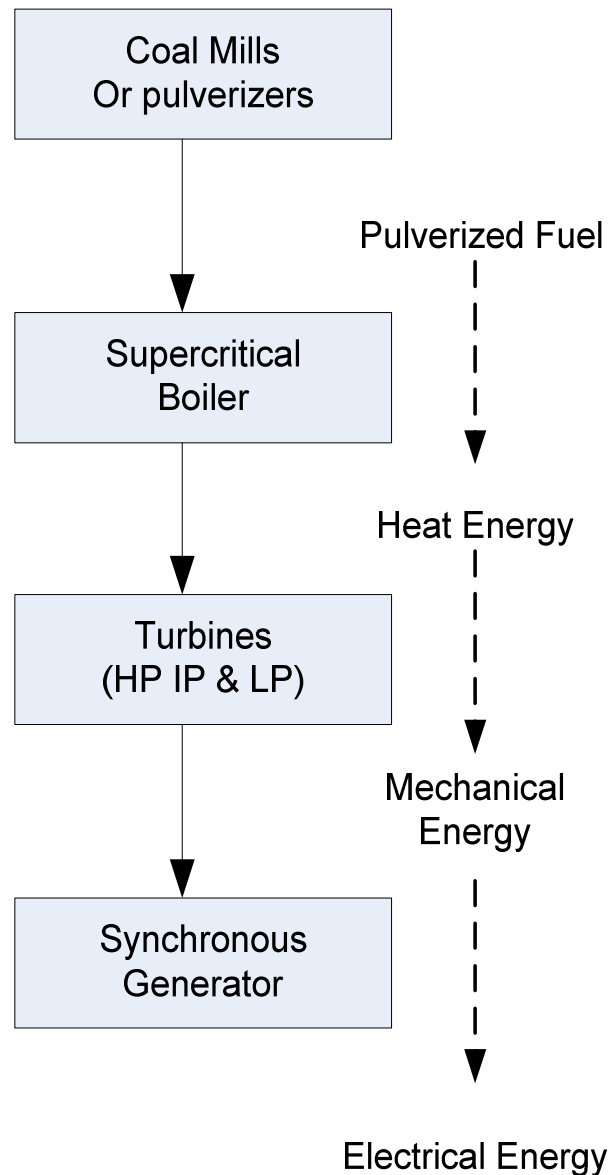


Fig1.1 Main components of a supercritical coal fired power plant

The mathematical model of a SCPP can take different structures, namely differential equations, transfer functions, statistical models, grey or black box models. Throughout the history of power plant modelling in general, simplified low order and detailed high order models have been developed. However, in case of differential equations modelling, some simplifying assumptions are usually made to transfer the model from its complex physical

structure to a simplified mathematical structure for suitable computer implementation and solving. On the other hand, black box models rely heavily on the plant data and the optimization approach for model design. This includes, but not limited to, neural networks, transfer functions, and identified state space models. The black box identification is found to be the dominant approach for SCPP modeling which is the simplest approach. Despite the various advantages of black-box modeling or neural network, they face some reservations in simulating some abnormal conditions (Lu. et al. 2000). Therefore, it is preferred to follow a hybrid approach of simplified mathematical model obtained from first principles and system identification by on-site measurement data.

However, it is very difficult to develop a generic model for supercritical power plants that reflect any SC power plant response. It is then necessary to represent a specific operating SC unit through comparison with its measured responses. Parameter identification by an optimization algorithm is the second challenge that must be faced to represent accurate responses. Parameter identification is an important optimization procedure that fits the model behaviour to the actual system. Actually, the optimization is not easy when adjusting all system parameters simultaneously, especially, for nonlinear systems so the optimization method of the whole model parameters should be robust enough to produce the optimal set of parameters. With emphasis on the power plant data, a model can be developed and identified in such away to minimize the error, or squared error, between measured and simulated responses. It should be noted that the conventional gradient optimization techniques, used in previous literature (Gibbs et al. 1991;Inoue et al. 2000;Shinohara and Koditschek 1996;Suzuki et al. 1979), have some limitations in dealing with nonlinear process models and multi-objective optimization. Intelligent optimization

schemes have more recent applications in nonlinear optimization. Fig1.2 shows the generalized scheme for model parameter identification. It is important to investigate the model response with different sets of data to validate its responses. This task can be conducted in collaboration with the research industrial partners who collect the different data sets from the real operating unit. The model should be verified in steady state and transient or dynamic conditions.

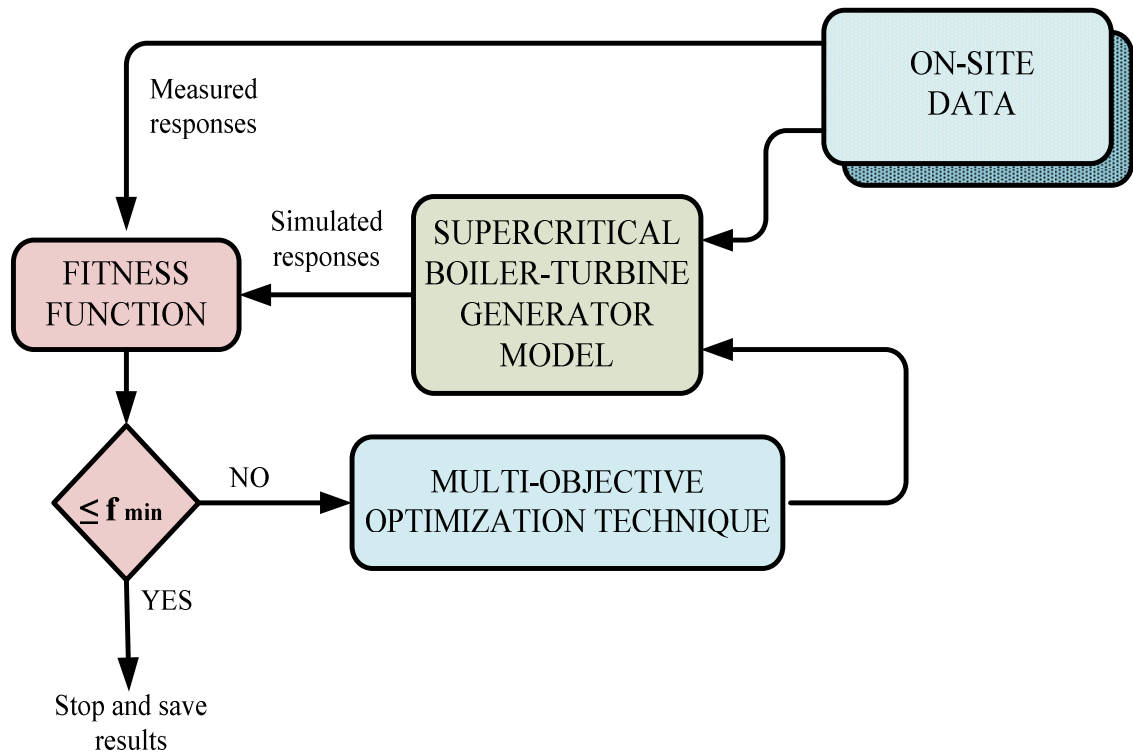


Fig 1.2 Parameter identification problem formulation

Then, the procedures of modelling and parameter identification throughout the research period are summarized as follows:

1. To derive the simplified mathematical model through analyzing the coal fired supercritical power generation process from coal grinding to electricity generation.

2. To optimize the model unknown parameters using an intelligent optimization algorithm based on on-site closed loop measurement data.
3. To investigate the simulation results and analyse the identified coefficients through testing the model with different sets of data and discussions with the research advisor and industrial partners.
4. To return back to the 2nd step if any improvements/modifications are required to satisfy the validation procedure as best as we can. This includes addition of some components or updating the model parameters.

After having identified model that can represent the main variation trends of the real plant, the model has to be tested by different sets of data to validate its performance. Also, research should be conducted to investigate the possible strategies to improve the model fidelity. To be realistic, power plants are not subjected to a single operating objective, but many different objectives. In practice, the most desired objectives of power plant operation, and consequently control, are given in the current literature (Ordys et al. 1999, Ramirez et al. 2001, Waddington et al. 1987):

- Matching the generation to the load request in a timely manner and this also ensures optimal frequency regulation (Ramirez et al. 2001). Actually, not only this kind of meeting load demand, it is also includes more rapid and large load demands which are associated if a fault occur in a neighbouring generating unit which then must be tripped from the power system grid.

- Ensuring optimal cycle efficiency at all operating conditions. This can be achieved by maintaining the boiler pressure and temperature within pre-scheduled operating signals.
- Maximizing the life of the equipment by reducing the fluctuation of the controlled variables in response to load changes.
- Ensuring optimal combustion to minimize environmental undesired effects and regulate the furnace pressure.

In fact, the objective, of the control system, for attainment of the above mentioned objectives differs from control strategy to another. For instance, the strategy may focus on power system frequency regulation instead of the boiler optimization (Inoue *et al.* 2000); alternatively the control system objective may be steam temperature and power optimization (Nakamura *et al.* 1981). However, the most popular objectives in the literature is enhancing load following capability (i.e. MW response of the plant) and keep the boiler variables within optimum ranges (Ramirez et al. 2001). Recent advanced control strategies, ensuring better automation, increased flexibility and reliability. (Oluwande. 2001) and (Ramirez et al. 2001) have reported most of these advanced controls which are:

- Artificial neural networks.
- Model based predictive control.
- Fuzzy feed-forward control.
- Gain scheduling and adaptation.
- Intelligent hybrid controllers.

- Cascaded controllers.
- Genetic Algorithm controllers.

For power plant control system synthesis, a mathematical experiment or theoretical test (through for instance: step responses) must be made on the model to study the various plant responses, the boiler pressure and temperature responses, then, investigate the suitable strategies to improve the SCPP responses. It is also worth mentioning that, the SC boilers have less stored energy than drum-type boiler units because there are no drums in once-through operation. As a result, when actuating the valve in response to load demand changes, the energy stored drops significantly in once-through boiler which makes its control much more complicated than drum type boilers in this matter. Following to valve opening to meet the load demand, there must be simultaneous increase in the fuel firing and feedwater flow to preserve the energy storage in the boiler and also to satisfy the energy balance required to meet the requested load. The desired speed of the power response, which is known as the MW response, the ability of generating units to change Megawatt output in response to changes in power system Megawatt requirements (F. DeMello et al. 1983), must be attained by prescribed specifications to provide the standard regulations for power system stability and frequency response of power plant.

The model should depend on the first principles of modeling and also on the data supplied by the plant manufacturer. The procedures of identification and investigation can be done by different sets of the plant data. The data sets are almost always on-site measurement data with the existing control strategy installed. Hence, a special control configuration should be assumed in such a way to make the addition of the new strategy logically and industrially acceptable. Overall power plant control architecture demands hierarchical operation. In other words, this control may starts initially from the

supervisory system which executes optimization function and optimal decision of the plant behaviour and ends with the plant local controllers or 1st level control. Two industrial configurations are well known in the literature of industrial control (Bullut *et al.* 2000, Poncia *et al.* 2001, Oluwande. 2001). They reported the use of multivariable control to correct the *reference* or the *action* of the existing classical controls. This issue along with all issues described regarding the adoption of the suitable control strategy is discussed in the thesis. These schemes provides increased automation which is better able to sustain the load of consumers while keeping the fluctuations in boiler steam pressure and temperature as small as possible. From some previous applications, the controlled action values are the dominant approach for controlling subcritical and supercritical power plants (Nakamura *et al.* 1981, Poncia *et al.* 2001). Controlled reference values scheme hasn't been fully applied yet to SCPP. Although some of these advanced schemes are already provided on some existing plants, the operational challenges are still not fully overcome and existing power plant responses are still not completely appreciated by power plant utilities. Consequently, a research should be conducted to investigate the SCPP responses clearly and study/explore the feasible strategies to improve their responses. Mainly, extracting other supplementary means that may be helpful in satisfying the UK grid code regulations mentioned in Section 1.1, the two configurations are mentioned in Figs 1.3 and 1.4. If the model is identified with closed loop data, the new control system should have similar configuration of Fig 1.3, 1.4, or hybrid between them. It should be noted that the control of SCPP is far more challenging because the boiler variables should be kept within supercritical conditions over wide operating range. Because there are no SCPP currently operating in the UK, the factors that influence the power primary response or MW response should be studied which help in satisfying the UK grid code. From all problems

discussed above, the research objectives have been understood and they are presented in the next section.

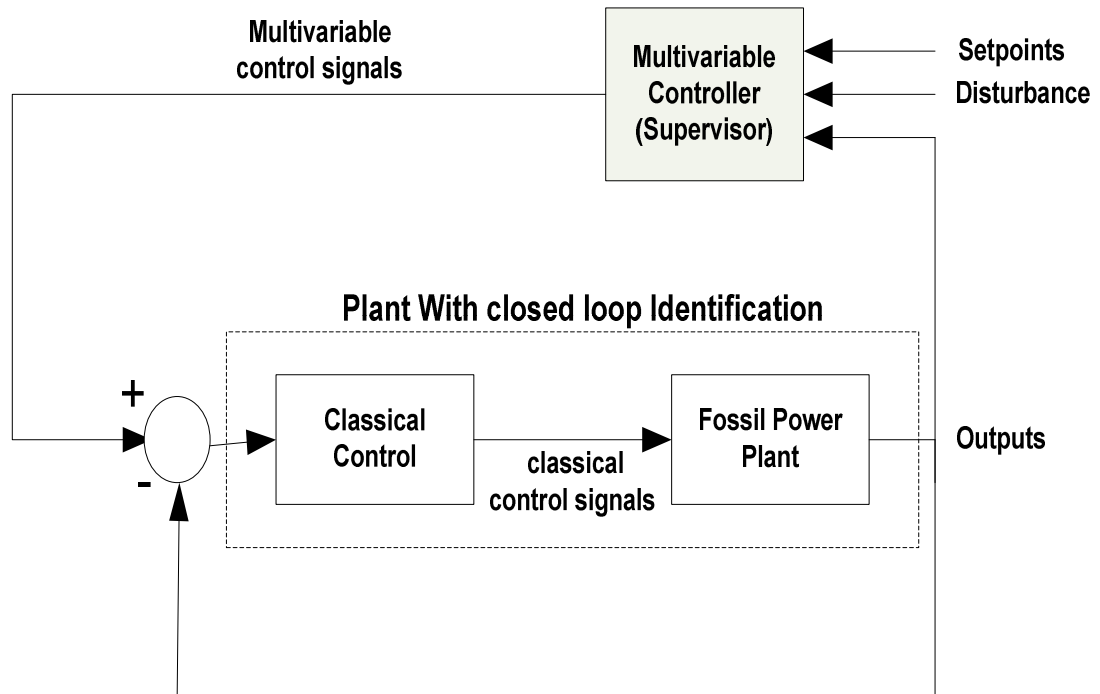


Fig1.3 Controlled *reference* or adjusted *reference* values

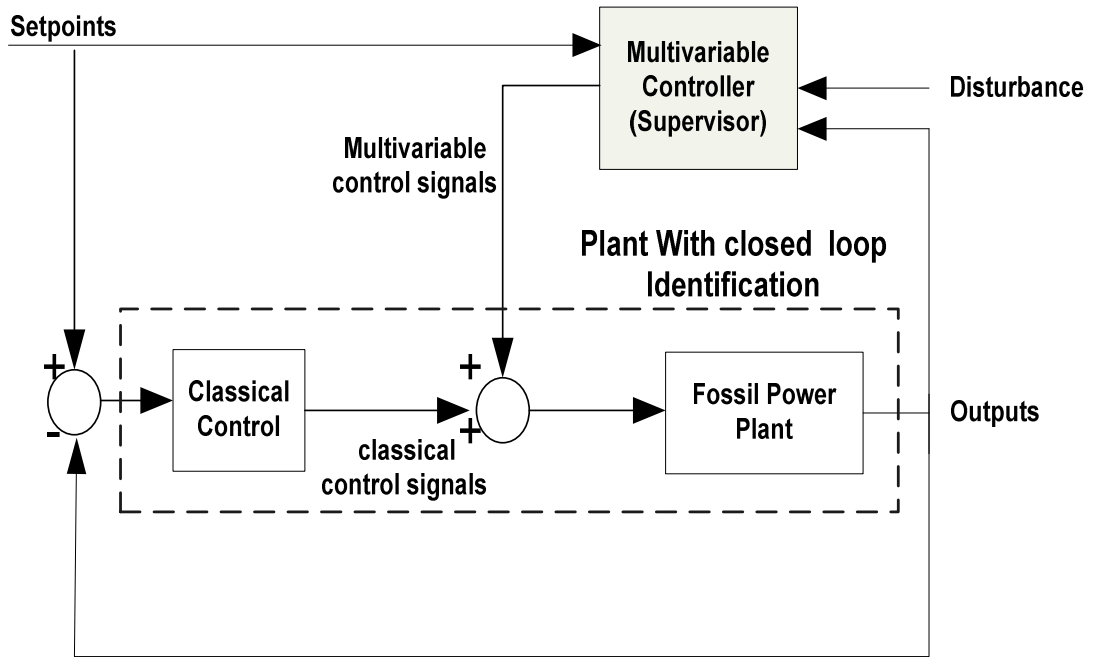


Fig1.4 Controlled *action* or adjusted *action* values

1.3 Research Objectives

The project is to achieve the following objectives

- To derive a mathematical model that represents the dynamic variation features of a coal fired supercritical power plant from coal grinding to electricity generation. The model unknown parameters will be identified by advanced optimization algorithm according to certain SC operating unit.
- To investigate the power plant dynamic responses over wide operating range with different operating data sets using the power plant

mathematical model.

- To investigate how much performance and operational flexibility can be improved by appropriate control strategy which meets power plant control objectives.

1.4 Coal as Fuel of Power Stations

Power engineering can be defined as the subject to study technical and scientific knowledge that is necessary for production of power system stations. It is a multi-disciplinary area that mixes the subjects of chemical, mechanical and electrical engineering. Environment, abounding/availability of fuels and their costs, have been important factors in decision making for creation of power generation technologies. The revolution of industry started with coal as dominant source of fuel and subsequently energy or power.

Coals are complex substances that are geologically formed from ancient vegetation by the combination of time, pressure, and heat of the earth over several millennia. Depending on how long the vegetable matter has been subjected to these conditions, the resulting coals assume several properties. The most ancient coals under high pressure would have converted practically all the vegetable matter into fixed carbon. Coal volatile matter is a complex mixture of organic materials, which volatilizes quickly on heating at around 300C° and burns in suspension in a furnace. The high the volatile matter, the smaller the ignition temperature and higher combustion speed. A broad classification of coals based on American Society of Testing and Materials ASTM D388 is given in Table1.1 below. (Rayaprolu. 2009)

Table 1.1 Coal classification

Class	Group	Fixed Carbon (FC) (%)	Volatile matter (VM) (%)
Anthracitic	Meta-anthracite	>98	<2
	Anthracitic	92-98	2-8
	Semi-anthracite	86-92	8-14
Bituminous	Low-volatile coal	78-86	
	Medium-volatile coal	69-78	
	High-volatile coal	<69	
Sub-bituminous	A,B, and C coals		
Lignitic	Lignite A		
	Lignite B		

Oil and natural gas started with coal in fuelling power generation stations. Nowadays, fossil fuels- coal, petroleum, and natural gas- together with hydro-electric and nuclear are the only means for delivering the largest quantities of electricity. Though significant research and development of renewable energy resources leads to considerable penetration of renewable electrical power supply in recent years, base-load generation of power will probably rely on coal and nuclear. Base-load is the load which the request of load power never goes below it (Weisman et al. 1985).

It is important to mention that nuclear power stations run at maximum output steady at all time and thus coal firing units are more flexible for load following, economic dispatch of generation, and even severe disturbances of load changes. In addition, nuclear power generation normally takes longer time from build to generation. Petroleum and natural gas shortages in the last three decades have caused significant increase and instability in the prices of natural gas and oil. Consequently, coal has become the most popular source of electric energy in the world for many years to come.

However, coal firing nowadays are demanded to operate more rapidly/flexibly to satisfy the load requirement in a timely manner and this is a challenge with different varied coal volatile matter and specifications. As a result, control system strategies for coal firing power plants are more advanced. Also, because coal has the largest percentage of carbon, it is the dirtiest fuel among other fossils due to emission resulting from coal combustion which includes carbon dioxide (CO₂) and nitrogen oxides (NO_x). Again, whatever the environmental restrictions, this kind of fuel is still the dominant fuel of electricity on the long run. One way to reduce these undesired emissions is to increase the energy efficiency of the plant which reduces the amount of the required fuel to be combusted. The next section shows some of these technologies which are currently in use in coal fired power plants.

1.5 Advances in Clean Coal Technologies

Thermal efficiency is a measure for the overall power plant performance. Two cycles are repeatedly found in this area of study which are *Rankine* Cycle and *Bryton* Cycle. Bryton cycle is usually used to describe gas turbines, while Rankine cycle is used to describe steam power generation plants. When these cycles are combined, it is termed as *combined* cycle. However, the clarification of SC coal power plant operating cycle is elaborated in the next chapter. Energy efficient methods contribute into improving the overall cycle efficiency and subsequently cleaner coal combustion is obtained. Clean coal technologies offer advanced solutions for coal environmental damage. There are three main methods for clean coal combustion technologies which are:

1. **Fluidized bed combustion boilers:** Fluidized-bed combustion (FBC) is a mature technology for the combustion of fossil and other fuels and is attractive because of

its many inherent advantages over conventional combustion systems (Miller et al. 2010). In fluidized bed combustion system, crushed coal, ash, and limestone are mixed together in a bed levitated by incoming combustion air. The combustion air enters the bottom of the furnace and flows upward through the bed, causing it to be suspended in the furnace. The boiler tubes are immersed in the fluidized bed. This results in a contact between the burning particles of coal and the boiler tubes. Very heat transfer rates of transfer are obtained, thereby reducing the furnace area and size (Weisman et al. 1985). The major contribution of FBC is the direct reduction in emission of pollutants. There are two types of FBC: bubbling fluidized bed, and circulating fluidized bed (See fig1.5).

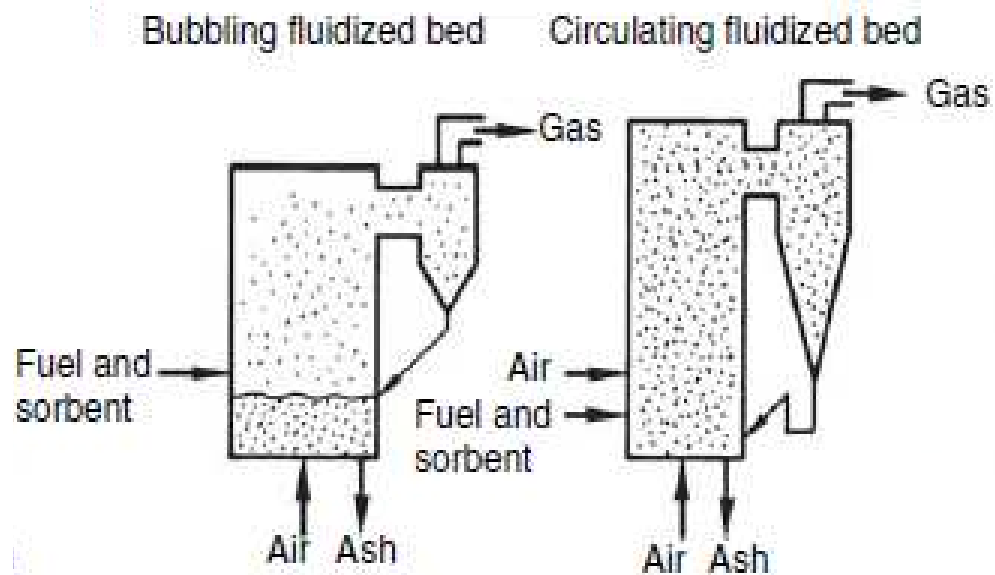


Fig1.5 Modes of FBC (Rayaprolu. 2009)

2. Advanced pulverized coal power plants (Supercritical and Ultra-supercritical

Boiler Technologies): Pulverized coal burning is the most widely used technology in coal firing applications. The main developments and contributions in this matter involve increasing the plant cycle efficiencies by elevating the boiler steam pressure and temperature. Unfortunately, the majority of existing coal fired power plants are working on subcritical pressure conditions. Supercritical and ultra-supercritical power plants should be an improved solution with more than 10% improvement in the thermal efficiency of the plant. SCPP came to operation in 1958 and USCPP, more recent, in 1990 (Nalbandian, 2009, Miller et al. 2010, Littman *et al* 1966). Although this technology is one of the leading choices to be adopted in the UK, the adoption of this technology may face some problems because subcritical units are regarded by industry to be more reliable than supercritical. Simplified schematic view of coal fired power plant is shown in Fig1.6. In a typical coal firing power plant, the raw coal enters the mill inlet tube and carries the coal to the middle of grinding rotating table. Hot primary air flows into the mill from the bottom to carry the coal output from grinding process to the classifier that is a multi-stage separator located at the top of the mill. The heavier coal particles fall down for further grinding and the pulverized coal is carried pneumatically to the furnace. Inside the boiler, the chemical energy released from combustion is converted to thermal energy. The heat is exchanged between the hot flue gases to the water through heat exchangers. The boiler contains thin tubes as heating surfaces which form the economizers, waterwall, low temperature superheater, platen superheater, final stage superheater, and reheaters. The water is forced at high pressure (SC pressure) inside the economizer and passes through all

those heating sections. Since pressure is above the critical point, the sub-cooled water in the economizers is converted to the supercritical steam in the superheaters without evaporation. The SC steam is then expanded through turbines to continue the rest of energy conversion processes.

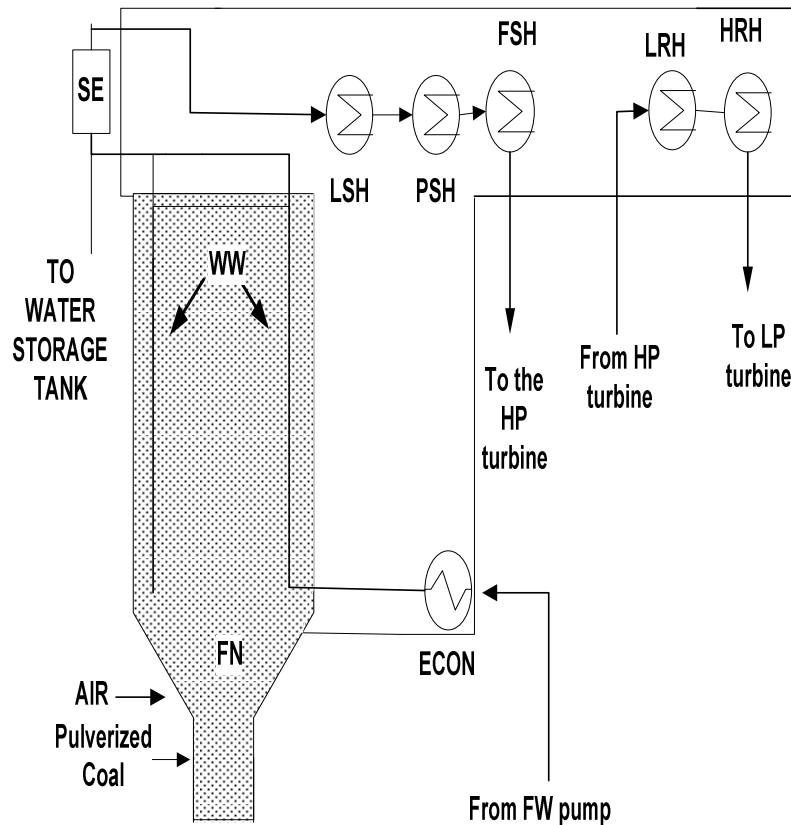


Fig1.6 Simplified schematic view of coal fired supercritical boiler process

The process of this technology will be more elaborated in the next chapter.

3. **Coal-Gasification:** Gasification is a process that upgrades the raw materials by removing the contaminants and convert to gaseous phase which is more suitable to be used as fuel for combustion. The idea is based on that gaseous fuels are burning cleaner than coal burning. Fewer nitrogen and sulphur oxides are produced during combustion process. Coal gasification is normally done by heating the coal with

steam and oxygen. For countries which have enormous coal reserves, coal gasification is so attractive (Miller et al. 2010). The most relevant example of coal gasification is the integrated gasification combined cycle (IGCC) plant. An IGCC power plant can achieve an efficiency of 45%. The process is described as follows: the coal is partially combusted in the gasifier which is used to produce significant amount of heat. This amount of heat can be used to generate steam which is required to energize the steam turbine. The delivered gas is cleaned and burnt in a gas turbine to generate the more power. The hot gas exhausted from the gas turbine goes to the heat recovery steam generator for further heat addition to the steam. Further development is needed to allow the concept of gasification to reach its full potential (Breeze. 2005).

1.6 Carbon Capture and Storage

Carbon capture and storage (CCS) is a technology that aims to prevent undesirable emissions of huge amounts of CO₂ from power generation plants. It can be divided into four main steps (Drage. 2011):

1. CO₂ capture.
2. CO₂ transport.
3. CO₂ injection.
4. CO₂ storage.

SC power plants can be fully integrated with a CO₂ capture system. CO₂ capturing from power generation systems may be achieved by three approaches: pre-combustion CO₂ capture, where carbon is separated from fuel before combustion process; oxy-fuel

combustion, in which coal is burnt in oxygen and CO₂-enriched environment; and CO₂ capture post-combustion process, where coal is traditionally combusted in the furnace and the CO₂ is taken-out from the flue gas (Miller et al. 2010). Fig 1.7 show simplified diagram for the three methods.

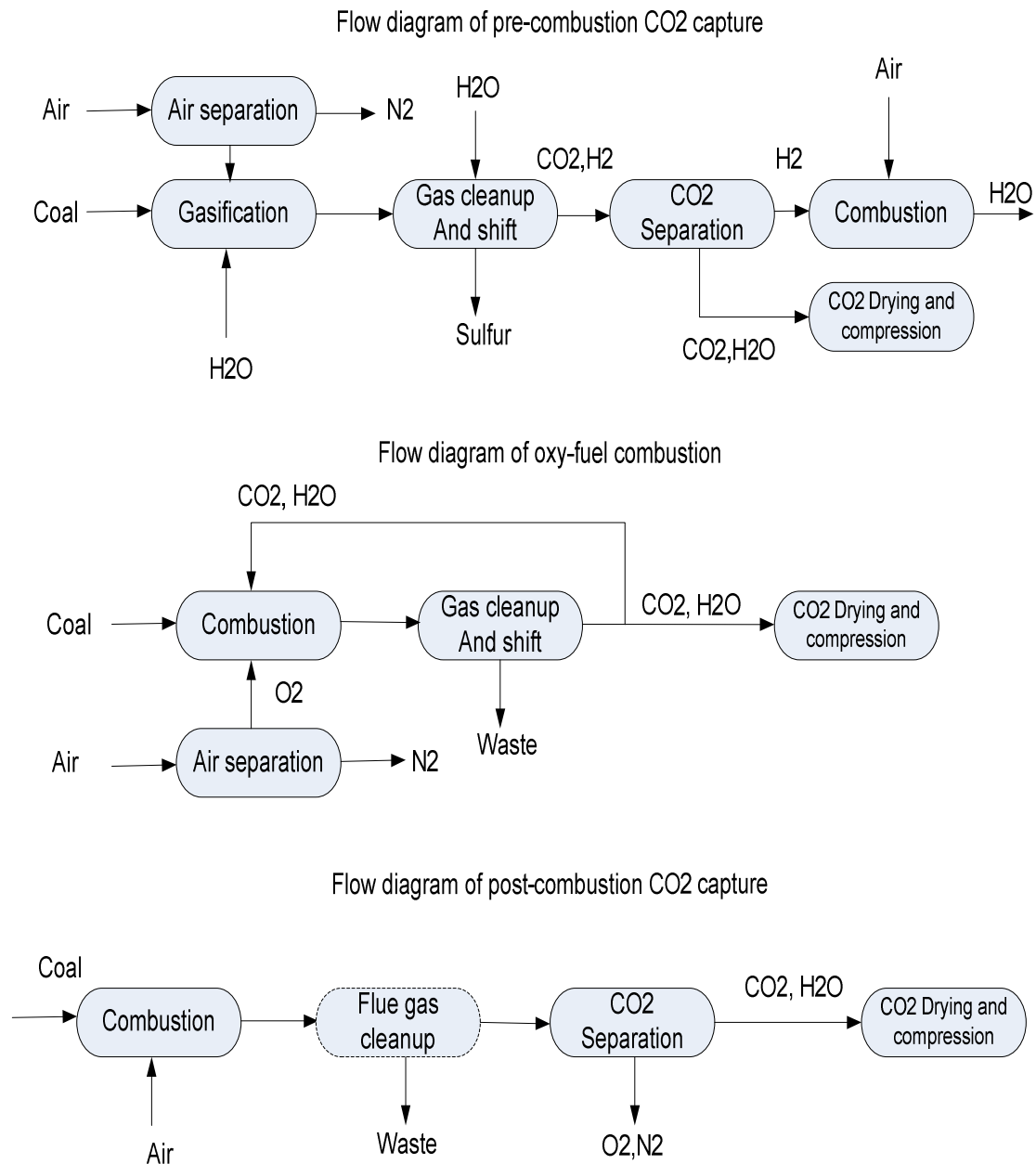


Fig 1.7 Carbon capture methods

The transport of CO₂ is commonly made by pipe lines. CO₂ is ideally compressed to pressures higher than 8 MPa. Thus it is still at supercritical conditions (this prevents two-phase flow which is more difficult to transport and elevate the density), thereby it will be less cost and easier to transport.

CO₂ storage is the final process of CO₂ management process. CO₂ (carbon) storage is defined as storing the CO₂ in a repository where it is usually to be placed. This involves the placement of CO₂ in the ocean, geologic storages, terrestrial storage, and mineral sequestration (Miller et al. 2010).

1.7 Major Contributions of the Thesis

The thesis contributions to this area of knowledge are:

1. A simplified nonlinear mathematical model, from control point of view, that describes the main features of a SC coal fired power plant is derived. The model covers the process from coal pulverizing to electricity output. The model is derived based on first principles of physics and engineering so this offers the chance to understand the whole power plant process through simulation study.
2. The model unknown parameters are identified by advanced optimization technique which is genetic algorithms (GA). GA is much improved over conventional optimization techniques that can simultaneously adjust all model parameters despite the complexity of the optimization problem. In addition, GA method deals with a coded parameter, not the amount of parameter itself. Also, the search is performed on a population of points that are distributed on the space of search, not only one point like mathematical gradient optimization. From simulations and comparison with real plant data, the identification results have shown that the

model can simulate the main variation trends of real supercritical coal fired power plant. In addition, the model has been investigated over a wide range of operation by other different sets of data and again the model dynamics are in agreement with the real power plant operational data.

3. A control strategy is implemented on the process model to regulate some of the plant variables. The control system is based on generalized predictive control that is widely used for power plant control. The MPC is designed to predict the optimal values of pulverized coal flow, feedwater flow, and valve position demand. Then, those predicted values are fed into the plant mill, boiler, and turbine local controls, instead of direct control signal application. In an analogy to the controlled reference correction mentioned in section 1.2, the control system has been implemented to increase the plant overall automation and improve the plant operational performance.
4. Under the proposed strategy the influences of coal mill control on the plant dynamic responses are studied in more details than previously. This has been conducted by implementing two controllers: one to regulate the primary air fan and the other is implemented to regulate the feeder speed, both receiving the MPC coal flow signal as reference. In two cases of existing and improved milling conditions, the simulations have been reported in the thesis. It is shown that the proposed control strategy improves the plant power primary response while keeping less fluctuation on the boiler pressure and temperature. Also, it is found that the coal mill primary air fan and feeder speed can be regarded as other supplementary

means which help in improving the plant power response and consequently play an important role in satisfying the national grid code. The facility which leads to these contributions is MATLAB[®] with some relevant toolboxes.

Some of these contributions have been presented / accepted as follows:

Events:

- ***Omar Mohamed*** “Study of Energy Efficient Supercritical Power Plant Dynamic Response and Control Strategy” MEG.II Christmas Event and Inaugural Lectures. Loughborough University. 2011 (2nd Best Poster Prize Award given).

Conferences:

- ***Omar Mohamed***, Jihong Wang, Bushra Al-Duri “Predictive Control of Coal Mills for Improving Supercritical Power Generation Process Dynamic Responses”. IEEE Conference on Decision and Control Dec 2012. Hawaii, USA, (Accepted and will be presented on Dec 2012).
- ***Omar Mohamed***, Jihong Wang, Bushra Al-Duri “Predictive Control Strategy of a Supercritical Power Plant and Study of Influences of Coal Mill Control on its Dynamic Responses”. Proceedings of UKACC 2012, Cardiff. (Accepted and presented on 5th of Sep 2012).
- ***Omar Mohamed***, Jihong Wang, Bushra Al-Duri, and Shen Gue “Modeling Study of Supercritical Power Plant and Parameter Identification Using Genetic Algorithm” Proceedings of the World Congress on Engineering 2010.London. Vol II, pp973-978.
- ***Omar Mohamed***, Jihong Wang, Bushra Al-Duri, and Shen Gue “Modeling Study of a Nonlinear Power Plant Supercritical Boiler-Turbine-Generator System and Identification of Unknown Parameters”. Proceedings of the 16th International Conference on Automation & Computing, Birmingham, 11 September 2010. pp147-152.
- ***Omar Mohamed***, Jihong Wang, Bushra Al-Duri “Study of a Multivariable Coordinate Control for a Supercritical Power Plant”. 17th International Conference on Automation and Computing. (ICAC) Huddersfield. UK. Sep. 2011. p. 69-74.

Book chapter:

- **Omar Mohamed**, Jihong Wang, Bushra Al-Duri, and Shen Gue” Mathematical Modelling of Coal fired power plant and model Parameter Identification using Genetic Algorithms”. Lecture notes in Electrical Engineering, a published book chapter in the edited book “Electrical Engineering and Applied Computing”. *Springer*,2011.

Journal:

- **Omar Mohamed**, Jihong Wang, Bushra Al-Duri “Study of a Multivariable Coordinate Control for a Supercritical Power Plant”. *International Journal of Energy Systems*, Scientific and Academic Publishing. Vol.2 No. 4, August 2012.

1.8 Thesis Organization

The thesis has been organized into eight chapters. Chapter 1 is introduction and the other thesis chapters are outlined below.

Chapter 2 is background information and overview of related research. The chapter contains background materials about supercritical power plant technology, its operating cycle and its improvements over subcritical drum type power plants. Also, a broad literature review about modelling, identification, and control of SC power plant is presented. Power plant simulation software packages are also reported with the adopted simulation tool in this research.

Chapter 3 contains the detailed step-by-step model derivation with its associated principles and assumptions. The fundamentals of thermodynamics which are used in the modelling procedures are first discussed. Then, with simplifying assumptions and approximations

that are commonly used, the boiler-turbine model has been developed and combined with the generator model. The model states and subsystems are demonstrated as blocks.

Chapter 4 presents the proposed parameter identification technique which is based on genetic algorithms (GA). The chapter starts with brief review for the optimization techniques that have been used in the literature for identification of SCPP models and the optimization approach that has been adopted in this research. The fundamentals and mechanism of GA are explained. Then, the on-site measurement data sets have been described to use them in parameter identification. Finally, the simulation results have been reported.

Chapter 5 deals with other simulations and studies on the model with different sets of operating data and describes the grinding process model which is combined to the boiler-turbine-generator system model. The model is compared with software developed by Eutech for chemical reactions and thermodynamic process simulations (Thermolib). The simulation results, both static and dynamic, are reported for the various plant variables.

Chapter 6 introduces the theory of generalized model predictive control (MPC) that is widely used for power plant control and automation. A historical background that summarizes other people's research is presented and discussed. Second, the principle of prediction and receding horizon control is presented and mathematically described. The optimization method used to decide the future control signals is discussed. An example for model predictive control application is given by simulation.

Chapter 7 reports simulation study of the supercritical coal fired power plant with its associated predictive control strategy. The developed process model has been adopted to simulate the power plant responses. Two controller schemes are investigated; one is the generalized predictive control strategy and another hybrid scheme which is composed of MPC in parallel with compensator. The simulations have shown the ability of mill control to influence the power output response of the power plant.

Further discussions on the research work, conclusion, and future recommendation are given in chapter 8.

Chapter 2

Overview of Coal Fired Power Plant Processes and Progress in Research

2.1 Introduction

The chapter gives background material on supercritical power plants and their improvements over subcritical drum type plants. It also reports a literature survey for research in supercritical power plant modeling, identification, and control. This chapter starts with describing the coal fired power generation process and the necessary energy conversion physics to obtain electricity from coal. It then gives an overview of the supercritical process in supercritical boilers with some illustrative thermodynamic graphs. Through comparison with subcritical drum type plants, the advantages of supercritical power plants and their improvements are reported. The literature review of the previous attempts to study the dynamic response of supercritical power plants and the possible strategies to enhance its responses are given. From the literature, it seems that supercritical power plant modeling still needs particular attention and more research for studying their time-based dynamic responses. Finally, the simulation tools and computer packages for power plant systems that are reported in the literature are presented. The tools mentioned are limited to those which make use of graphical presentation of plant objects and numerical simulation environment.

2.2 Coal Fired Power Generation Processes

It is likely that coal remains a dominant fuel for electricity generation from many years to come because of its stable price in comparison to other types of fuels. Also, coal fired power generation stations are flexible for load demand following in comparison to nuclear and renewable energy resources. In order to understand the whole process of energy conversions from fuel preparation to electricity generation, the typical modern coal fired power plant is considered as shown in Fig 2.1. In the power plant, the coal enters the mill or pulverizer and is crushed to become powder or pulverized, there it is mixed with primary air entering from forced draft fans, the mixture of pulverized-fuel and air enters the boiler at a high pressure and ignites (Rayaprolu. 2009). The water comes from the boiler feed pump enters the boiler through the deaerator which removes the non-condensable gases (Abdenmour *et al.* 1993). The pure water then goes to the first heat exchanger in the boiler which is the economizer, the water is heated in the economizer before it passes through the furnace water-wall to a separator vessel where water is separated from steam (this is achieved automatically by the drum in traditional coal fired stations). The steam passes into the superheater where its pressure and temperature are elevated to a high degree. The steam is then passed through a valve to the high pressure turbine (this valve controls the torque of the turbine and subsequently the power of the generator), the turbine usually generates mechanical power from three combined turbines, a HP (high pressure) turbine, an intermediate pressure IP turbine and a low pressure LP turbine. The low energy steam exhausted from HP turbine passes through the reheater for further heating before it is introduced to the intermediate and low pressure turbines, the

mechanical energy gained by the turbine is used to drive the rotor of the generator to a constant speed which is the synchronous speed, from the rotor's mechanical rotation and the coupling magnetic field from the exciter, the voltage is then induced in the winding of the stator by Faraday's law. If the generator is connected to the power grid the electric current passes through the stator winding which produces a rotating magnetic field rotates in the air-gap at the same speed of the rotor.

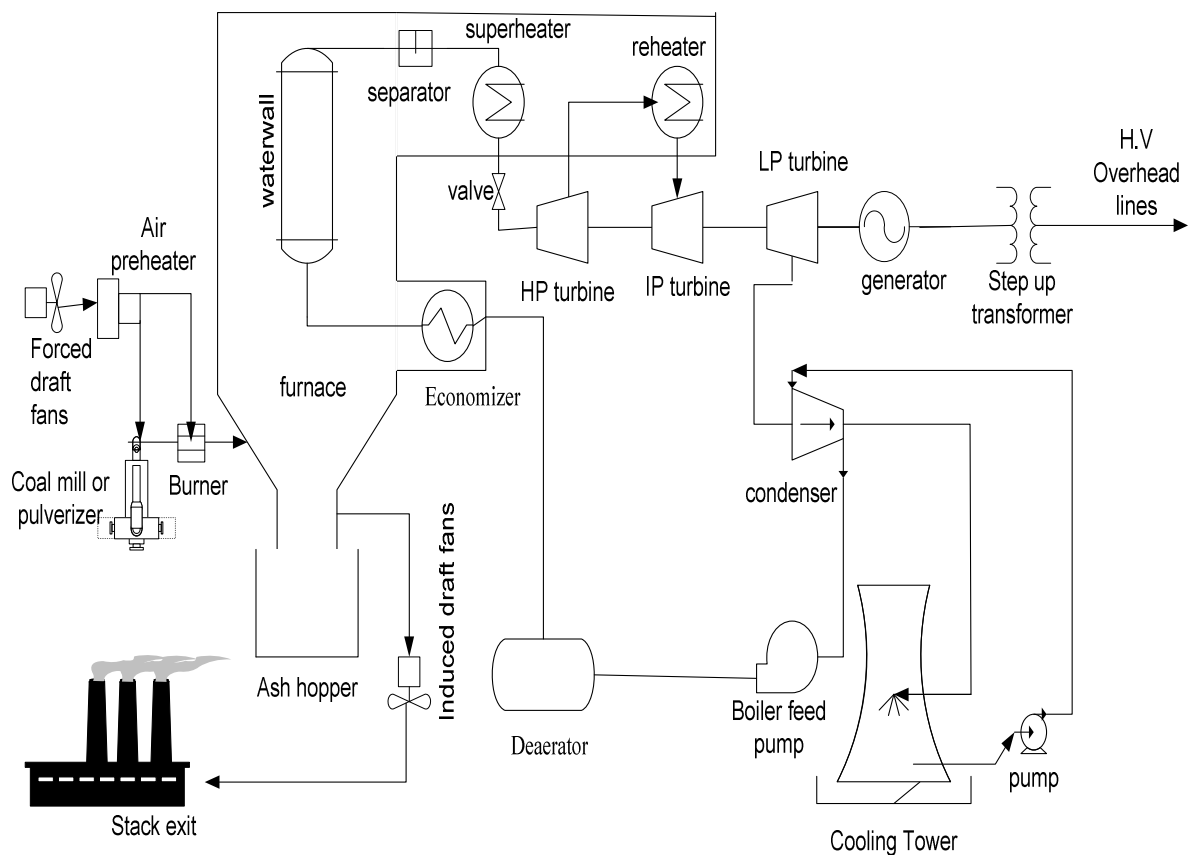


Fig 2.1 simplified diagram for typical coal-fired power station

The exiting steam from LP turbine is condensed to water by the condenser where it mixes with the cooling water from the cooling tower, the condensed water is then passed to the deaerator via the boiler feed pump to complete the cycle and the remaining water from the condenser is sprayed to the cooling tower to cool the water before it is pumped back to

the condenser. The spent fuel ends in the ash hopper and the exhaust gas is drawn out by the induced draft fans and discharged through the stack (Wylen *et al.* 1994, Lee *et al.* 2007, Wei. 2007). A brief description of energy conversion processes that occur in coal firing stations is given. The next section presents fundamentals of utility boilers in general before the introducing the supercritical boiler process and its improvements over subcritical boiler.

2.3 The Rankine Cycle

The process of steam power plant can be summarized by a certain demonstration cycle. Consider the ideal four process cycle shown in Fig 2.2, in which point 1 is saturated liquid and point 3 is either superheated or saturated vapour. As mentioned, steam power plants are working according to a certain operating cycle. That is, the water goes through several processes before it returns to its original state. The simple thermodynamic description of steam power plant can be formulated by ideal Rankine cycle. The four processes are as follows (Wylen *et al.* 1994):

- 1-2 Reversible adiabatic pumping process occurs in the pump.
- 2-3 Constant pressure (Isobaric) heat transfer to the boiler.
- 3-4 Reversible adiabatic steam expansion in the turbine.
- 4-1 Constant-pressure heat transfer in the condenser.

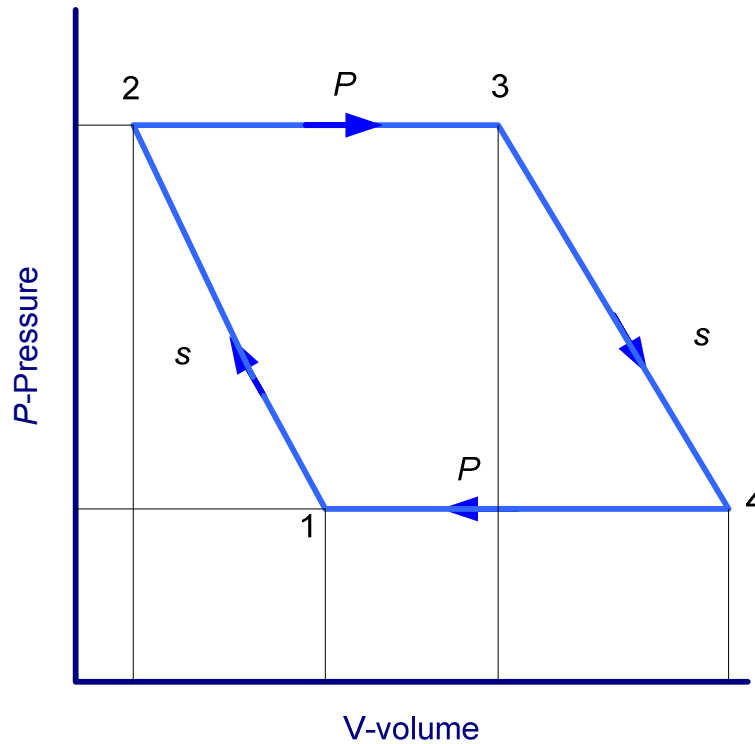


Fig 2.2 Four process cycle for steam power plant.

It is suitable to demonstrate the processes on T-s (Temperature-entropy) diagram as shown in Fig 2.3 where there is possibility for superheated vapour as operation of 1-2-3'-4'-1. The change of water from state to another is indicated by the numbers. For instance the process 1-2 represents the working fluid is pumped from low to high pressure. In process 2-3, the high pressure water is heated at constant pressure inside the boiler to convert it to saturated vapor. In 3-3', the saturated vapor becomes superheated vapour. Process 3'-4' or 3-4, represents the steam expansion in the turbine. Finally, the steam is condensate at constant temperature to obtain saturated water at 4'-1 or 4-1. However, there is a heat loss area which is represented by $a-1-4-b-a$. Also, the heat transmitted to the water is described by the area $a-2-2'-3-b-a$. The thermal efficiency η_{th} can be defined as the ratio of the work introduced by the turbine to the total heat of steam, that is:

$$\eta_{th} = \frac{W_{net}}{Q_{total}} = \frac{\text{area } 1-2-2'-3-4-1}{\text{area } a-2-2'-3-b-a} \quad (2.1)$$

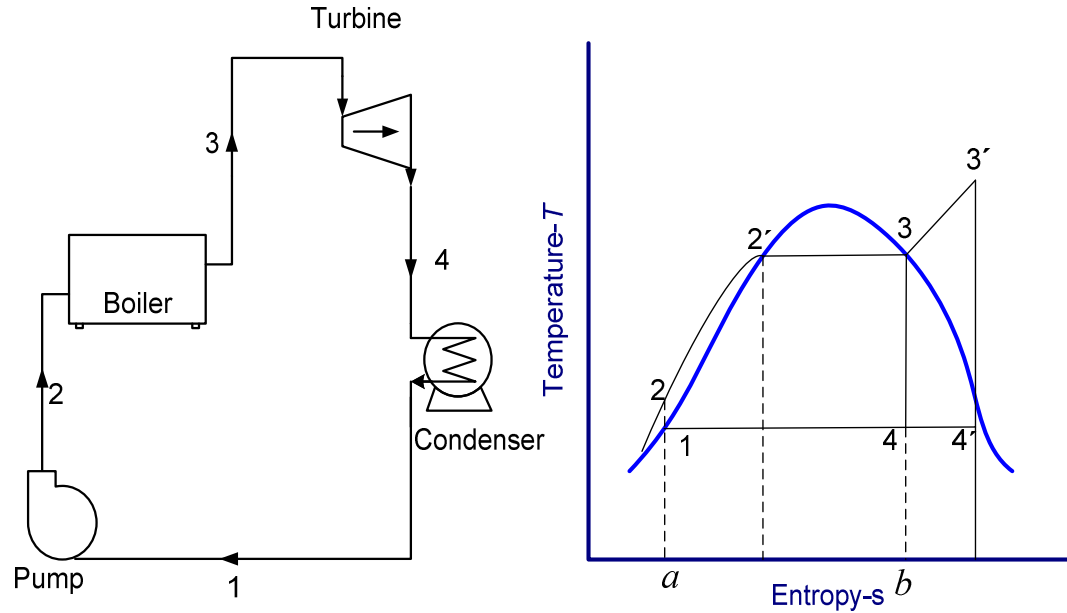


Fig 2.3 Steam Power Plant operating on the Rankine cycle (Wylen *et al.*1994).

Before discussing the improvements of SC boilers over subcritical boilers, a background about supercritical boiler technology is presented.

2.4 Supercritical boilers technology

A boiler is a system that heats water to get steam. In other words, the chemical energy in the fuel is converted to heat energy in the steam. Boilers can be classified by several fashions; it may be based on usage, construction, or operating pressure. Boilers are classified according to the operating pressure to subcritical and supercritical boilers. The most important parameter of the boiler is its thermal efficiency; boiler efficiency is measured according to gross calorific value (GCV) or net calorific value (NCV) and the later is more popular in Europe and countries following the European standard which the

efficiency indicates that how much of the available heat of fuel is converted to a heat in steam. The boiler efficiency is always measured with ambient conditions because they have significant effect on the boiler efficiency (Rayaprolu 2009).

The main losses that affect boiler efficiency are mentioned from larger percentage of losses to smaller percentage:

-*Stack loss*: this loss results from moisture and the exhausted heat of vaporization from the stack.

-*Unburnt fuel loss*: this loss results from the presence of unburnt fuel in the bottom ash.

-*Radiation loss*: results from heat transfer by radiation from exterior surfaces to the surroundings.

The efficiency of the boiler has significant effect on the power plant overall efficiency. It is worth to mention that improving the efficiency reduces the CO₂ emissions because the required amount of fuel to be combusted is reduced. Improving the efficiency can be made by elevating the value of pressure and temperature of the boiler to the supercritical region (Rayaprolu 2009). The mathematical modeling of supercritical boilers cannot be achieved before understanding the supercritical process, the parts and features of supercritical boiler.

"Supercritical" is a thermodynamic expression that means the state of a substance where there is no clear difference between the liquid and the gaseous phase (i.e. it is termed as fluid). Water reaches this state at a pressure above 22.1 MPa. Consider the temperature-volume diagram shown in Fig 2.4 for water contained in a cylinder. The heat is transferred to the water at constant pressure, say 1MPa. The water is transferred gradually from liquid phase to vapor phase and the volume is increased. Let the process takes place at higher

pressure, say 10 MPa, the required temperature for vaporization is also higher. At point N, the slope is zero and there will never be two phases present, we simply term the substance as fluid. At point N the pressure is 22.1 MPa and the temperature is 374.14°C for water. Beyond this point the fluid is in supercritical conditions (Wylen *et al.*1994, Sonntag *et al.* 1998). It is worth mentioning that the power plants that work at this condition have some advantages and improvements over subcritical power plants.

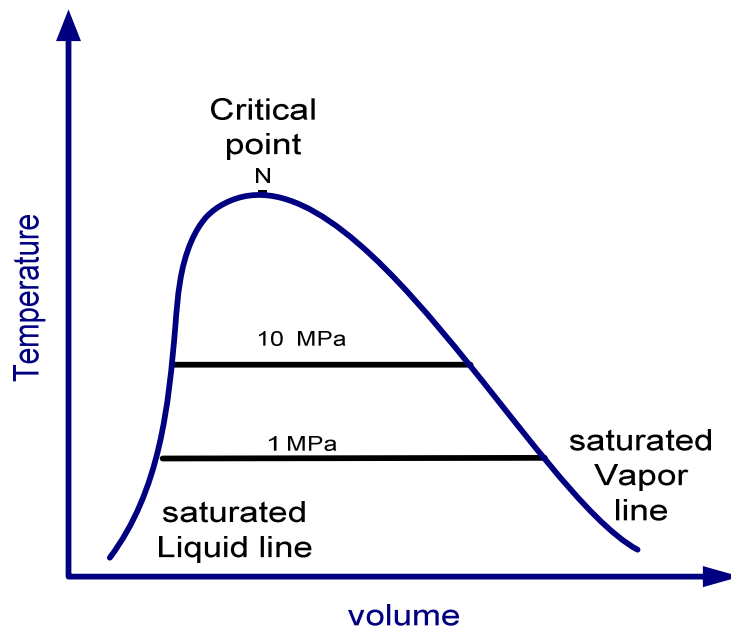


Fig 2.4 Temperature volume diagram showing solid and vapour phases (not to scale)

The discussion mentioned above can be summarized by Fig 2.5. It demonstrates how the three phases of liquid, solid, and gaseous can exist together in balance or equilibrium. Along line 1 the gaseous and solid phases are in equilibrium, along line 2 (dashed line) the liquid and solid phases are equilibrium. Line 3 is the vaporization line which show that the liquid and gaseous phases are in equilibrium (Wylen *et al.*1994).

At the triple point, the stable equilibrium of liquid, solid, and vapour can coexist (for water the triple point pressure and temperature respectively are 0.6117KPa 273.16 C°).

Consider point A, as shown in the figure, when the temperature is increased and the pressure is constant and less than triple point pressure the substance goes from solid to gaseous phases directly at point B. Line CD shows that the substance passes through solid state to liquid state and then from liquid state to gaseous state at higher temperature and so on (Wylen *et al.* 1994).

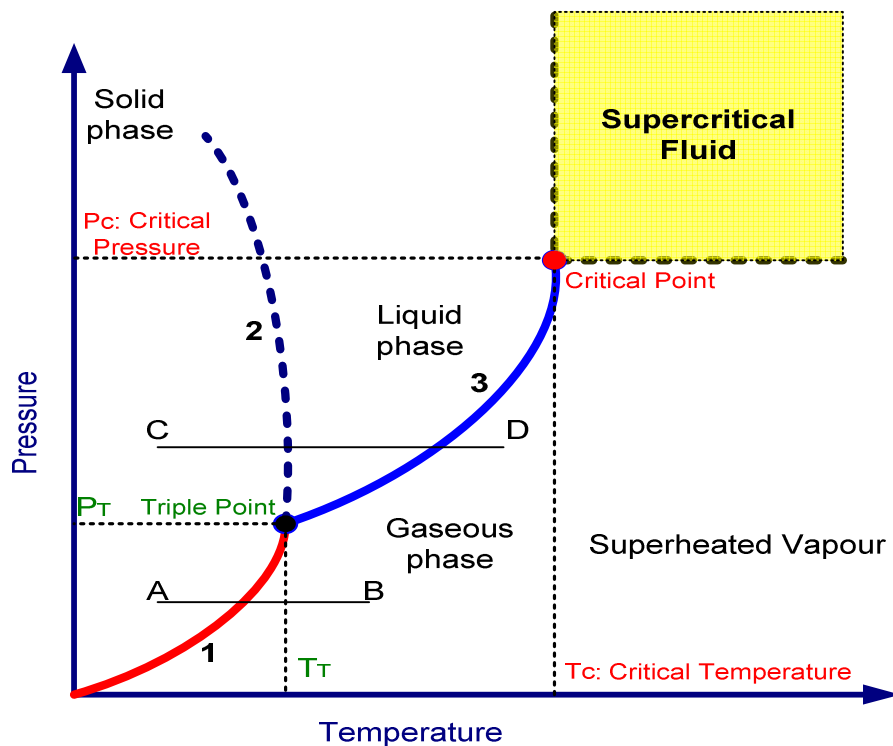


Fig 2.5 Pressure-Temperature diagram for a substance such as water (Sonntag *et al.* 1998)

The difference in cycles between subcritical and supercritical plants is explained in more details in Section 2.7.

2.5 Types of supercritical boilers:

Supercritical boilers have firstly come into power plant units in early 1960s and faced some problems related to failure of materials (Nalbandian. 2009, Miller *et al.* 2010). These problems of material failures include waterwall tube breaks resulting from high

temperature and erosion of start-up valves due to high differential pressure (Miller et al. 2010). In the last decades, SCPPs have gained many improvements in their materials to overcome some of the materials failure problems so that it can be regarded as well established technologies that play an important role in improving environmental conditions and reducing CO₂ emissions. In the last decade, SCPPs has achieved overall cycle efficiencies of 43-45%. This indicates how much of the *available heat of fuel is converted* into the heat in steam (Rayaprolu 2009). Ultra-supercritical (USC) power plants, which have steam temperature starting from 600C° and approaching 720 C° steam pressure above 25MPa and approaching 35MPa, have net efficiencies of 45-47 % (Rayaprolu 2009, Miller et al. 2010). Some of these USC units are in operation (Those having operating pressure of 31MPa and temperature of 600-620 C°) while some of them are still in planning stage (boiler operating pressure up to of 35MPa and temperature of 700-720 C°) (Rayaprolu 2009).

There are three types for supercritical once through boilers:

- Two pass boilers.
- Single pass or tower type boilers.
- Down shot boilers.

All of these types consist of the same parts of boiler; they are different only in construction. Figs 2.6, 2.7 and 2.8 (Rayaprolu 2009) show the two-pass, tower-type, and down-shot respectively. However, the same modeling approach is applicable to any one of them.

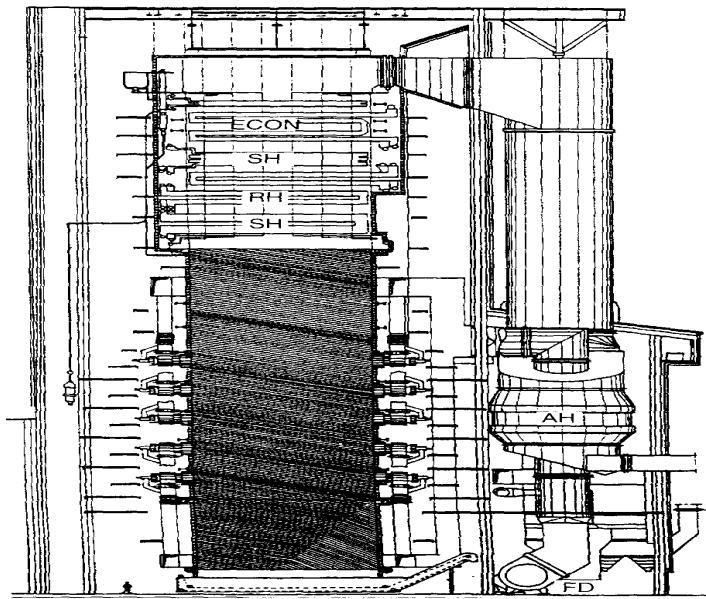


Fig 2.6 Tower-Type SC boiler

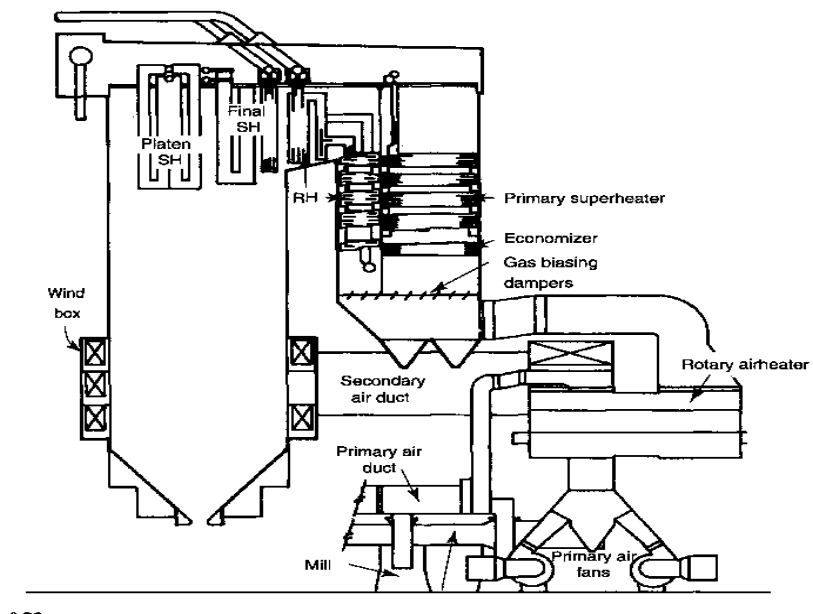


Fig 2.7 Two-pass SC boiler

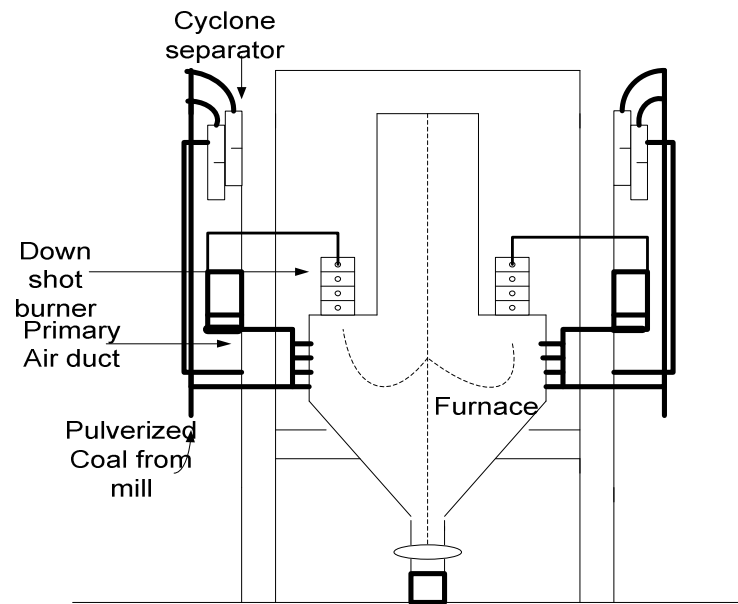


Fig 2.8 Down-shot SC boiler.

2.6 Main parts of supercritical boiler

The parts of supercritical boiler can be organized as three main parts which are: evaporator surface, superheaters and reheaters, and back-end equipment.

2.6.1 Evaporator surface

The evaporator surface consists of: the furnace and the boiler bank. The furnace is the enclosure around the firing equipment, which is made of water-cooled surfaces to cool the gases to an acceptable level to the superheater without worrying about tube getting overheated, and to provide enough time for the burning fuel for complete combustion. Heat transfer inside the furnace is radiation; the firing device is a combustor or burner. The dimensions of the firing equipment and flames govern the shape of the furnace. The furnace pressure is controlled by induced draft fans, and the temperature of the furnace is controlled by fuel rate input.

Furnace and boiler bank are the two evaporator surfaces in the boiler. A boiler bank is a large surface made up of tubes extended between water and steam. The heat is mostly transferred by convection (Rayaprolu 2009).

2.6.2 Superheaters and reheaters (SH & RH):

The efficiency of the steam cycle is improved by higher steam pressure and temperature in the superheaters as well as the reheaters. The SH is simply a heat exchanger which heats steam to a higher temperature for further improvements of the efficiency and produces dry steam suitable for turbine blades. The types of superheaters can be classified according to design or arrangements. For the superheater, temperature must be controlled in order to gain higher efficiency at all operating conditions, this task is achieved by using an attemperator which limits the steam temperature within a margin of $\pm 5^{\circ}\text{C}$ (water spray control). Besides the temperature control, the attemperator can also control the tube metal temperature of SH and RH. In the attemperator, the process is a direct contact to the SH where the feed water flow (FW) bypasses the ECON and evaporator nodes and joins the superheated steam directly through the spray attemperator (Rayaprolu 2009).

The steam from the high pressure turbine is reheated in the reheater before it can be introduced to the low pressure and intermediate pressure turbines where the most of remaining energy is used to produce mechanical power. The attemperation in the reheater is only for urgent emergency events and not for regular temperature control because it will reduce the overall cycle efficiency. The temperature control of the reheater is performed using flue gas re-circulation.

The design structures for these heat exchangers are varied widely Fig 2.9 shows typical design arrangements which will be for superheater or reheater.

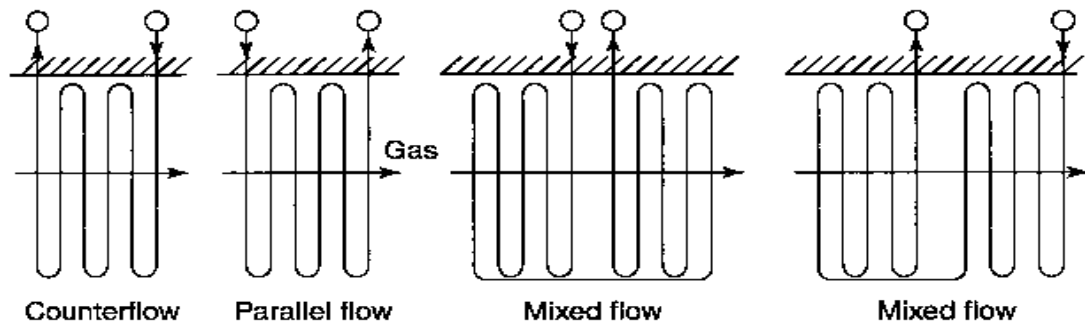


Fig 2.9 Typical design arrangement for superheater or reheater (Rayaprolu 2009).

2.6.3 Back-end equipment

Economizer and airheater are called back-end equipment. They are the last of the heat traps positioned according to boiler construction. Back-end equipment may consist of only economizer or a combination of ECON and AH, depending on the fuel and process. Economizer surfaces transfer heat from flue gases to pressurized and sub-cooled feedwater on its way to the furnace waterwall, and the heat is transferred through convection. As its name implies, it improves the economy or efficiency of the boiler.

Airheater is a control volume of supercritical unit that absorbs heat from the products of combustion after they have passed through the steam-generating and superheating stages, and it is usually the last heat trap in the boiler (Rayaprolu 2009).

2.7 Subcritical vs. Supercritical Boilers

This section presents the main differences between subcritical and supercritical boilers.

The boilers can be classified according to the operating pressure to:

- Subcritical boilers.

- Supercritical boilers.

Subcritical boilers have to work below the supercritical pressure of water. For subcritical boilers, water is heated in the boiler to generate steam. The steam is separated from boiler water in a steam drum and sent to the steam turbine. The remaining water in the drum re-enters the boiler for further heating and conversion to steam. The steam drum acts as energy storage element which provides easier control of large load demands/rejections and boiler pressure. This aspect for drum-type boilers has been proved by practical events from power plant utility and also by theoretical simulations (Kundur. 1983, Durrant. 1982, Abdenmour. 2000). Fig 2.10 shows a simplified cycle for subcritical drum power plant.

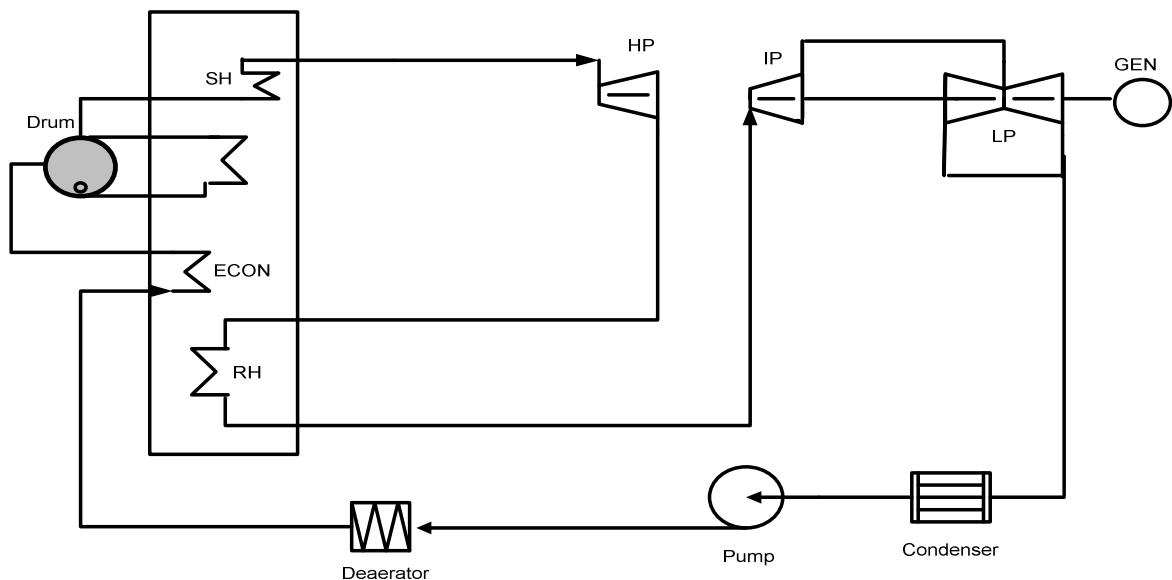


Fig 2.10 Subcritical drum-type plant cycle

The subcritical boiler can be drum type or once-through type, but in supercritical boilers the drum cannot be used because the steam cannot be separated automatically from water as in drum boiler. Hence, the supercritical boiler has to be a once through boiler. For the once-through supercritical design, feedwater enters the boiler, is converted to steam after the separator, and is passed directly to the steam turbine. The supercritical pressure for water is the thermodynamic condition, where there is no clear difference between liquid and vapor states. Supercritical boilers operate above the water critical pressure.

Supercritical once-through boilers do not have steam drum to track demand changes (Energy storage element). However the cost of materials construction for achieving supercritical pressure in supercritical boilers is higher. Following to turbine valve opening, the fuel and feedwater flows increase in order to follow the load demand and also to preserve the energy stored in the boiler, the summary of these dynamics of SC boilers can be also found in (Laubli *et al.* 1970). Fig 2.11 shows simplified supercritical once-through power plant flow.

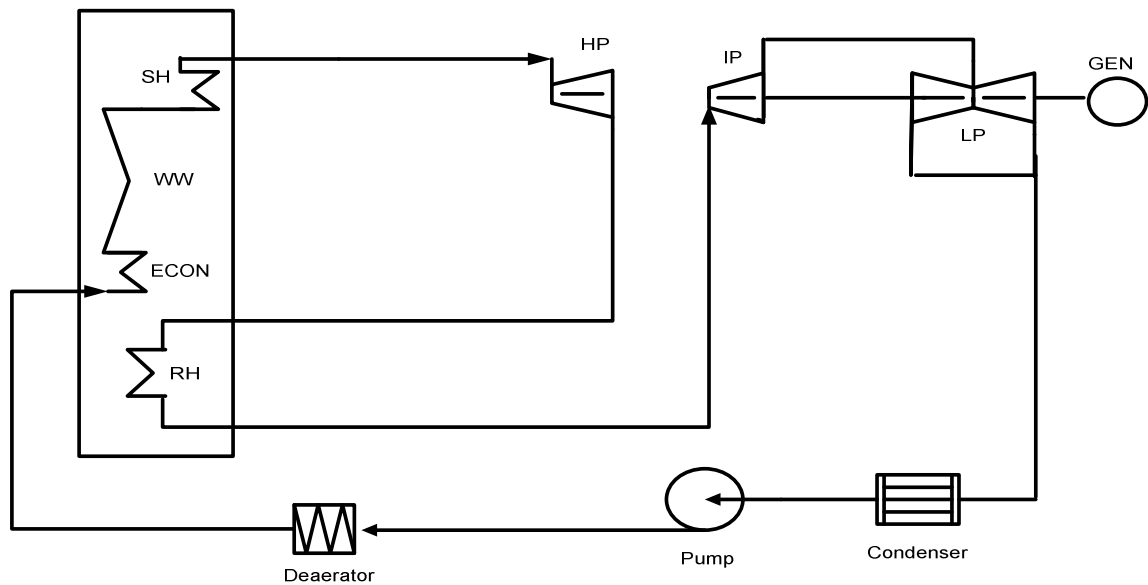


Fig 2.11 Supercritical once-through plant cycle

The efficiency of the thermodynamic process of coal-fired power plants describes how much of the energy that goes to the cycle is transferred into electrical energy. The greater the output of electrical energy for a given amount of energy input, the higher the cycle efficiency. If the energy input to the cycle is kept constant, the output can be increased by selecting elevated pressures and temperatures for the water-steam cycle. To clarify this, consider the simple steam cycle or T-s diagram shown in Fig 2.12, it is the same as that described in Fig where s is the entropy which can be defined by the inequality:

$$ds \geq \frac{\delta Q}{T} \quad (2.1)$$

where

ds : Net change in entropy

δQ : Net change in the heat transferred

T : Temperature

As shown in the Fig 2.12 the left hand side of the curve is for liquid phase. The right hand side is for vapour phase. Fig 2.12 is the same as that described in Fig 2.3, process from point 1 to 2: the water is pumped from low to high pressure and so on. At critical point there is no clear definition of the substance if it is liquid or vapour. Again recalling the cycle efficiency that can be calculated as follows:

Cycle efficiency = Work done by turbine / total heat of steam

= Area under 1234561 / area under 12345 in Fig 2.12

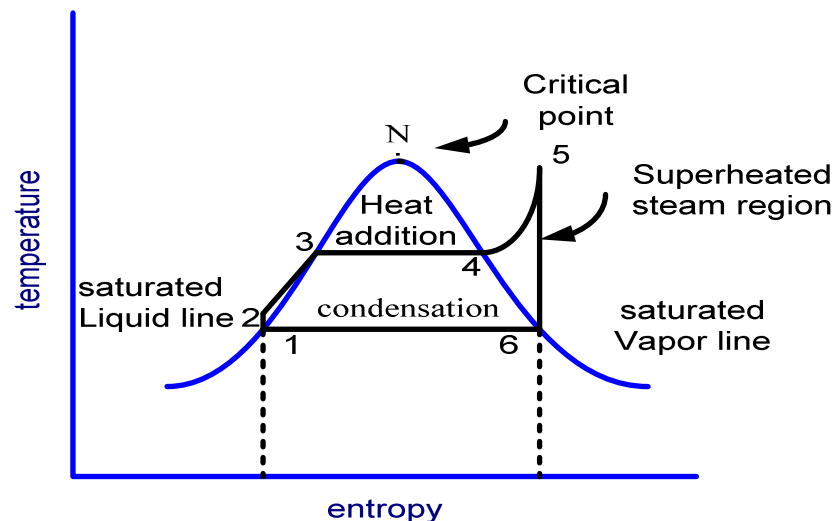


Fig 2.12 T-S Diagram of steam and water.

The subcritical and supercritical cycles are presented in Fig 2.13. The differences between the two operating cycles show that the supercritical cycle efficiency is greater than subcritical cycle because the area under the curve in supercritical cycle is higher (Rayaprolu 2009).

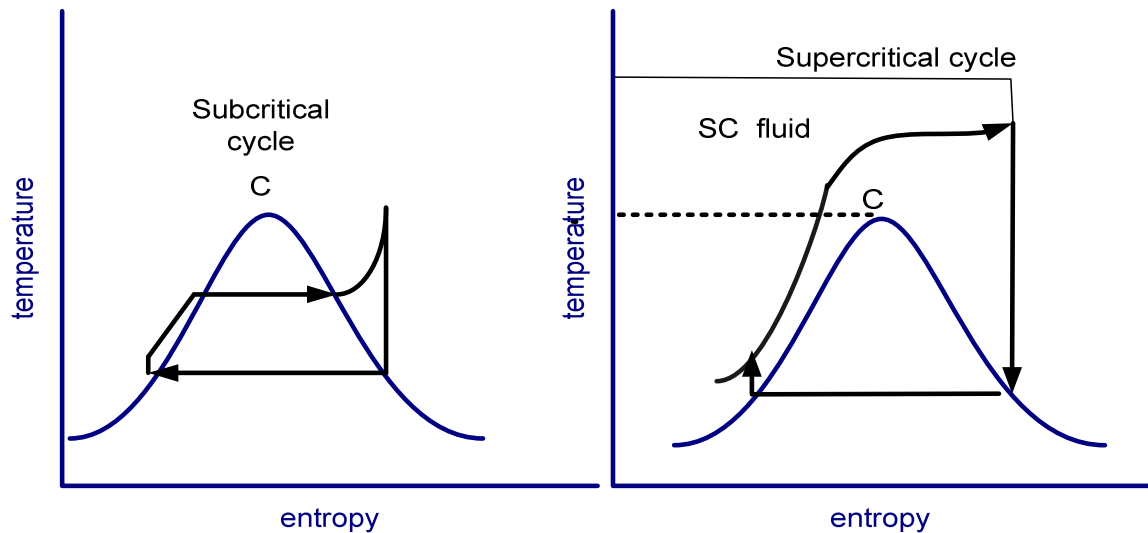


Fig 2.13 T-S Diagram for sub- and supercritical cycles (Rayaprolu 2009).

2.8 Summary for the features of supercritical boilers

The once-through nature of the supercritical boiler indicates that the fluid passes from the boiler feed pump to the turbine only once. In other words, there are no drums in SC boilers for water recirculation. The SC boiler has separator vessels instead of heavy drums. In once-through boilers, the boiler feed pump and turbine throttle valve are used mainly to control the flow of steam in the boiler, and subsequently the electrical power output of the generator. The temperature of heat exchangers in the boiler is controlled by various ways. For instance, the steam temperature in the superheater is controlled by fuel firing rate and regulated by attemperator, and the reheater's temperature is controlled by gas recirculation. SC power plant is more efficient compared with conventional one. Therefore, SC boilers

should be built for very large capacity in order to cover the largest percentage of load demand, which means that the grid should be large enough. However, the boiler materials in case of supercritical boilers are expected to be more expensive because they must be designed for high pressure operation and metallurgy. Some other aspects of supercritical power plants over subcritical power plants are:

1- Less fuel consumption because of efficiency improvement.

2- Lowered CO₂ emissions due to reduced fuel combustion. Improvements in the efficiency lead to lower fuel combustion for delivering the same amount of power. (10% improvement in the efficiency nearly means reduction of more than 25% in CO₂ emissions) (Vocke. 2007).

3- Easier to integrate with CO₂ capture and storage system.

4- Lower thermal inertial for supercritical boilers because there is no drums or water circulation in once-through mode. The drum slows down the boiler dynamics.

5- The drum which is walled with higher thickness is replaced with small separator vessels (Rayaprolu 2009).

6- More flexible to operate in constant or sliding pressure modes which improves plant dynamics, reduced stress on the equipment, and efficiency even in part loads while in drum type plants, the drum generates steam only at the constant pressure mode (Rayaprolu 2009).

7- Rapid response due to load changes which make it suitable not only for base load operation, but also for fast load demand tracking. (Laubli *et al.* 1970).

2.9 Overview of Research in SC Power Plant Modeling and Control

Simulation of fossil fuel plants relies mainly on derivation of mathematical descriptions for the main subsystems of power plant and formed together to build simulator. This section reports a literature survey for supercritical fossil fuelled power plants mathematical modeling, parameter identification, and control. To avoid confusion, this area of research can be basically spread into three main surveys of disciplines, mathematical modelling, unknown model parameters identification, and the SCPP control systems development and progress.

2.9.1 Mathematical modeling of SC Power Plant Process

Starting with modeling review, the objectives of previous research do not differ greatly from the current research objectives. Investigating the dynamics of once-through supercritical units studied firstly by simulation of the Eddystone I unit of Philadelphia Electric Company in 1958 and the Eddystone model was progressed for simulation of Bull Run supercritical generation unit in which several modification and improvements are included (Littman *et al.* 1966). The plant was simulated by linearized mathematical model based on physical principles. But there were no field data available for comparison and verification since the Bull Run unit was not in full operation at that time.

F. Laubli *et al.* (1970) provided both field tests and computer simulation results to perform theoretical tests for supercritical units (Gas fired and coal fired with various ratings) to show the flexibility of supercritical boiler as partner in power system design and operation. The capability of these units to follow the load demand rapidly is proved. However, no details are given about how those simulators are developed.

Yutaka Suzuki *et al.* (1979) investigated the capacity of a 450MW oil-fired once through supercritical boiler in order to improve the control system of the operating plant. The model was based on nonlinear partial differential equations of mass and energy conservations; the model has forward and backward links resulted from some algebraic equations of steam flow which are used to interconnect the boiler subsystems together. Simulation results proved the reasonableness of the model.

Shinohara *et al.* (1996) proposed a simplified nonlinear model based control for supercritical boiler-turbine. Also, the model was based on mass and energy balances with some simplifying assumptions to satisfy the required simplicity for simulation. However, few simulation results are reported to match EPRI simulator results rather than measured data.

Inoue *et al.* (2000) presented lumped pressure node mathematical model of fossil fuel supercritical plant for power system frequency simulation studies. The paper provided justification for using simplified low order model with its associated controls to study the SC plant dynamic response to frequency excursions.

In the work reported in (Zindler *et al.* 2008), a physical principle model for of a 800MW hard coal supercritical plant is described and the dynamic simulation performed with the aid of special computation tool called Enbipro program (Energy balancing program). This software was developed at the Technical University of Braunschweig, Institute for Heat- and Fuel Technology. Simulations were done at fast load changes to investigate the plant fulfillment to Great Britain Grid Code (GBCD). However, no measured responses are given for the 800MW unit to compare with these simulations. It is concluded that other primary measures like, for instance, condensate stop, is necessary during the time period to

supply the remaining power output required by GBGD. Condensate stoppage is a similar action to steam throttling of the boiler by the control valve which produces faster primary power response with lower time lag.

It is important to mention that all models which are mentioned above are based on physical principles of mass and energy conservations. The literature also includes other modeling approaches. For instance, Zhong-xu *et al.* (2008) presented a mixed empirical / mechanism analysis model which is composed of nonlinear transfer functions. It was fitted to 660MW supercritical unit to establish empirical model for the unit. Also, the empirical model for supercritical plants can be designed by an autoregressive-moving average (ARMA) (Nakamura *et al.* 1981).

The other empirical approach which has been found in the literature is modeling via neural network. Lee *et al* (2007, 2010) presented the performance of diagonal re-current neural network (DRNN) for modeling the various subsystems of SC power plant and ultra-supercritical power plants. The DRNN are trained with suitable data provided by operating units (500MW and 1000MW) and the given simulation results proved the validity of the NN model over wide operating range.

The survey of modeling can be divided into two main approaches: The group of models that are based on first principles or thermodynamic principles and their parameters are either identified by optimization routine or calculated by steam properties. The other group of models are based on black-box identification of certain transfer functions, ARMA or neural networks. Although neural networks are able to handle many uncertainties in the plant that are extremely difficult to describe mathematically, empirical models, in general, have no physical feature as they depend mainly on the data supplied by plant manufacturer not on physical laws. On the other hand mathematical models that are based on the system

physics are able to reflect the response of intermediate variables or reasonably estimate them if they are immeasurable. In this research study, a time based dynamic response mathematical model has been derived for 600MW supercritical coal fired plant. The model described a long process from coal grinding up to synchronous generator dynamics including the couplings and interactions between the turbine and generator. A combination between physical laws modeling and parameters identification has been conducted to offer a simplified model for 600MW SCPP that represent the main features of the real plant characteristics. The main tasks of this model are to study /observe the dynamic response of SCPP without actual operation of the plant and also to investigate the possible ways to improve its MW response while keeping optimal operating efficiency. Generally, the results of dynamical models that have been reported in the previous research do not have to be exactly matched to the plant response. This is because of the plant uncertainties and other computational requirement. Then, the target is to design mathematical model that simulate the main dynamical trends of real plant. Fig 2.14 shows example results of plant/model response from previous research (Suzuki *et al.* 1979).

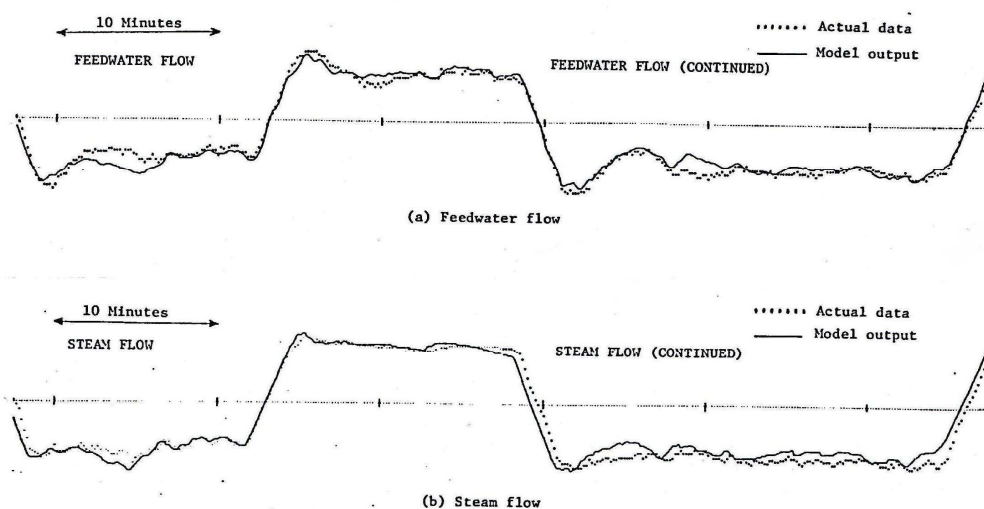


Fig 2.14 Simulation results as an example from previous research (Suzuki *et al.* 1979).

The next survey is to investigate the methods of optimization used for identifying the models' parameters.

2.9.2 Unknown Parameter Identification for Modeling

Parameter identification of mathematical models for a supercritical fossil fuel unit is an optimization problem to be solved so that the simulated results trend results agree optimally with plant data trends. The real plant data are either real on-site measurement records or data supplied by plant detailed simulator. These parameters cannot be known precisely for a specific plant and thus, parameter identification is an unavoidable procedure, especially for simplified low order models.

The review for this procedure includes many optimization techniques that have been used to identify some or all model parameters simultaneously. In (Suzuki *et al.* 1979), the values of some unknown parameters have been identified to minimize the sum of squares differences between the actual boiler output and simulated result. Fletcher-Reeves optimization method was used for identifying the parameters sequentially (Kowalik *et al.* 1986). All model parameters couldn't be adjusted simultaneously by this method so the identification was conducted sequentially and systematically among the variables.

Nakamura *et al.* (1981) performed statistical identification to fit a multivariate autoregressive model to obtain a practically useful state space representation suitable for optimal control. The practical implementation of the model for control purposes indicated the reliability and accuracy of the identified parameters.

Rovnak *et al.* (1991) used multivariable least square regression method to identify the coefficients of a simple autoregressive moving average ARMA model which is a matrix of

transfer functions used to predict the response of ninth order supercritical boiler process model.

Gibbs *et al.* (1991) applied nonlinear least square method to identify a reduced order model (ROM) for supercritical gas-fired power plant that has been adopted for control system design. By using data from detailed simulator, the parameters are identified with match the detailed simulator.

In this research, Genetic Algorithms technique has been used to identify the parameters of the model for 600MW coal fired supercritical unit. The parameters can be easily identified simultaneously with this method. Also, it is proved that GA is a robust optimization technique which can perform nonlinear system identification (Kumon *et al.* 2000, Wei *et al.* 2007). No doubt, GA is much improved over conventional mathematical optimization methods which are previously used, especially for complex nonlinear processes. This method and its features over other methods is described in details in Chapter 4. The last survey is concerned with the branch of SCPP control.

2.9.3 Research Progress in Control of SCPP

In once-through supercritical power plants, a coordinated control of the boiler-turbine system is used. That is several targets and conditions must be fulfilled simultaneously. This includes the ability to give the required MW response to the load request, keeping continuous optimal operation, and minimizing the fluctuations in the boiler variables which are the main reason for reducing the life of the equipments. However, to achieve those operating objectives, power plant still need more advanced control with higher automation and more flexibility which require learning and adopting one of these advanced technologies in this study.

The optimal control system was firstly implemented practically into a 500 MW supercritical oil-fired power plant in 1978 to control the boiler steam temperature and the work was published by (Nakamura *et al.* 1981). The work was done to demonstrate the advantage of the proposed optimal controller over the conventional PID controller. While keeping the first layer control, the optimal linear quadratic regulator LQR was located in parallel with the first level dynamic controller. Dynamic programming DP has been used in the controller algorithm to minimize a certain performance criterion.

Rovnak *et al.* (1991) proposed multivariable dynamic matrix control DMC and applied the controller to ninth order nonlinear supercritical plant simulator. The DMC, using linear models identified by step response tests, has been tested over wide range of load change.

Gibbs *et al.* (1991) presented preliminary results of multivariable; practical, nonlinear, model based predictive control. The nonlinear predictive controller was applied through nonlinear optimization routine to regulate the steam temperature of gas fired supercritical power plant.

MPC for 400MW SC gas fired power plant was published also by (Trangbaek. 2008) which is the most relevant to this study. Based on augmented linear state space model for prediction, the MPC was applied on 22nd order nonlinear process model that created in MATLAB[®] environment and simulation results show successful performance for bounded operating region without violating the plant operation constraints.

Lee et al. (2007) and Lee et al. (2010) applied neural network modified predictive control to 500MW and 1000MW operating units respectively. Then, the authors designed what they called (modified optimal predictive control) also by NN and all set-points are nicely

tracked. The controller utilizes particle swarm optimization with on-line identification to provide the required information from the NN model to the controller.

Zhong-Xu *et al.* (2008) reported a generalized intelligent coordinated control system for supercritical unit. The overall control system is made up of combination of classical and intelligent control. The controller has been tested and it has given satisfied responses for following the active power changes. However, no detailed descriptions for the model development and its controller are given.

From the review, it is clearly noticed that the predictive control is the dominant approach for control system design of fossil fuel supercritical units regardless of whether it is based on intelligent techniques implementation or based on mathematical equations and optimization. This is actually applied to subcritical power plants without serious difficulties (Rossiter *et al.* 1991, Prasad *et al.* 1997, Hogg *et al.* 2000, Poncia *et al.* 2001, Li *et al.* 2006, Choi *et al.* 2010) and many others.

In this research, model based predictive control strategy has been applied to SCPP process model in a MATLAB[®] environment. The MPC improves the dynamic response of SCPP by using the MPC as adjuster the reference of existing controls. The MPC algorithm is discrete time linear with extra states. The MPC algorithm adopted in this study is best described in (Ricker. 1990). One of the control signals is the raw coal flow, the second is the feedwater flow and the third is the turbine valve command. The controller has shown good performance around known operative conditions of the prediction model. However, the contribution of this research is reported in Chapter 1 and the details of each branch work are spread in the next chapters. The next section reports the power plant simulation tools that have been found in the literature.

2.10 Power Plant Simulation Tools:

Power plant is a complex process which embeds highly nonlinear features. For physical or mathematical models, a care should be taken in choosing the simulation tool that has the necessary programming language for solving the model equations or optimization problem of parameter identification procedure.

The published work in the last two decades for power plant simulations has shown more advanced simulation technologies than the past one(Lu. 1999). Those tools offer graphical or blocks presentation for the power plant systems which is composed from mathematical operations, integrators, differentiators, transfer functions in s-domain and so on. It therefore has the advantage of easier modification even for the people who are not the main model frame builders. Also, they can be easily understood and adapted with other objects. The graphical simulation also offers the ability to access any variable in the plant without much effort.

Some packages that are commonly used for this area of research are:

1. MATRIXx: it is a computer aided design tool which performs steps for physical system modeling, identification, and control. The package is a powerful lab which has aspects of matrix interpretation graphical environment for the devices, and flexible command language. It is best described in (Gregory *et al.* 1982).
2. Easy5: the Boeing Engineering Analysis Software Package (Easy5®) is a power plant simulation package that simulates power plant systems using modular principle of system simulation. The package has been developed using FORTRAN language and has been widely used in (Armor *et al.* 1982, Oluwande *et al.* 1992).

3. ACSL: MGA Software have designed ACSL Code, that is Advanced Continuous Simulation Language for Modular Modeling System (MMS) users. By using ACSL macros, which are structured in FORTRAN, the MMS model can be implemented. (Lu. 1999, Peet *et al.* 1993, Armor *et al.* 1982).
4. Modelica OOM: OOM is an object oriented modeling approach written in modelica language. The approach is based on using paradigms in such a role to represent the system components. It can be found in (Maffezzoni. 1992, Maffezzoni *et al.* 1999, Flynn *et al.* 2003.).
5. MATLAB[®] and SIMULINK[®]: MATLAB[®] (matrix laboratory) is a simulation tool that developed by MathWorks. The most relevant package to MATRIXx is MATLAB[®] so it performs the generalized matrix operations, provides a graphical representation for objects that are generally used for creating physical systems and their associated controls. From the literature, it is found that MATLAB[®] is the most widely used for simulating power plant dynamics. It has been chosen to conduct the task of simulation in this research because it can be easily linked with advanced optimization tools and/or advanced control strategies that are originally built in MATLAB[®] environment.

2.11 Summary

This chapter introduces background material concerning supercritical power plants processes and supercritical boilers. It gives a description of the process of coal fired power plant from coal pulverizing to electrical power production from the synchronous machine. This has been clarified also by description of Rankine Cycle that is normally used to represent the operational cycle of thermal steam power plants. The types of supercritical boilers according to the industrial structure is mentioned and followed by the comparison

between subcritical and supercritical boilers. The improvements of supercritical boilers over subcritical boilers have been known to justify the choice of supercritical power plants as advanced solution for base load power generation systems. The chapter also presents a wide range literature review which moves from the first research in this area of study up to the current and recent published research. It has been divided into three main subjects of research which are: mathematical modeling of supercritical power plants, parameter identification, and control system development including the attempts of this thesis. It is found that the area of modeling supercritical power plant is not extensively studied as in modeling subcritical power plant. It is still not clear what is the best dynamic response that can be gained from supercritical power plants and therefore, supercritical power plant modeling is still an active research area. Finally, a separate section that gives some simulation tools used for power plant simulation studies. It is important to mention that the simulation tools are not limited to that mentioned in this chapter, but those mentioned are the tools which are clearly detailed in the literature.

Chapter 3

Mathematical Modeling of a Supercritical Coal Fired Power Generation Process

3.1 Introduction

Mathematical modeling of large scale power plants is prerequisite for control system implementation and/or plant performance study on a personal computer environment. However, there is a need to study the physical principles of the various subsystems in the power plant to derive the mathematical descriptions of these components. Power plant mathematical models are generally rooted from physical laws that governing the plant subsystems. In this chapter, a simplified mathematical model for supercritical boiler-turbine-generator system is introduced. The model is based on *first principles* of thermodynamics, engineering, and many published reports and research articles (Salisbury *et al.* 1950, Adams *et al.* 1965, IEEE Committee. 1977, Thomas *et al.* 1979, Usoro *et al.* 1983, Yu. 1983, Hemmaplardh *et al.* 1985, Kola *et al.* 1989, Rovnak *et al.* 1990, Kundar. 1994, Shinohara *et al.* 1996, Maffezzoni *et al.* 1997, Ong. 1998 Lu. 1999, Sonntag *et al.* 1998, Lu *et al.* 2000, Inoue *et al.* 2000, Makovicka *et al.* 2002, Liu *et al.* 2003, Andersson. 2003, Chaibakhsh *et al.* 2007, Wei *et al.* 2007, Trangbaek *et al.* 2008, Dehghani *et al.* 2008, Gu *et al.* 2009). Through the modeling procedures and analysis, some assumptions and approximations are adopted to reduce the complexity of the plant processes for suitable computer simulation. In the following sections, a brief review for the previous research effort for modeling SC power plants is reported, identifying the boiler-turbine-generator inputs and outputs for modeling, then the principles and fundamentals of

thermodynamics are then presented and used for deriving the boiler-turbine model and coupling it to synchronous generator model. Finally, the proposed method for simulation is presented.

3.2 A historical review

From the literature survey, it has been found that several models have been reported with emphasis on different aspects of the boiler characteristics. Studying the response and control performance of once-through supercritical (SC) units began on 1958 when work was started on a simulation of the Eddystone I unit of Philadelphia Electric Company and the work was extended for simulation of Bull run SC generation unit (Littman *et al* 1966). Suzuki *et al.* (1979) modelled a once-through SC boiler in order to improve the control system of an existing plant. The model was based on nonlinear partial differential equations, and the simulation results for steam and feedwater flows indicated that the model is valid. Shinohara *et al.* (1996) presented a simplified state space model for SC once-through boiler-turbine and designed a nonlinear controller. Inoue *et al.* (2000) introduced pressure node model description for power system frequency simulation studies. All above mentioned researches applied the principles of thermodynamics for modelling. Apart from this research, Zhong-Xu *et al.* (2008) reported a model which is composed of nonlinear polynomials and gains used to fit 660MW coal firing SC unit. No details are given on the responses which are used for identification/verification. Intelligent techniques contributions have yielded an accurate performance for modeling. Lee *et al* (2007, 2010) showed the performance of diagonal recurrent neural network (DRNN) for modeling SC power plant with sufficiently accurate results. The DRNN are trained with suitable data provided by operating units (500MW and 1000MW). It is important to

mention that, power plant manufacturers and companies are mainly interested in developing detailed simulators which can provide better and more accurate responses and handle many uncertainties in the plant. However, detailed simulators are not normally adopted for control system applications because they often embed high computation demands (Inoue *et al.* 2000, Chaibakhsh *et al.* 2007). My research is addressed to have an analytical model for a certain portion of SC coal-fired plant from coal grinding to the frequency of infinite bus to simulate the main features of real power plant and investigate the available opportunities to improve its responses. The coal mill model is available for normal grinding process and its parameters have been extensively validated (Zhang *et al.* 2000, Wei *et al.* 2007). SC boiler model with full set of parameters and clear detailed information is difficult to find in the reported literature as no details have been given in the published researches' models and/or their full set of parameters. There is an urgent demand to have this model in advance, link it to other plant subsystems, and tune its parameters to match the real system data provided by the plant manufacturer. The next section defines the inputs and outputs used for modeling the boiler-turbine-generator system to be used for identifying the parameters and control system study.

3.3 The boiler-turbine process description

The major boiler components are illustrated in Fig 3.1. The unit is once-through supercritical 600MW power plant process. Choosing 600MW capacity boiler is mainly because the data for such a power station for model validation could be obtained. The hot water from the feedwater heater is heated in the economizer before it is introduced to the superheating stages through the waterwall. The superheater consists of three sections which are low temperature superheater, platen superheater, and final stage superheater. The main steam outlet temperature is about 571C° at steady state and a pressure of 25.5

MPa. There are 2 reheating sections in the boiler for reheating the reduced thermal energy steam exhausted from the high pressure turbine. The inlet temperature of the reheater is around 309 C° and the outlet temperature is nearly 571 C° and average pressure of 4.16MPa. The reheated steam is used to energize the intermediate pressure turbine. Finally, the mechanical power is generated through multi-stage turbines to provide an adequate expansion of the steam through the turbine and subsequently high thermal efficiency of the plant. Fig 3.1 completes the description of the plant.

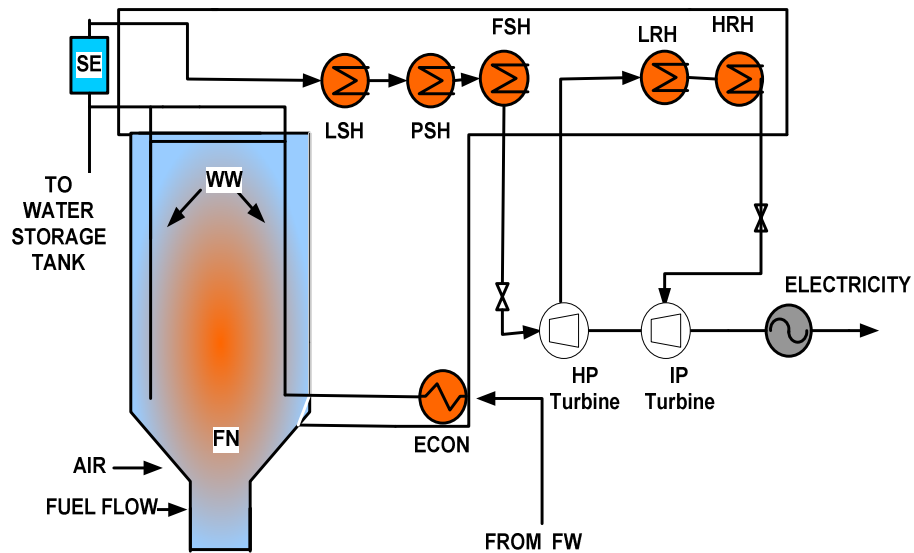


Fig.3.1 once-through unit schematic diagram

3.4 Thermodynamic principles for boiler-turbine modeling

The modelling is based on dividing the various components in the boiler and turbine into sub-control volumes and start modeling each control volume by mass and energy conservations. The control volume is a set with a clear boundary in a selected space in which a thermodynamic process takes place (Fig 3.2). It usually contains certain devices

that involve mass flow such as (turbine, pump, heat exchanger...etc). The mass balance principle is based on the fact that we cannot create or destroy the mass, but it is changed from one form to another or from a phase to another. The energy balance equation states that the total variation of energy in the control volume equals to the difference between the total energy entering the system and the total energy leaving the system and also the energy is transferred from one form to another and cannot be destroyed. The generalized energy balance equation (Sonntag *et al.* 1998):

$$\frac{dE_{CV}}{dt} = Q_{CV} - W_{CV} + \sum w_i h_i - \sum w_o h_o \quad (3.1)$$

Where E_{CV} is the energy contained by the control volume. Q_{CV} is the heat transfer in the control volume. w_i and w_o are the input and output mass flow rates respectively. h_i and h_o are the entering fluid enthalpy and leaving fluid enthalpy respectively. In (3.1), the concept of balance means that the variation rate of the energy inside the control volume equals the change rate of the thermal energy supplied by the heat transfer plus the energy change rate of fluid which is being pushed by the surroundings minus the energy change rate of fluid out from the control volume minus the power used for the work done by the system if there is a movable parts in the control volume.

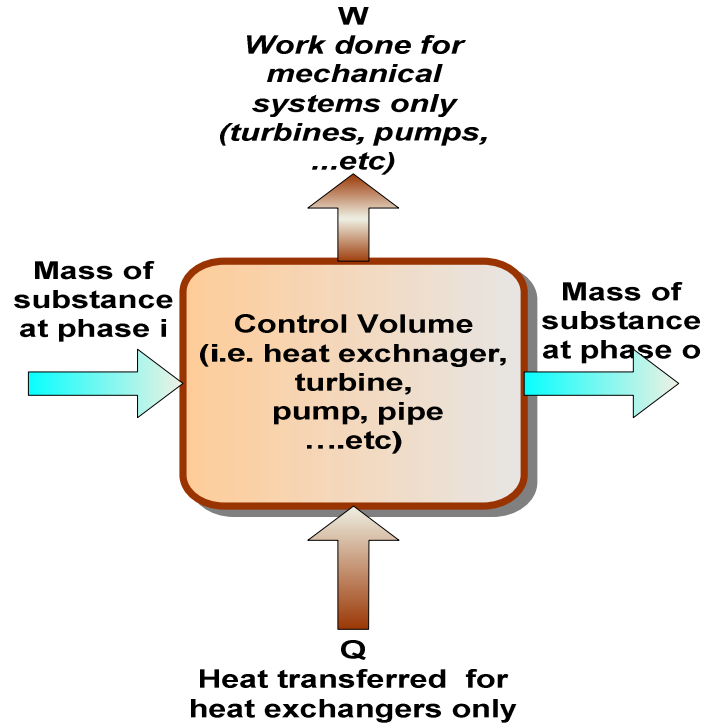


Fig.3.2 Illustration of the concept of control volume

The mass conservation principle states that the mass dynamics inside the control volume equals to the mass flow rate entering the control volume at phase i minus the mass flow rate leaving the control volume at phase o . The notations phase i and phase o are used to generalize the phase of the substance to make the principle applicable for liquid, vapour, or even supercritical conditions. Therefore, the mass balance equation or conservation of mass is derived as (Sonntag *et al.* 1998)

$$\frac{d(V\rho)}{dt} = \sum w_i - \sum w_o \quad (3.2)$$

The enthalpy is an extensive thermodynamic property of the vapor, liquid or fluid, and it equals to the internal energy plus the multiplication of the pressure and the volume of the substance (Sonntag *et al.* 1998)

$$h = u + Pv \quad (3.3)$$

The total energy for a substance or control volume can be calculated by

$$E_{cv} = U_{cv} + PE + KE \quad (3.4)$$

Where:

PE: potential energy results from vertical force that moves the mass vertically a distance dz

KE: kinetic energy results from force that moves the mass horizontally a distance dx

U_{cv} : Internal energy of the control volume which is defined as the thermal energy of the control volume and any other form of energy rather than kinetic and potential energy.

After definition of *PE* and *KE*, Equation (3.4) becomes:

$$E_{cv} = U_{cv} + \frac{1}{2}M\mathbf{V}^2 + MgZ \quad (3.5)$$

where \mathbf{V} the speed of the particles fluid, Z is represents the vertical elevation of the control volume, and g is acceleration due to gravity. Then (3.5) per unit mass will become

$$e = u + \frac{1}{2}\mathbf{V}^2 + gZ \quad (3.6)$$

where e is the total energy per unit mass of substance and u is the internal energy per unit mass of a substance. From (3.4),

$$dE_{cv} = dU_{cv} + dPE + dKE \quad (3.7)$$

The differences of the potential and kinetic energy are commonly negligible quantities because the fluid speeds in the inflow and outflow of heat exchangers are nearly the same.

In addition, the elevation hasn't been changed (Sonntag *et al.* 1998). Therefore, (3.7) becomes

$$dE_{CV} = dU_{CV} \quad (3.8)$$

and the energy balance equation becomes (Sonntag *et al.* 1998)

$$\frac{dU_{CV}}{dt} = Q_{CV} - W_{CV} + \sum w_i h_i - \sum w_o h_o \quad (3.9)$$

Equation (3.9) represents the energy balance equation of a control volume which can be a heat exchanger, a turbine, a pipe...etc. These principles are applied to analyze the boiler-turbine model.

3.5 The Boiler Heat Exchanger Modeling

This section presents a step-by-step derivation of a heat exchanger model in the boiler. This will be applicable to the economizer, waterwall, superheater, and reheater. The state variables in the heat exchanger can be pressure, temperature, or enthalpy.

Further to the simplifying assumptions and approximations which are adopted in deriving the system model, the following assumptions are made; those assumptions are general and taken in many research work subcritical and supercritical boilers (Adams *et al.* 1965, Shinohara *et al.* 1996, Lu *et al.* 2000)

- The working fluid pressure and temperature are uniform at any cross-section of the heat exchanger.
- The combustion gas path is not presented, only the fluid path is modeled.

- The three superheaters are grouped as one superheater, as well as the two reheaters are presented by one reheater in the model

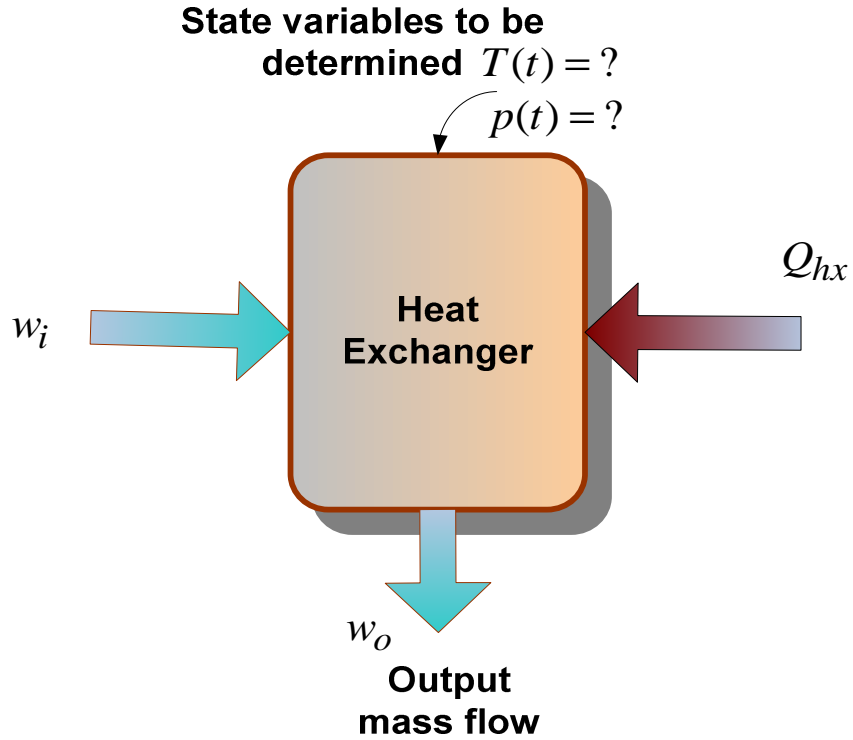


Fig 3.3 Diagram of the heat exchanger to be modeled.

As stated in the previous section, this heat exchanger, which is illustrated in Fig 3.3, is governed by the mass and energy balance equations. The variables mentioned in Fig 3.3 are w_i and w_o which are the input and output mass flow rates respectively, $T(t)$ and $p(t)$ are the state variables to be determined which are the pressure and temperature of the heat exchanger. Q_{hx} is the heat transfer rate in the heat exchanger.

The mass balance equation for a heat exchanger is

$$\frac{d(V\rho)}{dt} = w_i - w_o$$

where ρ is the fluid density, V is the effective volume of the fluid inside the heat exchanger. The flow of mass in the heat exchanger can be expressed as:

$$w_{hx} = \rho_{hx} \cdot V_{hx}$$

The mass of fluid w_{hx} equals its density multiplied by effective volume V_{hx} of fluid inside the heat exchanger. Since the effective volume of the fluid inside the heat exchanger is nearly the same volume of the heat exchanger, the effective volume is regarded as constant (Lu, 1999) and the mass balance equation becomes:

$$V_{hx} \frac{d\rho_{hx}}{dt} = w_i - w_o \quad (3.10)$$

For any differentiable function of two variables, the function can be expanded as (Thomas *et al* 1979):

$$\frac{df(x, y)}{dt} = \frac{\partial f}{\partial x} \cdot \frac{\partial x}{\partial t} + \frac{\partial f}{\partial y} \cdot \frac{\partial y}{\partial t}$$

Since ρ is a differentiable function of the temperature and pressure, (3.10) can be expanded as follows

$$V_{hx} \left(\frac{\partial \rho_{hx}}{\partial p_{hx}} \bigg|_T \cdot \frac{dp_{hx}}{dt} + \frac{\partial \rho_{hx}}{\partial T_{hx}} \bigg|_p \cdot \frac{dT_{hx}}{dt} \right) = w_i - w_o \quad (3.11)$$

where p_{hx} and T_{hx} are the pressure and temperature of the working fluid inside the heat exchanger. The density can be expanded on the enthalpy and pressure instead of pressure and temperature (Lu, 1999). However, the data provided contain a temperature and pressure sets of the main steam so it is preferable to extend (3.11) to the pressure and temperature. The analytical models (Inoue *et al.* 2000, Chaibakhsh *et al.* 2007, Makovicka

et al. 2002, Rovnak *et al.* 1991) also involve temperature models with different structure.

The energy balance equation

$$\frac{dU_{hx}}{dt} = Q_{hx} + w_i h_i - w_o h_o \quad (3.12)$$

The work rate term has been omitted from (3.12) because the heat exchanger has no movable parts as the case of turbine and pumps. Since the internal energy U of a control volume equals to the enthalpy minus the multiplication of the pressure and volume (Sonntag *et al.* 1998),

$$U = H - pV$$

where H , P and V are the enthalpy, pressure, and volume of the fluid in the control volume, the specific volume or enthalpy equal to the enthalpy or volume divided by the mass of the fluid.

$$U = M(h - pv)$$

where h and v are the specific enthalpy and specific volume respectively.

Since $\rho = \frac{M}{V}$ and $v = \frac{V}{M}$ then

$$U = Mv(h\rho - p)$$

$$U = V(h\rho - p) \quad (3.13)$$

Taking the first derivative of (3.13), under the assumption of constant volume:

$$\frac{dU_{hx}}{dt} = V_{hx} \frac{d(\rho_{hx} \cdot h_{hx})}{dt} - V_{hx} \frac{dp_{hx}}{dt}$$

$$\frac{dU_{hx}}{dt} = V_{hx} \left(h_{hx} \frac{d\rho_{hx}}{dt} + \rho_{hx} \frac{dh_{hx}}{dt} \right) - V_{hx} \frac{dp_{hx}}{dt}$$

The enthalpy is also a thermodynamic property depends on the pressure and temperature, then the internal energy equation becomes,

$$\begin{aligned} \frac{dU_{hx}}{dt} = & V_{hx} \left[h_{hx} \left(\frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{dp_{hx}}{dt} + \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p \cdot \frac{dT_{hx}}{dt} \right) + \rho_{hx} \left(\frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{dp_{hx}}{dt} + \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p \cdot \frac{dT_{hx}}{dt} \right) \right] \\ & - V_{hx} \frac{dp_{hx}}{dt} \end{aligned} \quad (3.14)$$

By equating the right hand sides of (3.12) and (3.14)

$$\begin{aligned} & V_{hx} \left[h_{hx} \left(\frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{dp_{hx}}{dt} + \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p \cdot \frac{dT_{hx}}{dt} \right) + \rho_{hx} \left(\frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{dp_{hx}}{dt} + \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p \cdot \frac{dT_{hx}}{dt} \right) \right] \\ & - V_{hx} \frac{dp_{hx}}{dt} = Q_{hx} + w_i h_i - w_o h_o \end{aligned} \quad (3.15)$$

$$\begin{aligned} & V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T + \rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - 1 \right) \frac{dp_{hx}}{dt} + V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p + \rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p \right) \frac{dT_{hx}}{dt} = \\ & Q_{hx} + w_i h_i - w_o h_o \end{aligned}$$

Equations (3.11) and (3.15) are the mathematical model of a generic heat exchanger. This will be applicable to the various heat exchangers (economizer, waterwall, superheater, and reheater). From (3.11)

$$\frac{dT_{hx}}{dt} = \frac{w_i - w_o - V_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \frac{dp_{hx}}{dt}}{V_{hx} \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p}$$

$$\frac{dT_{hx}}{dt} = \psi - \xi \cdot \frac{dp_{hx}}{dt} \quad (3.16)$$

where

$$\xi = \frac{V_{hx} \left. \frac{\partial \rho_{hx}}{\partial p_{hx}} \right|_T}{V_{hx} \left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p} = \frac{\left. \frac{\partial \rho_{hx}}{\partial p_{hx}} \right|_T}{\left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p}$$

And
$$\psi = \frac{w_i - w_o}{V_{hx} \left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p}$$

Equation (3.16) represents the temperature model equation for the heat exchanger.

The energy balance equation is

$$V_{hx} \left(h_{hx} \left. \frac{\partial \rho_{hx}}{\partial p_{hx}} \right|_T + \rho_{hx} \left. \frac{\partial h_{hx}}{\partial p_{hx}} \right|_T - 1 \right) \frac{dp_{hx}}{dt} + V_{hx} \left(h_{hx} \left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p + \rho_{hx} \left. \frac{\partial h_{hx}}{\partial T_{hx}} \right|_p \right) \frac{dT_{hx}}{dt} = Q_{hx} + w_i h_i - w_o h_o$$

To make the equation in compact form, the energy balance equation becomes

$$\alpha_1 \frac{dp_{hx}}{dt} + \alpha_2 \frac{dT_{hx}}{dt} = Q_{hx} + w_i h_i - w_o h_o \quad (3.17)$$

where

$$\alpha_1 = V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T + \rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - 1 \right)$$

$$\alpha_2 = V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p + \rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p \right)$$

Substituting (3.16) in (3.17)

$$\alpha_1 \frac{dp_{hx}}{dt} + \alpha_2 \left(\psi - \xi \frac{dp_{hx}}{dt} \right) = Q_{hx} + w_i h_i - w_o h_o$$

$$\frac{dp_{hx}}{dt} = \frac{Q_{hx} + w_i h_i - w_o h_o - \alpha_2 \psi}{\alpha_1 - \alpha_2 \xi} \quad (3.18)$$

$$\begin{aligned} \alpha_1 - \alpha_2 \xi &= V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T + \rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - 1 \right) \\ &\quad - V_{hx} \left(h_{hx} \frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p + \rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p \right) \frac{\frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p} = \\ &\quad V_{hx} \left(\rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - \frac{\rho_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p} - 1 \right) \end{aligned}$$

And

$$\alpha_2 \psi = (w_i - w_o) \cdot \left(h_{hx} + \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p} \right)$$

Substitute the two equations into (3.18)

$$\frac{dp_{hx}}{dt} = \frac{Q_{hx} + w_i(h_i - h_{hx} - \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p}) - w_o(h_o - h_{hx} - \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p})}{V_{hx}(\rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - \frac{\rho_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p} - 1)}$$

Integrating both sides of the last equation

$$p_{hx} = \int \frac{Q_{hx} + w_i(h_i - h_{hx} - \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p}) - w_o(h_o - h_{hx} - \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p})}{V_{hx}(\rho_{hx} \frac{\partial h_{hx}}{\partial p_{hx}} \Big|_T - \frac{\rho_{hx} \frac{\partial \rho_{hx}}{\partial p_{hx}} \Big|_T \cdot \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_p} - 1)} dt \quad (3.19)$$

And finally we get,

$$\dot{p}_{hx}(t) = \frac{Q_{hx} + w_i I_i - w_o I_o}{C_{hx}} \quad (3.20)$$

where,

$$I_i = (h_i - h_{hx} - \frac{\rho_{hx} \frac{\partial h_{hx}}{\partial T_{hx}} \Big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}} \Big|_T})$$

$$I_o = (h_o - h_{hx} - \frac{\rho_{hx} \left. \frac{\partial h_{hx}}{\partial T_{hx}} \right|_p}{\left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_T})$$

$$C_{hx} = V_{hx} (\rho_{hx} \left. \frac{\partial h_{hx}}{\partial p_{hx}} \right|_T - \frac{\rho_{hx} \left. \frac{\partial \rho_{hx}}{\partial p_{hx}} \right|_T \left. \frac{\partial h_{hx}}{\partial T_{hx}} \right|_p}{\left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p} - 1)$$

In which C_{hx} can be named as heat storage coefficient (Gu *et al.* 2009, Maffezzoni *et al.* 1997), time constant (Inoue *et al.* 2000, Chaibakhsh *et al.* 2007, Rovnak *et al.* 1991) or capacity (Kola *et al.* 1989, Hemmaplardh *et al.* 1985) of a certain heat exchanger. I_i and I_o are I/O gains for the heat exchanger subsystem. Equation (3.20) is the dynamical equation of the pressure and the temperature can be found by (3.16)

$$\frac{dT_{hx}}{dt} = \psi - \xi \cdot \frac{dp_{hx}}{dt}$$

Therefore T_{hx} will be obtained by

$$T_{hx} = \int (A(w_i - w_o) - B \cdot \frac{dp_{hx}}{dt}) dt$$

$$\dot{T}_{hx} = A(w_i - w_o) - B \cdot \dot{p}_{hx} \quad (3.21)$$

Where

$$A = \frac{1}{V_{hx} \left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p}$$

$$B = \frac{\left. \frac{\partial \rho_{hx}}{\partial p_{hx}} \right|_T}{\left. \frac{\partial \rho_{hx}}{\partial T_{hx}} \right|_p}$$

Equation (3.20) and (3.21) are the pressure and temperature models of the heat exchangers which are listed below.

3.5.1 Economizer Model

The water is supplied to the economizer by the feedwater heater. The function of the economizer is to preheat the water before introducing it to the waterwall or the first pass of the furnace which is also a heat exchanger. According to the derived equations for pressure and temperature of heat exchanger, the economizer is modeled by the following two equations:

$$\dot{p}_{econ} = \frac{Q_{econ} + w_{fw}I_{i1} - w_1I_{o1}}{C_{econ}} \quad (3.22)$$

$$\dot{T}_{econ} = A_1(w_{fw} - w_1) - B_1 \cdot \dot{p}_{econ} \quad (3.23)$$

3.5.2 Waterwall model or Furnace inner tubes Model

The analysis of waterwall is concerned with the pressure and temperature of SC fluid inside the waterwall. Therefore the equation describing it will be:

$$\dot{p}_{ww} = \frac{Q_{ww} + w_1 I_{i2} - w_2 I_{o2}}{C_{ww}} \quad (3.24)$$

$$\dot{T}_{ww} = A_2(w_1 - w_2) - B_2 \cdot \dot{p}_{ww} \quad (3.25)$$

3.5.3 Superheater model and throttle pressure model

The superheater is a heat exchanger that has the greatest temperature in the boiler. The temperature must be kept within a specified limit (usually $\pm 5\%$) from the nominal temperature to keep the cycle efficiency optimum (Rayaprolu. 2009). The water attemperator is used usually with PID or PI controllers to maintain the steam temperature within specified limits (Lu. 1999). The flow of water attemperator to control the SH temperature is inserted in the SH model which depends on a signal from PI controller that depends on the difference between the SH temperature and its set-point temperature. The set point temperature can be manually set or varying with flow of steam in the boiler (Usoro *et al.* 1983). In the actual boiler, there are three superheaters while in the model; these superheaters are lumped to one superheater (Fig 3.4). This assumption is based on that the three superheaters nearly have the same temperature and pressure dynamics. Therefore the superheater model

$$\dot{p}_{sh} = \frac{Q_{sh} + w_2 I_{i3} - w_3 I_{o3}}{C_{sh}} \quad (3.26)$$

$$\dot{T}_{sh} = A_3(w_{spray} + w_2 - w_3) - B_3 \cdot \dot{p}_{sh} \quad (3.27)$$

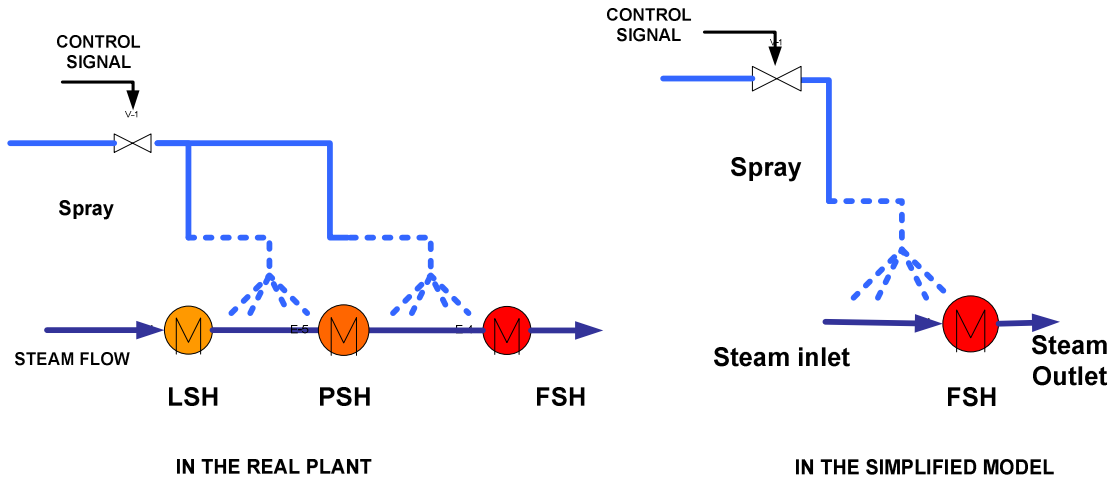


Fig 3.4 the spray water in the real power plant and in the model

where w_{spray} is the spray water flow from the attemperator. The main steam pressure, throttle pressure, or boiler outlet pressure has the can be modeled as (Hemmaplardh *et al.* 1985, Gu *et al.* 2009):

$$\dot{p}_{ms} = \frac{w_3 I_{i4} - w_{ms} I_{o4}}{C_{ms}} \quad (3.28)$$

3.6 Heat Transfer in the boiler

The flow of heat from the gas combustion to the metal tube and metal tube to the fluid inside the tube can be modeled in two different ways. One is to consider the heat transfer equations which relate the combustion gas temperature to the metal tube temperature and fluid temperature by the heat transfer equations in each heat exchanger either by radiation, conduction, or convection. This formula can be found in Adams *et al.* (1965), Lu *et al.* (2000), Usoro *et al.* (1983). But the heat is actually transferred in the boiler by a combination of radiation, conduction and convection in a very complicated manner. Another relationship is to relate the combustion heat to the fuel flow through a constant

which is the fuel calorific value or lower heating value (i.e. $w_f \propto Q_c$) and then the main combustion heat Q_c is proportionally related to the heat transferred from the wall of the heat exchanger to the fluid inside it Q_{hx} and this can be found in many subcritical and supercritical power plant models (Shinohara *et al.* 1996, Chaibakhsh *et al.* 2007, Hemmaplardh *et al.* 1985, Kola *et al.* 1989, Liu *et al.* 2003, Trangbaek *et al.* 2008). The later relationship has been adopted in this research because it is more convenient for computer simulations, and thus, the heat transfer rates are modeled by constant gains multiplied by the fuel flow through 1st order transfer function.

$$Q_{econ} = k_{econ} \cdot Q \quad (3.29)$$

$$Q_{ww} = k_{ww} \cdot Q \quad (3.30)$$

$$Q_{sh} = k_{sh} \cdot Q \quad (3.31)$$

$$Q_{rh} = k_{rh} \cdot Q \quad (3.32)$$

where $Q = \frac{cv \times w_f}{1 + T_1 s}$. cv is the calorific value of the fuel, the time T_1 is the time constant

required for combustion, w_f is the flow of pulverized coal to the furnace. Substituting the transfer function through (3.29)-(3.32) and multiplying the calorific value by the proportional gains to get the following functions with unknown parameters or gains:

$$Q_{econ} = \frac{K_{econ} \cdot w_f}{1 + T_1 s} \quad (3.33)$$

$$Q_{ww} = \frac{K_{ww} \cdot w_f}{1 + T_1 s} \quad (3.34)$$

$$Q_{sh} = \frac{K_{sh} \cdot w_f}{1 + T_1 s} \quad (3.35)$$

$$Q_{rh} = \frac{K_{rh} \cdot w_f}{1 + T_1 s} \quad (3.36)$$

K_{econ} , K_{ww} , K_{sh} , K_{rh} are unknown parameters to be identified which are resulted from multiplying the calorific value by the proportional gains.

3.7 Mass flow rates

3.7.1 Intermediate mass flow rates

The mass flow rates inside boiler tubes are expressed by the one-phase flow equation between two lumped heat exchangers which is a function of the pressure differences between two lumped heat exchangers. This will be applicable to the intermediate flow rates w_1 , w_2 , and w_3 . This relationship is adopted in many research articles that reported plant models based control (Gu *et al.* 2009, Hemmaplardh *et al.* 1985, Trangbaek *et al.* 2008). The equations are:

$$w_1 = k_1 \sqrt{p_{econ} - p_{ww}} \quad (3.37)$$

$$w_2 = k_2 \sqrt{p_{ww} - p_{sh}} \quad (3.38)$$

$$w_3 = k_3 \sqrt{p_{sh} - p_{ms}} \quad (3.39)$$

where k_1 , k_2 , and k_3 are unknown parameters or gains to be identified.

3.7.2 Outlet mass flow rates

The outlet mass flow rates are expressed as (Shinohara *et al.* 1996, Salisbury *et al.* 1950):

$$w_{rh} = k_4 \cdot \frac{P_{rh}}{\sqrt{T_{rh}}} \cdot \mathfrak{N}_{IV} \quad (3.40)$$

$$w_{ms} = k_5 \cdot \frac{P_{ms}}{\sqrt{T_{ms}}} \cdot \mathfrak{N}_{CV} \quad (3.41)$$

In the first version of the model, a simple linear relationship is assumed ($w_{ms}=k_4 \cdot p_{ms} \cdot \mathfrak{N}_{IV}$ & $w_{rh}=k_5 \cdot p_{rh} \cdot \mathfrak{N}_{CV}$) as in (Hemmaplardh *et al.* 1985, Trangbaek *et al.* 2008) and then they are replaced with equations (3.40) and (3.41) to have better coupling between the pressure and temperature models of the boiler. Equations (3.40) and (3.41) are obtained from assuming that the steam is a perfect or ideal gas (Salisbury *et al.* 1950). Even though the SC steam is not perfect gas, this relationship gives reasonable presentation for the steam flow through the valve (Shinohara *et al.* 1996, Salisbury *et al.* 1950). The detailed derivation of (3.40) and (3.41) is presented in details in the text (Salisbury *et al.* 1950). The simulation results reported by (Shinohara *et al.* 1996) have shown good agreement between the reported model and EPRI simulator. In this research the presented model will be tuned to real power plant measurement records. The parameters k_4 , k_5 are then regarded to be unknown parameters to be identified or optimized to track the trends of the real plant.

3.8 Turbine Model

As a control volume, the turbine receives the energized SC steam from the FSH. Through the enthalpy drop, the thermal energy is converted to mechanical energy in the turbine.

The same process occurs to the IP turbine through the reheater. The energy balance equations of the turbines (Sonntag *et al.* 1998):

$$w_{ms} \cdot (h_{ms} - h_{out}) = P_{hp} \quad (3.42)$$

$$w_{rh} \cdot (h_{rh} - h_{out}) = P_{ip} \quad (3.43)$$

There are many turbine models in the literature which are rooted from the two equations above. Two different model equations are found and investigated; one is based on assuming that the steam expansion in turbine is an adiabatic and isentropic process which results in the nonlinear equations reported in Rovnak *et al.* (1991) and Chaibakhsh *et al.* (2007). It is important to mention that, those models are accurate only when there is no frequency effect involved to the turbine behaviour (Chaibakhsh *et al.* 2007). In that case, the turbine models proposed originally by IEEE committee in 1972 is preferable and they are adopted in other researches and texts thereafter (Inoue *et al.* 2000, Gu *et al.* 2009, Hemmaplardh *et al.* 1985, Kola *et al.* 1989, Andersson. 2003). In those models, the steam flow is proportionally related to the mechanical output through constant parameters (i.e. (3.42) and (3.43) reduce to: $K_{hp} \cdot w_{ms} = P_{hp}$, $K_{ip} \cdot w_{rh} = P_{ip}$). The power outlet from the turbine is controlled through the position of the control valves, which control the flow of steam to the turbines. Certain fractions of the total power are extracted in the different turbines (Andersson. 2003) which are only the IP and HP turbines in the plant. This is modelled by the unknown parameters K_{hp} ; K_{ip} in addition to the steam chest time constant T_{CH} in the model shown in Fig.3.5 below.

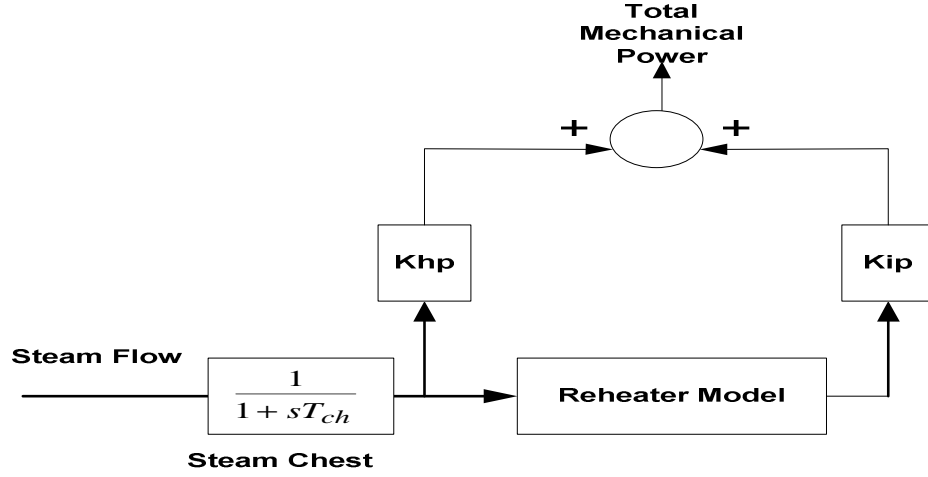


Fig.3.5 A Simplified Single Reheat Turbine Model

3.8.1 Reheater Model

Though the reheater is a heat exchanger or steam generating unit, it is located to receive the steam exhausted from the HP turbine, reheat it, and discharge it to the IP turbine. The main task of the reheater is to reheat the reduced thermal energy steam out from the HP turbine to gain more thermal energy which is used to energize the intermediate and low pressure turbines. There are two reheaters in the actual boiler which can be considered as one reheater in the model. The reheater model:

$$\dot{p}_{rh} = \frac{Q_{rh} + w_{hp}I_{i5} - w_{rh}I_{o5}}{C_{rh}} \quad (3.44)$$

$$\dot{T}_{rh} = A_3(w_{hp} - w_{rh}) - B_3 \cdot \dot{p}_{rh} \quad (3.45)$$

3.9 The synchronous generator model:

The process in synchronous generator is as follows: the mechanical energy gained by the turbine is used to drive the rotor of the generator to a constant speed which is the synchronous speed. Because of the rotor's mechanical rotation and the coupling magnetic

field from the exciter, the voltage is induced in the winding of the stator by Faraday's law. If the generator is connected to the power grid, the electric current passes through the stator winding, which produces a rotating magnetic field rotates in the air-gap at the same speed of the rotor. Of course the magnetic field should be rotating because of the three phase winding which are placed in the stator slots. There are many models for synchronous generators in the literature depending on the direction or purpose of study (Yu. 1983, Kundar. 1994, Ong. 1998). A third order nonlinear synchronous generator model (Yu. 1983, Dehghani *et al.* 2008) is adopted in the modeling study. The model reflects the dynamic behavior of the three states in the generator which are the rotor speed or frequency, the rotor angle and the transient internal voltage of the armature. The synchronous generator is coupled to the turbine by of the mechanical power which is equivalent to the mechanical torque in p.u quantities and also through the torque-balance equations which reflect the interactions between the turbine and generator dynamics. The synchronous generator model is then:

$$\dot{\delta} = \Delta\omega \quad (3.46)$$

$$J \cdot \dot{\omega} = \Gamma_a = \Gamma_{mech} - \Gamma_e - D \cdot \omega \quad (3.47)$$

$$\dot{e}_q' = \frac{1}{t_{do}} (E_{FD} - e_q' - (x_d - x_d') \cdot i_d) \quad (3.48)$$

Where:

$$\Gamma_{mech}(p.u) \approx P_{mech}(p.u) = \frac{P_{mech}}{600} \quad (3.49)$$

$$\Gamma_e(p.u) \approx P_e(p.u) \approx \frac{V}{x_d'} \cdot e_q' \cdot \sin \delta + \frac{V^2}{2} \cdot \left(\frac{1}{x_q} - \frac{1}{x_d} \right) \cdot \sin 2\delta \quad (3.50)$$

$$i_d = \frac{e'_q - V \cos \delta}{x'_d} \quad (3.51)$$

The first equation relates the system inertia to the mechanical, electrical, and damping torques in the system. The second is given to describe the dynamics of the rotor angle while the third presents the dynamics of the transient internal voltage in the armature. The last one is derived in detail with some assumptions and substitutions in the reference (Yu. 1983). The equivalent E.M.F in excitation coil E_{DF} is constant and the generator is in over-excited operation which is likely. This is because the excitation controls influences only the reactive power and has no significant effect on the real active power of the generator, which is mainly affected by the mechanical torque input from the turbine. The links between the turbines and generator is through the mechanical torque and the torque equilibrium equations which are presented in the next section.

3.10.1 The Turbine-Generator Interactions:

It has been understood that the turbine output mechanical power has a direct effect on the generator dynamics, especially, the rotor angle and electrical power output of the generator. Also the turbines' torques and speeds dynamics should be influenced by the generator operating conditions or load variations because they are coupled on the same shaft. The turbine speeds are actually the same (one virtual speed). In addition, as the electrical torque increase, the HP and IP torques must be increased to achieve the required torque and energy balances. When research has been done about this, it has been found that the mass spring system equations can be used to reflect the coupling effect which can be found in (IEEE Committee. 1977, Yu. 1983), the concept of balance is shown in Fig 3.6:

$$\dot{\omega}_{hp} = \frac{1}{\mathbf{M}_{hp}} [\Gamma_{hp} - D_{hp} \cdot \omega_{hp} - K_{hi}(\theta_{hp} - \theta_{ip})] \quad (3.52)$$

$$\dot{\theta}_{hp} = \omega_b(\omega_{hp} - 1) = (\omega_{hp} - 1) \quad \text{p.u} \quad (3.53)$$

$$\dot{\omega}_{ip} = \frac{1}{\mathbf{M}_{ip}} [\Gamma_{ip} - D_{ip} \cdot \omega_{ip} + K_{hi}(\theta_{hp} - \theta_{ip}) - K_{ig}(\theta_{ip} - \delta)] \quad \text{p.u} \quad (3.54)$$

$$\dot{\theta}_{ip} = \omega_b(\omega_{ip} - 1) = (\omega_{ip} - 1) \quad \text{p.u} \quad (3.55)$$

$$\Gamma_{hp} = \frac{P_{hp}(\text{p.u})}{\omega_{hp}(\text{p.u})}, \quad P_{hp}(\text{p.u}) = \frac{P_{hp}}{600} \approx \Gamma_{hp}(\text{p.u})$$

$$\Gamma_{ip} = \frac{P_{ip}(\text{p.u})}{\omega_{ip}(\text{p.u})}, \quad P_{ip}(\text{p.u}) = \frac{P_{ip}}{600} \approx \Gamma_{ip}(\text{p.u})$$

$$\Gamma_{mech}(\text{p.u}) = \Gamma_{ip} + \Gamma_{hp} \approx P_{mech}(\text{p.u})$$

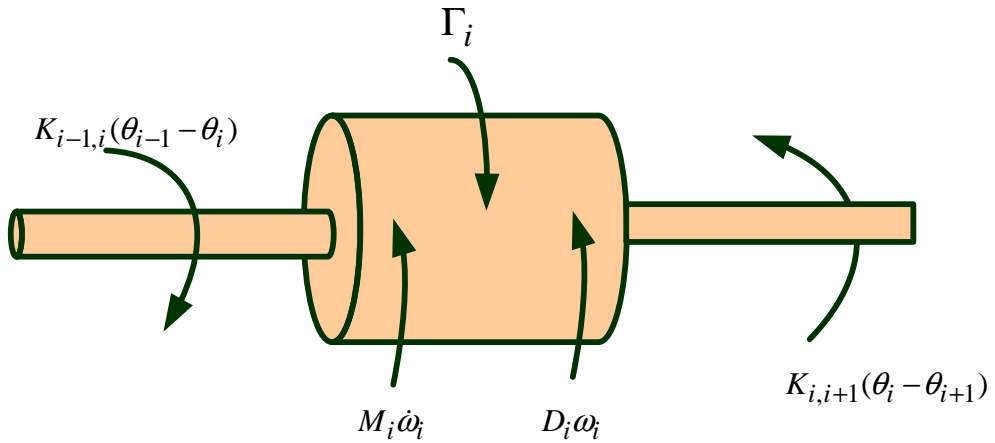


Fig 3.6 The i^{th} mass spring system (Yu. 1983)

Where \mathbf{M} is the inertia constant θ is the mechanical angle, for generators ($\theta_g = \delta$) which has been already substituted in (3.54). D is the damping factor. ω is the mechanical speed. Γ is the mechanical torque. The variables of each component are indicated by the subscripts hp ip and g for HP turbine, IP turbine, and the generator rotor. The torques are linked to the other part of turbine model. p.u. or normalized values are adopted in the equations for consistency between the torque balance equations and the synchronous generator. Actually, the speeds of the turbines must be the same ($\omega_{hp} = \omega_{ip}$). Although they are implemented separately as mentioned in the equations above; they are the same in reality and by simulation. The coupling effect between the turbines and generator has been comprehensively studied and introduced.

3.10 Summary of the whole systems and the proposed simulation tool:

This chapter introduces detailed procedures for getting a simplified model for supercritical-boiler-turbine-generator system to support my investigations on the power plant responses. It highlights the previous attempts and research being conducted for modeling and simulation of SC plants. The following plant portions are modeled the SC boiler-turbine-generator:

- The fluid path pressure and temperature of the SC boiler from the economizer to the main steam outlet, while the fuel is related to the heat released through its calorific value and proportional coefficient
- The turbines (IP and HP turbines).
- The turbine generator coupling effects and interactions.
- The synchronous generator.

The whole model subsystems are shown in Fig 3.7 as a block diagram.

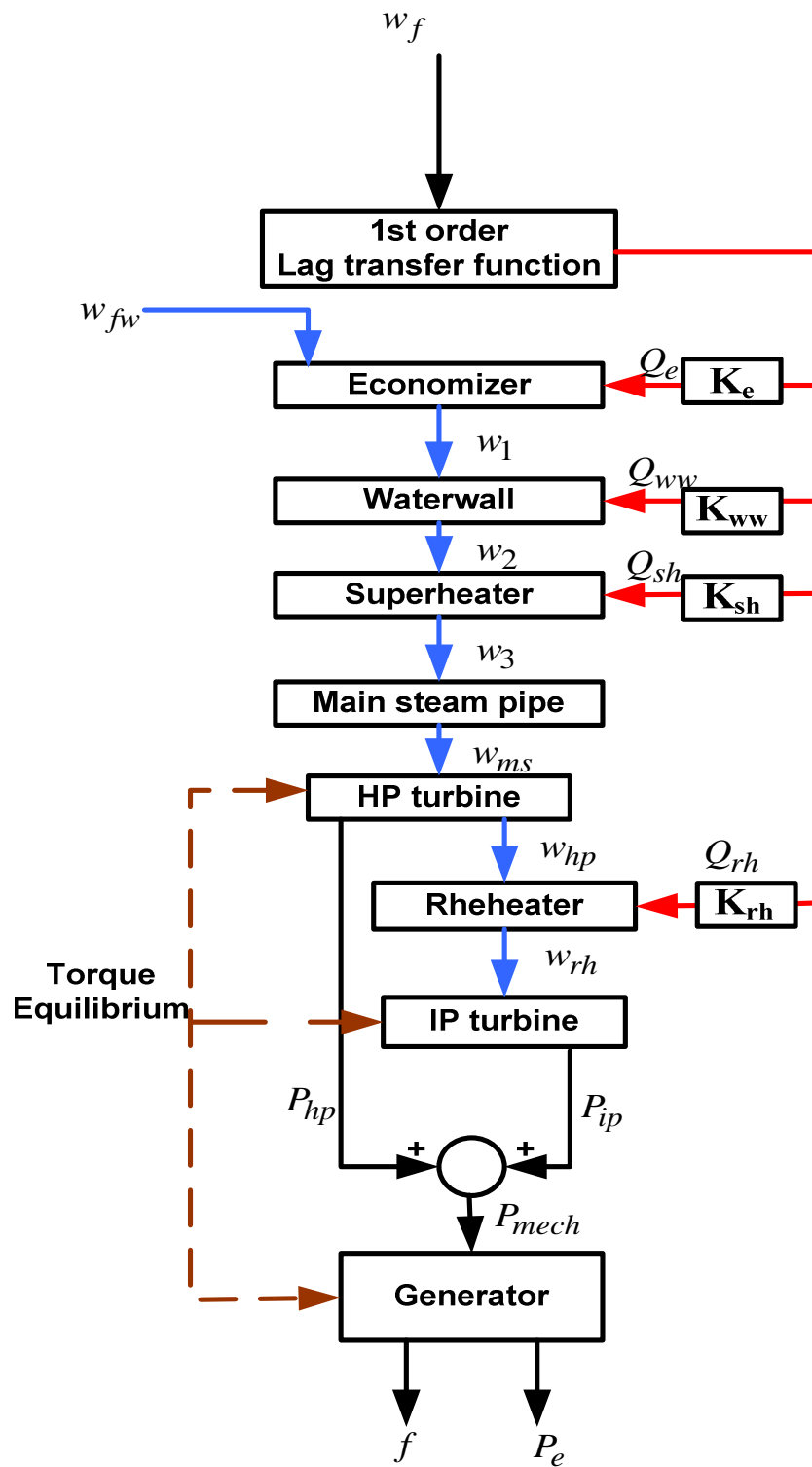


Fig.3.7 Blocks description of Boiler-turbine-generator system

The model has many unknown parameters. Most of the boiler model parameters can be evaluated by computing the physical thermodynamic properties of water/steam. However, the plant models which are based only on thermodynamic properties have to be detailed high order models such as those in Adams. (1965) and Littman. (1966) in order to get results with sufficient accuracy which requires huge and serious team work. To save time and effort in calculating these coefficients, it is helpful to consider them as unknown parameters and adjust them to the real plant by robust multi-objective optimization technique. There are many lumped parameter plant models with different structure reported in the literature up to the current attempts and research (Shinohara *et al.* 1996, Chaibakhsh *et al.* 2007, Trangbaek *et al.* 2008) which indicates the validity of the proposed modeling approach. In particular, there are many simulation tools for simulating power plant dynamical systems which are developed either by companies or Universities (Lu. 1999). MATLAB[®] and SIMULINK[®] have been chosen to implement the proposed model, the reasons behind that are:

- 1- Graphical presentation allows access and observation the model behavior at any point.
- 2- It has lots of toolboxes which can be interfaced easily with the Simulink model (such as Genetic Algorithm tool box for parameters identification).
- 3- Several control strategies can be implemented by MATLAB[®] in the future (Such as Model Predictive Control Toolbox).
- 4- It is interesting and important to simulate complex systems such as supercritical power plants with a widely used tool such as MATLAB[®].

The whole model package described above is implemented in MATLAB/SIMULINK[®] environment by gains, integrators, summing nodes, first order lags...etc. The next chapter

presents the optimization technique for parameter identification to match the plant response in the data provided by the plant manufacturer.

Chapter 4

Parameter Identification for Modeling

4.1 Introduction

Identification of the unknown model parameters is an essential task to be conducted to simulate the actual plant responses and use it for control system studies. Simplified model without appropriate selection of the parameters is abortive. This chapter describes the parameter identification procedures that have been carried out to identify the unknown parameters and presents the simulation results. The model contains 47 unknown parameters to be identified so the model can represent the real power plant performance to match the real measurement record for some state variables in the model. Throughout the research period, the parameters have been updated to get improved simulations of the real power plant. The on-site measurement data provided for the SCPP cover all processes of the plant under coordinated control from start-up (recirculation mode), synchronization with the power system, once-through mode, up to the shut down process. Other sets of data are available for once-through operation in steady state and load change conditions. The chapter starts with brief review for the optimization techniques that have been used in the literature for identification of SCPP models and the optimization approach that has been adopted in this research. The theory and fundamentals of proposed optimization method is presented in separate section. Then, the on-site measurement data sets have been described to use them in parameter identification. Finally, the simulation results have been reported which indicate the validity and robustness of the optimization method that has been adopted.

4.2 A review:

Parameter identification of mathematical models of supercritical fossil fuel unit is an optimization problem to be solved so that the simulated results trends agree optimally with plant behavior. Methods of parameter calculation/optimization are applicable for physical systems which exhibit various nonlinearity and governed by their special physical laws (e.g. mechatronics systems, robotic systems, industrial machines, vehicles...etc), not just power plants (Kumon *et al.* 2000, and Ljung. 1987). The parameters calculation for physical systems in general and power plant systems in particular, can be achieved either by data gathered from real power plant or from the physical properties of the system where there are no driven data sets is required. Starting the review from the data based parameter identification methods, the real plant data are either real on-site measurement records or data supplied by plant detailed simulator. The review for this procedure includes many optimization techniques that have been used to identify SCPP models parameters. Suzuki *et al.* (1979) applied Fletcher-Reeves optimization method to identify some unknown parameters to minimize the sum of squares differences between the actual boiler output and simulation mode. The parameters have been identified sequentially because there are many unknown. Nakamura *et al.* (1981) performed statistical identification to fit a multivariate autoregressive model to obtain a practically useful state space representation suitable for optimal control. The practical implementation of the model for control purposes indicated the reliability and accuracy of the identified parameters. Rovnak *et al.* (1991) used multivariable least square regression method to identify the coefficients of a simple autoregressive moving average ARMA model which is transfer functions used to predict the response of ninth order supercritical boiler process model. Gibbs *et al.* (1990) used nonlinear least square method to identify a reduced order model for supercritical gas-

fired power plant that has been adopted for control system design. The data have been extracted from detailed simulator. Zhong-xu et al. 2008 fitted nonlinear polynomials to 660MW SCPP to formulate a complete process empirical model of SCPP for control system applications. In this research, Genetic Algorithms (GA) technique has been used to identify the SCPP model parameters.

(GA) method is a random search of population of points (not a single point) that are widely spread through the search space. It can easily handle many nonlinear multi-objective optimization problems for other nonlinear models for subcritical boilers and power station pulverizers (Liu *et al.* 2003, Chaibakhsh *et al.* 2007, Wei *et al.* 2007). These features make GA advantageous compared with conventional gradient mathematical optimization techniques although faster solutions can be found by conventional mathematical gradient techniques. The details of these features are presented in the next section.

No-driven data method is more popular in the earlier research of power plant modeling. In Littman et al. (1966), the model parameters were calculated from steam tables and specific heat of tube metal. Shinohara *et al.* (1996) reported alternative method of parameter calculation which is based on polynomials fitted to subcritical steam tables to construct the model of SCPP. In fact these are the only research which has been found in SCPP modeling literature which reports approach of parameter calculation with no data involved in the procedure. Methods in an analogy to this approach are reported other research articles for subcritical drum type units modeling (Usono et al. 1983, Lu. 1999, Lu et al. 2000).

4.3 Genetic Algorithms

The genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness” (i.e., minimizes the cost function). The method was developed by John Holland over the course of the 1960s and 1970s and finally popularized by one of his students, David Goldberg, who was able to solve a difficult problem involving the control of gas-pipeline transmission for his dissertation (Goldberg. 1989, Haupt *et al.* 2004). In every generation, a new set of strings is created using bits and pieces of the fittest of the old ones; genetic algorithms efficiently exploit historical information to speculate on new search points with expected improved accuracy. Genetic algorithms, basically, perform three processes:

- 1- Reproduction.
- 2- Crossover.
- 3- Mutation.

Reproduction is a process in which the GA re-copies the strings of the coded parameters according to their fitness function values. The probability that determines which string should survive and which one dies depends on the corresponding value of the fitness function. *Crossover* is usually performed by mating two strings randomly in a mating pool and exchanging a portion of the characters of string with another, the new generation may be surprisingly better than the previous one for optimizing the fitness function value. *Mutation* is the rate of chance of creating a different random string that is not based on reproduction and crossover. Mutation is found to be useful in some cases where the reproduction and cross over lose some of the effective values of the parameters, thus, it is

considered as secondary action or mechanism for genetic algorithm search (Goldberg 1989, Math Works. Inc 2004). The mutation rate can be controlled in genetic algorithm toolbox as will be shown later. The scheme of simple GA operation is shown in Fig 4.1.

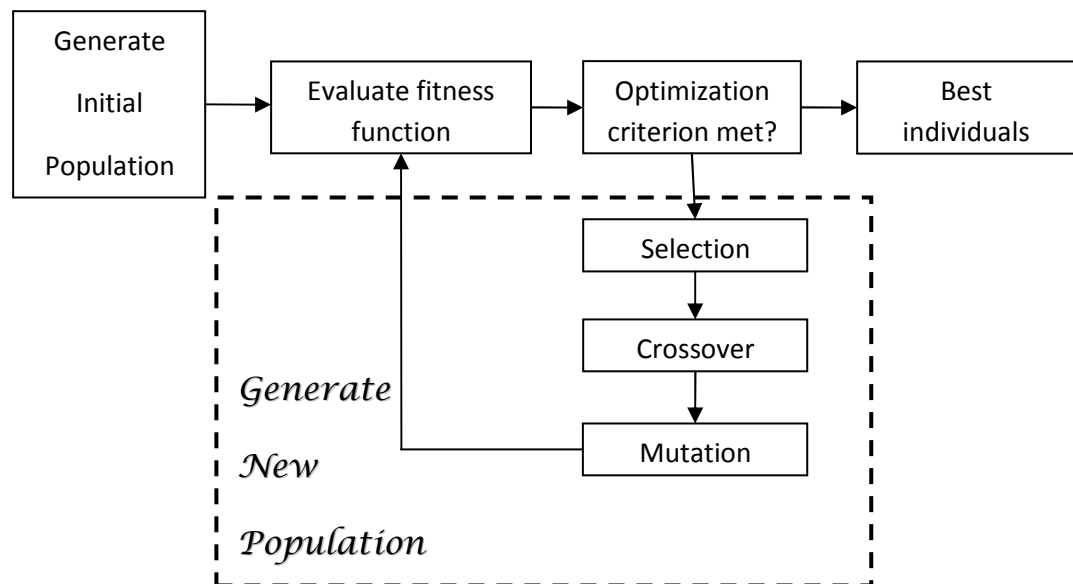


Fig 4.1 The flow diagram of genetic algorithms

The following outline summarizes how the genetic algorithm works (Math Works. Inc.2004, Goldberg. 1989):

- 1- The algorithm begins by creating a random initial population.
- 2 -The algorithm then creates a sequence of new populations. At each step, The algorithm uses the individuals in the current generation to create the next population. To create the new population, the algorithm performs the following steps:
 - Scores each member of the current population by computing its fitness value.
 - Scales the raw fitness scores to convert them into a more usable range of values.

- Selects members, called parents, based on their fitness.
 - Some of the individuals in the current population that have lower fitness are chosen as *elite*. These elite individuals are passed to the next population.
 - Produces children from the parents. Children are produced either by making random changes to a single parent—*mutation*—or by combining the vector entries of a pair of parents—*crossover*.
 - Replaces the current population with the children to form the next generation.
- 3 -The algorithm stops when one of the stopping criteria is met.

MATLAB[®] contain toolbox for GA and direct search. This toolbox can be linked to any MATLAB[®] and/or SIMULINK[®] file for the purpose of optimization. The GA tool is shown in Fig.4.2. The tool can be used as it is, or M-File can be generated from the file menu which replaces the tool window.

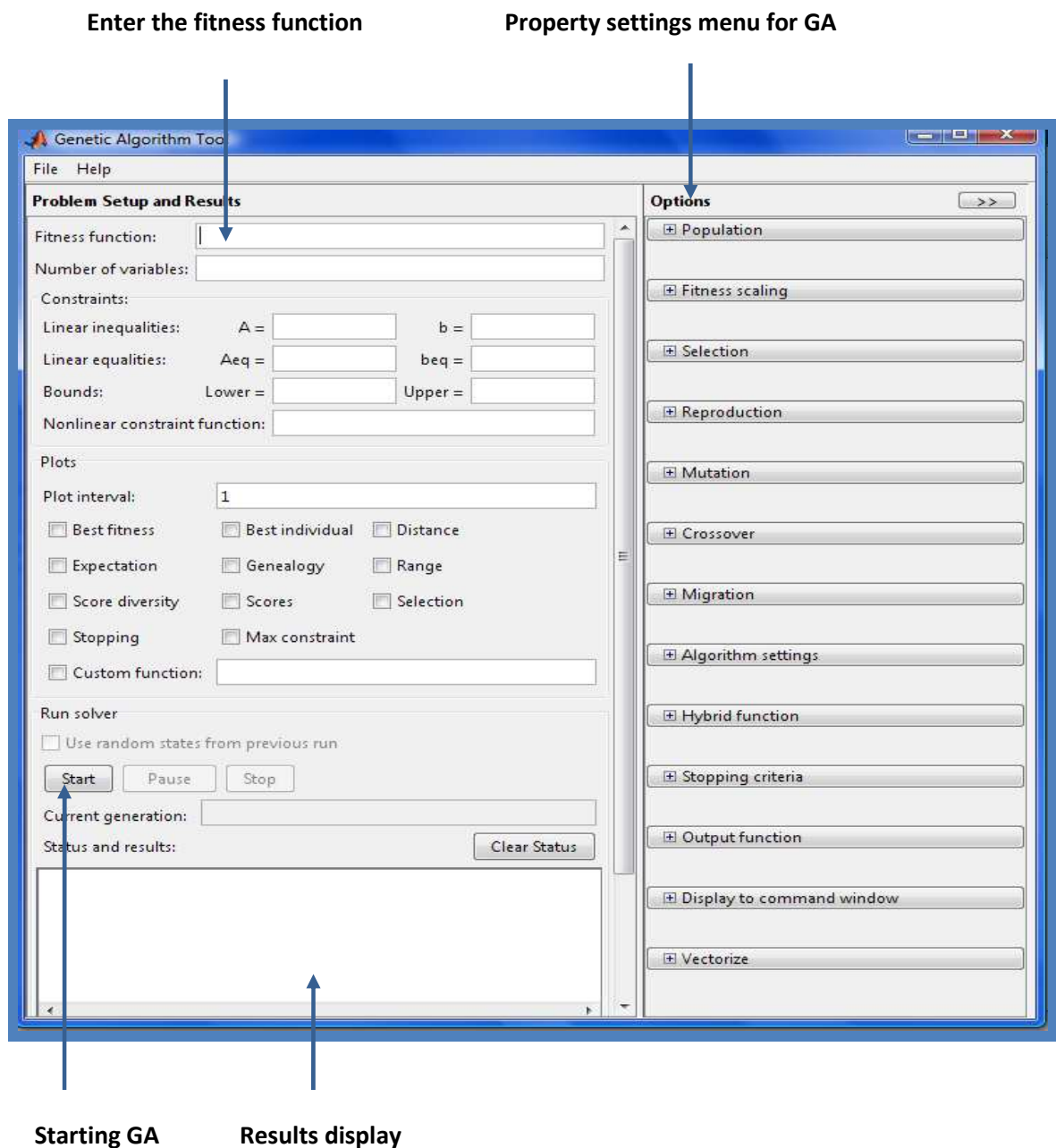


Fig 4.2 Genetic algorithm tool

The M-File name has been placed in the fitness function blank in the tool of Fig 4.2 As clearly shown in the figure, there is also a place for the upper and lower bounds in the **problem set up and results** portion. Furthermore, GA parameters can be adjusted by the **option** portion. The tool can be run by clicking on start bottom shown on the tool figure.

The proposed tool for identification has been briefly described. Refer to user's guide (Math Works. Inc 2004) for more detailed explanations.

It is well known that GA performance is much improved over the traditional mathematical optimization methods. This is because GA method deals with a coded parameter, not the amount of parameter itself. Also, the search is performed on a population of points that are distributed on the space of search, not only one point like mathematical gradient optimization. Some optimization problems have global optimal point among many other local optimal points. With appropriate settings of GA operations (i.e., termination criterion, number of generation, mutation rate...etc), the GA solution shall not be trapped in local optimal point and the global optimal point can be reached. A general example has been used to assess the performance of GA.

4.4 Rosenbrock's Function

This section presents an example that shows how to find the global minimum of Rosenbrock's function; the convergence to the true optimal or global optimal point is difficult, and hence, this function is commonly used for evaluating the performance of GA. For two dimensions, the function is written as follows:

$$f(x_1, x_2) = 100(x_2 + x_1^2)^2 - (1 - x_1)^2 \quad (4.1)$$

The function plot is shown in Fig. 4.2, the global optimum point is located at (1, 1) which is inside a narrow, long, parabolic shaped valley.

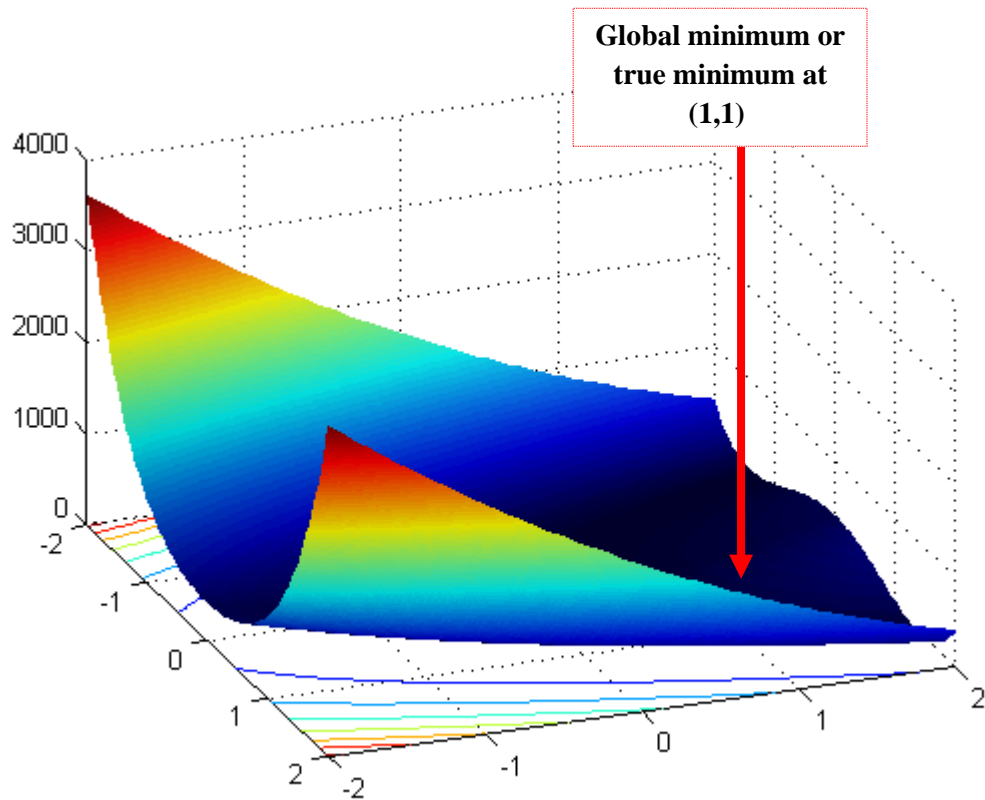


Fig 4.3 2-dimensional Rosenbrock's Function

The global optimal points can be found by GA with appropriate selection of GA parameters. Fig.4.3 shows the fitness function convergence.

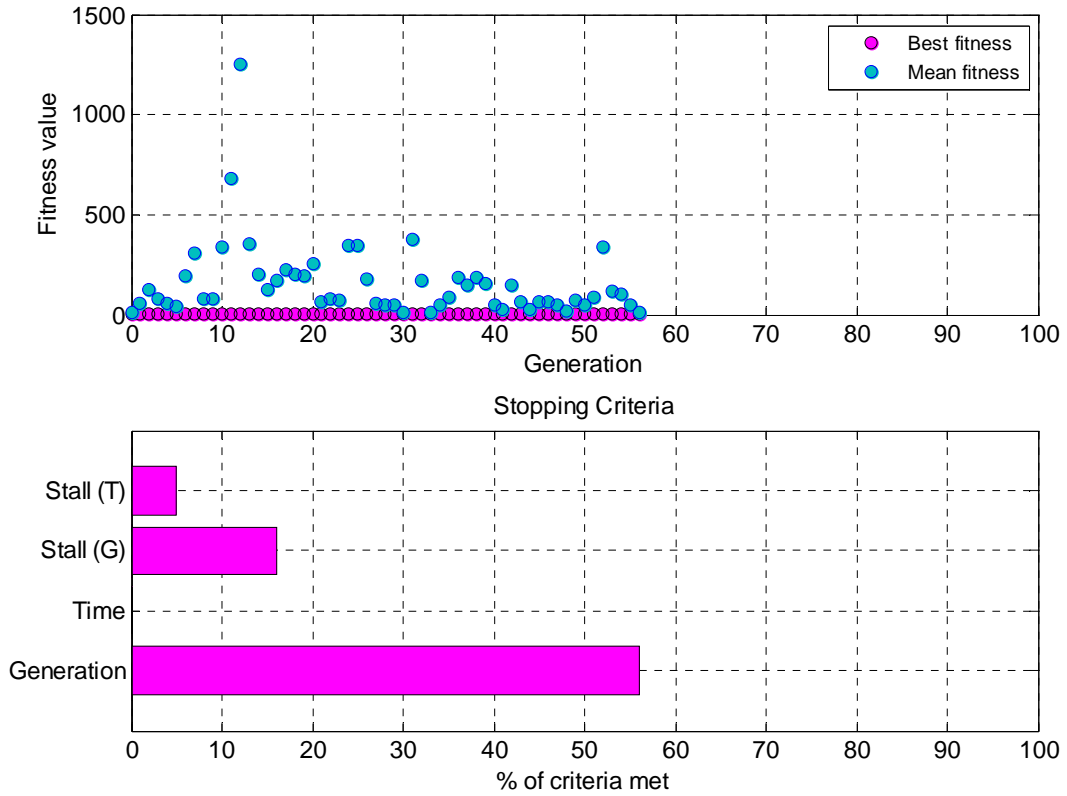


Fig. 4.4 the GA performance for optimization

From the figures, the optimization performance converges to (1.00000, 1.00000) after 56 generations. In most GA application to nonlinear system identification, the modification of GA parameters is carried out repeatedly during research for continuous improvements of simulation results.

4.5 Justification of Using GA

From the previous example and our background about GA and its application in the literature, these major reasons behind adopting this technique are summarized as follows:

- The ability of GA to adjust all model parameters simultaneously, not in a sequential manner as in conventional optimization techniques used in previous research (for instance: Suzuki et al. 1979).

- The performance of GA to evaluate the global optimal solution, which is mainly because of its parallel distributed random search and mutation, not as in conventional gradient optimization in which the final solution may be captured in a local optimal point.
- For nonlinear identification, GA handles the problem with higher quality and superior results such as those reported in (Liu *et al.* 2003, Chaibakhsh *et al.* 2007, Wei *et al.* 2007).
- Simplicity of GA mechanism, operation, and interface with the implemented mathematical model.

However, the improvements of GA over gradient optimization techniques, used in previous research, are not the only reasons behind using the GA. There are other computational intelligence techniques which are not adopted for this research like, for instance, neural network and particle swarm optimization. Despite it is known that neural network NN are very accurate approach and can handle many uncertainties which are difficult to model with mathematical models, however, they rely massively on the on-site data supplied by plant manufacturer for NN training, not on physical principles This is reflected as clear limitation for NN to simulate some emergency abnormal conditions which are fairly simulated by physical based models (Lu *et al.* 2000). Particle swarm optimization (PSO) has few similar approaches and applications to GA and their performances are closed to each other (Zachariades *et al.* 2009, Boeringer *et al.* 2003). However, it is found that GA applications in identification of nonlinear model parameters are more widely which assure the robustness and successfulness of this technique (Kumon *et al.* 2000, Yue *et al.* 2009). Therefore it has been decided to resolve our own research

problem of model parameter optimization with GA. The next section describes the model parameter identification.

4.6 Model Parameter Identification

In this section, the model identification procedure will be presented. The data provided for covering all processes of 600MW SC coal firing power plant. The optimization approach that discussed in the previous section is applied to all unknown parameters of the system model to match the plant real response.

4.6.1 Data Analysis and Description:

The data that have been collected for 600MW SC coal fired power station is closed loop response data with existing generic coordinated control installed. The data covers all plant processes from start-up or re-circulation mode to the shut down process. The model has been designed to simulate only once-through mode for the station and other operating conditions are excluded from this study and left as future research work. The once-through operation should be extracted from the data and used for model parameter identification. Fig.4.5 show portion of the data for the measured power to be supplied by the generator. The once through mode starts nearly on 35% of rated conditions (Leyzerovich. 2007, Chaibakhsh *et al.* 2007, Trangbaek *et al.* 2008). In starting, the water is separated from steam in separator (like drum boilers) and recirculated in the water-wall for further heat addition. After start-up, the once-through mode will be allowed by closing the recirculation valves which are embedded between the evaporator and superheaters surfaces (Chaibakhsh *et al.* 2007, Trangbaek *et al.* 2008). Closing the re-circulation valves indicates that the water is fully converted to SC steam. The identification data set covers the operating range from 40% to the rated loading conditions. The once-through sets of

data are mentioned in table.4.1 in which the 1st set of data will be used for identification and other sets will be used in Chapter. 5 for further investigation on the model.

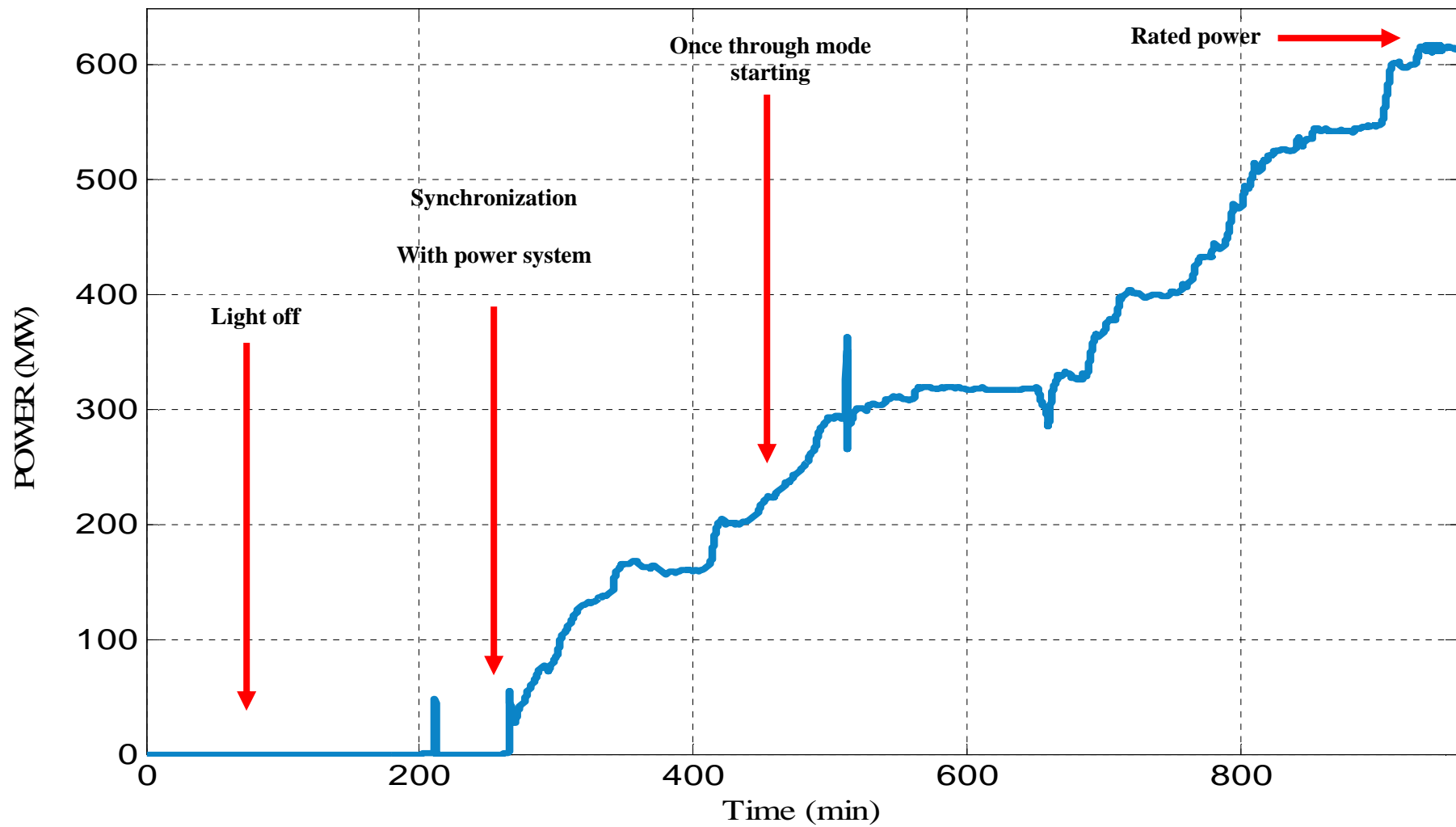


Fig.4.5 A set of data with indicated operating conditions

Table 4.1 Data sets for once through operation for model parameter identification and investigation

Data Sets	Descriptions	Usage
Data set.1	16 th June.2009. 02:50:55~11:23:55	Identification
Data set.2	16 th June.2009. 11:24:00~22:59:45	Investigation
Data set.3	15 th July.2009. 07:50:00~23:00:00	Investigation
Data set.4	25 th June.2009. 09:34:50~12:12:00	Investigation

4.6.2 Parameter Identification Using GA:

GA is a robust method for simultaneous adjustment of model parameters and multi-objective-optimizations. This is because it has the ability to reach optimal solution without knowing the system explicitly. It has been proved that GA is a robust optimization method for nonlinear system identification (Wei *et al.* 2007). The choice of fitness function is very important for good convergence. The square of error between measured and simulated responses is taken (Liu *et al.* 2003, Chaibakhsh *et al.* 2007) which can be written as:

$$ff = \sum_{n=1}^N (R_m - R_{si})^2 \quad (4.1)$$

N is the number of points of the recorded measured data, R_m and R_{si} are the measured and simulated response respectively. The SCPP responses which are used for parameter identification / validation are:

1. The boiler main steam pressure (MPa).
2. The boiler main steam temperature (C°).
3. The output power of the plant (MW).
4. The frequency deviation or speed deviation (p.u).

5. The steam flow (Kg/s).

These responses provided from the data are used to identify the system unknown parameters with the adopted objective function. The plant inputs for data set.1 are inserted to the mathematical model and the simulink file of the model is linked to GA optimization files to tune the model parameters. The identification scheme is mentioned in Fig.4.6 and the GA properties are mentioned in Table 4.2. Model parameters are mentioned in tables 4.3, 4.4, and 4.5. Simulation results are presented in the next section.

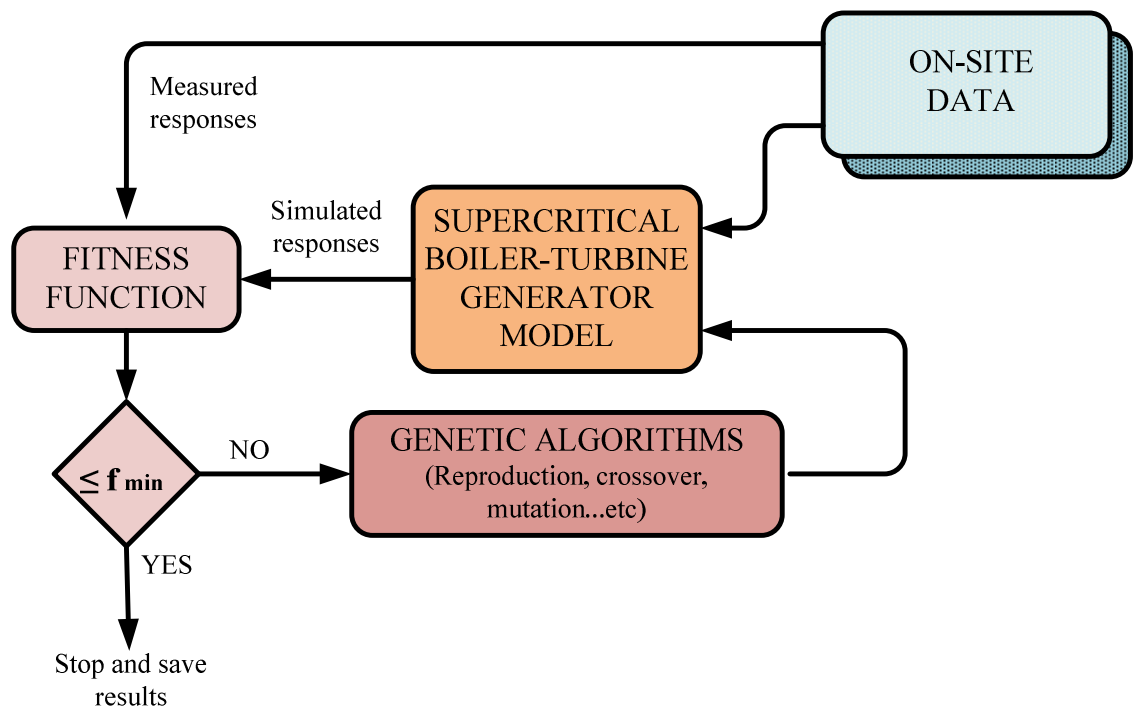


Fig. 4.6 Identification procedure for supercritical boiler turbine generator system

Table.4.2 GA Parameters

Population size	50
Generation	100-150
Mutation rate	0.1-1
Crossover function	Scattered
Migration direction	Forward
Selection function	Stochastic uniform

Table 4.3 SC Boiler Model Parameters

$I_{i1}=9.8565$	$I_{o1}=13.696$	$I_{i2}=12.4256$
$I_{o2}=13.2992$	$I_{i3}=9.6233$	$I_{o3}=12.9320$
$I_{i4}=19.2787$	$I_{o4}=27.000$	$I_{i5}=12.0123$
$I_{o5}=12.0123$	$C_{econ}=180.3288$	$C_{sh}=204.4324$
$C_{ms}=100.4310$	$C_{rh}=123.4300$	$K_{econ}=11.3198$
$K_{ww}=5.7785$	$K_{sh}=35.6430$	$K_{rh}=25.000$
$t_1=10.4353$	$k_1=554.4036$	$k_2=364.3338$
$k_3=864.3867$	$k_4=460.5432$	$k_5=5234.01$
$A_1=2.1643\text{e-}07$	$A_2=-1.2850\text{e-}07$	$A_3=1.0487\text{e-}06$
$A_4=-1.003\text{e-}06$	$B_1=-4.9393$	$B_2=-0.1922$
$B_3=-3.7375$	$B_4=-1.9320$	$C_{ww}=140.6435$

Table.4.4 Turbines Model parameters

$K_{hp}=0.3983$	$K_{ip}=1.1093$	$M_{hp}=0.1821$
$M_{ip}=0.3213$	$D_{hp}=0.1$	$D_{ip}=0.1$
$K_{hi}=19.7643$	$K_{ig}=1.2000$	

Table.4.5 Generator Model Parameters

$J=0.0234$	$D=0.0517$	$x_d=2.1107$
$t'_{d0}=0.1310$	$x_q=1.559$	$x'_d=0.5664$

4.6.3 Simulation Results

Simulation results are found for data set 1 while other sets of data will be used for further study on the model in the next chapter. The model outputs are compared by the adopted on-site measurement data. From the results, it can be seen that the model is able to simulate the main variation trends of the power plant for once-through operation. The results are reported from Fig.4.7 to Fig.4.11.

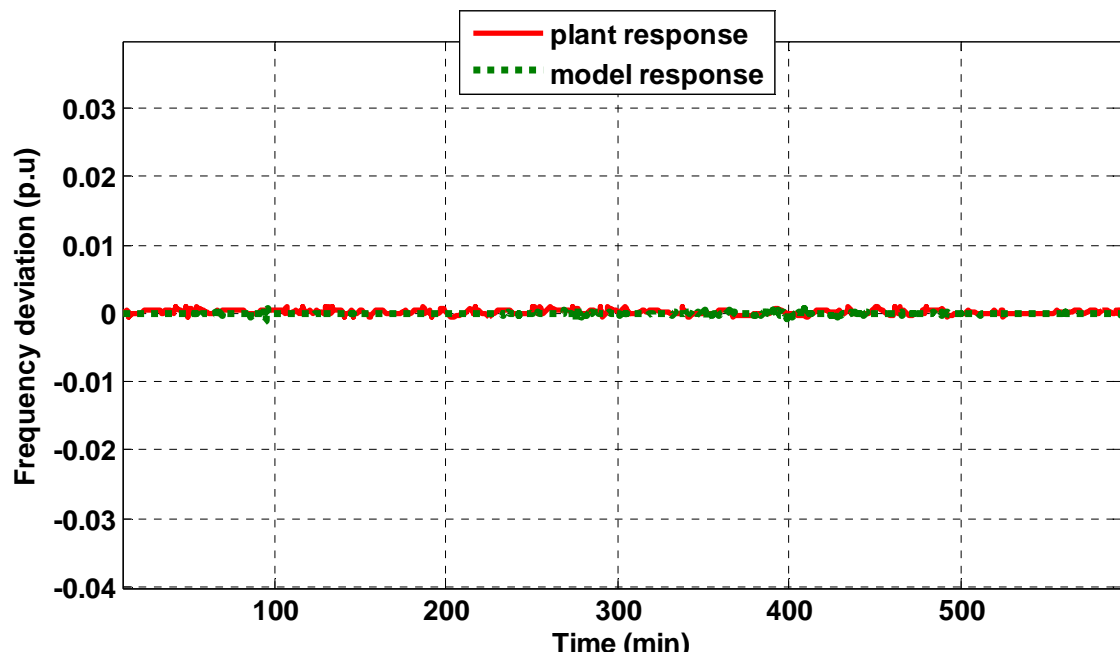


Fig. 4.7 measured and simulated frequency deviation

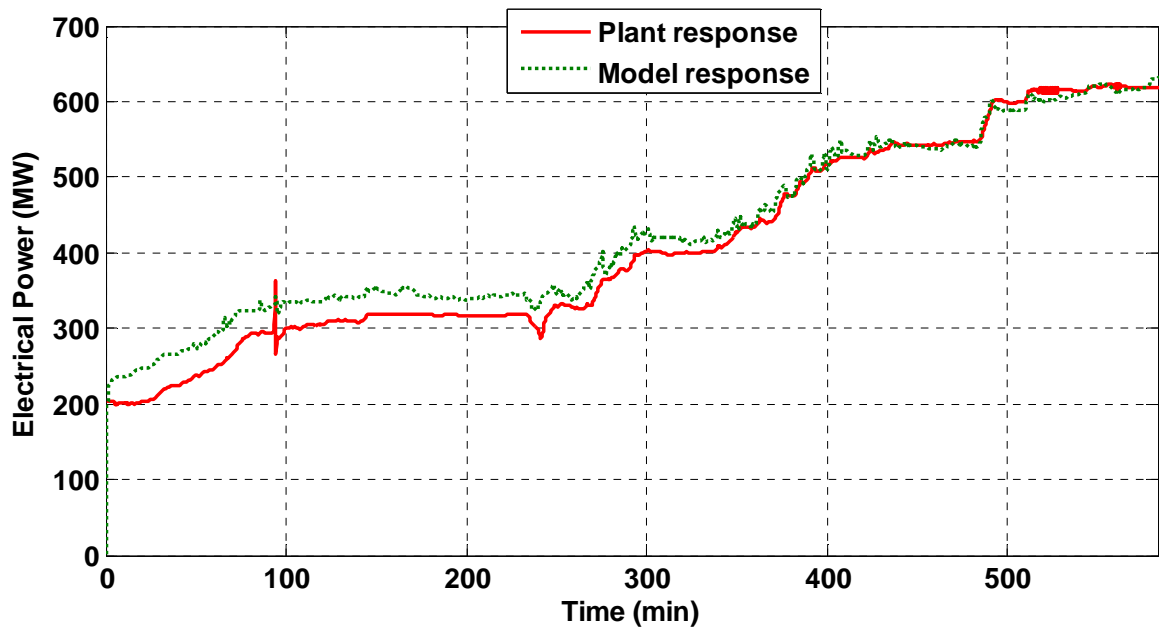


Fig 4.8 measured and simulated Electrical Power

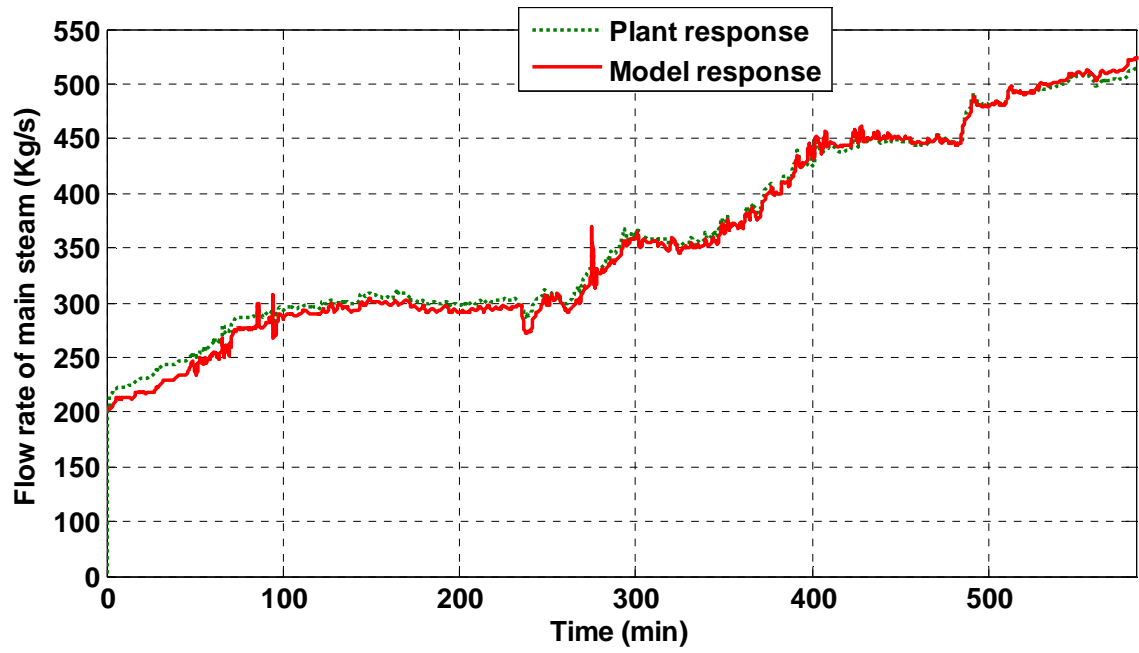


Fig 4.9 measured and simulated Steam flow rate

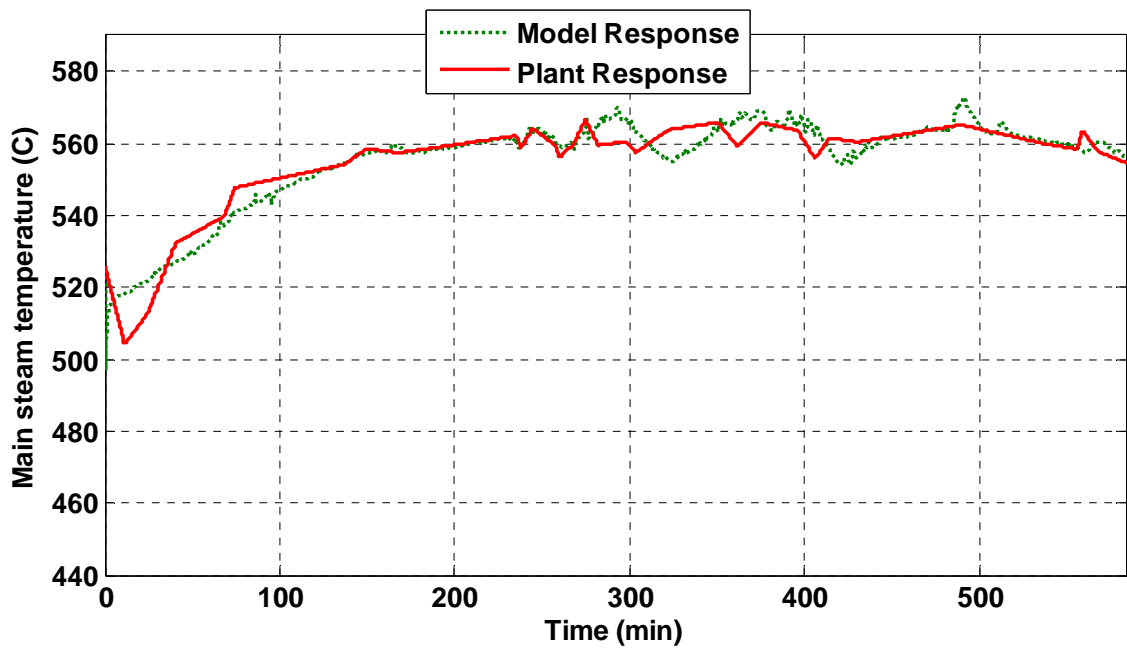


Fig.4.10 measured and simulated main steam temperature

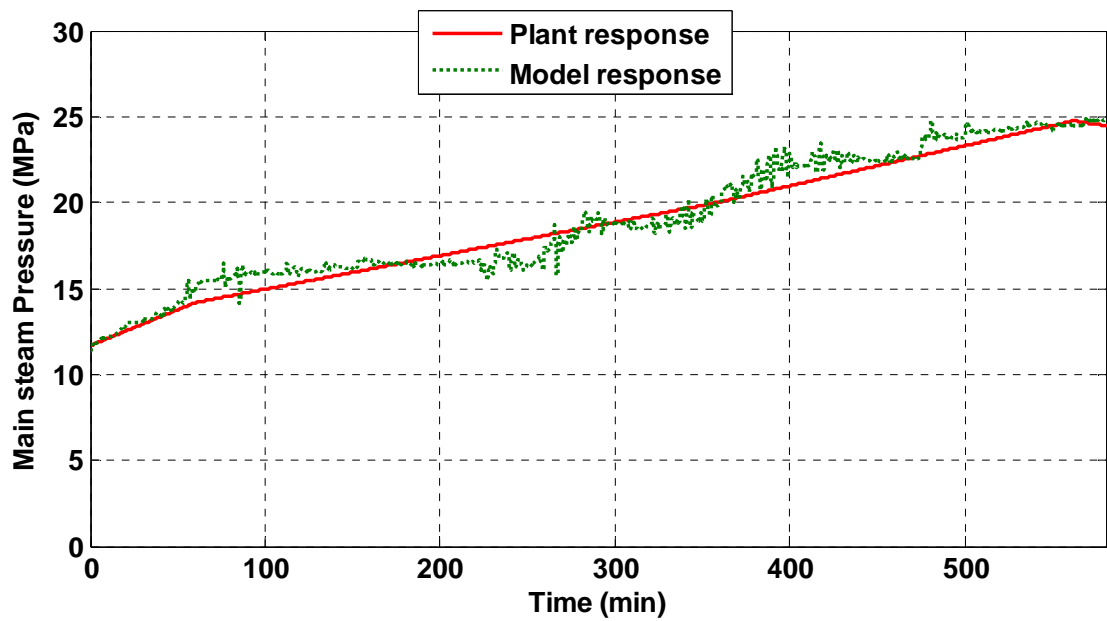


Fig.4.11 Measured and simulated main steam pressure

The reported results have shown that the model is able to simulate the main variation dynamics of the real SCPP. However, there are some unexpected small discrepancies and deviations which results form the plant uncertainties. In Fig 4.8, there is a mismatch between the model and the plant power responses over the range 0-350min. However, the plant once-through operation may start from 35% or from 45% of loading in some standards for power plant operation. However, the model response has shown good agreement at higher load operation which confirms this analysis of the simulation results. Also, in Fig 4.10, there are some deviations from 280-500 min in the temperature responses. It is believed that those deviations are resulted from the influences of flue gas flow in the real plant SH. In the model, flue gas is not included and the SC fluid circuit is modeled with the spray attemperator which is the only factors that affect/control the temperature dynamics in the model. Also, the set-point of the temperature attemperator may not be the same as that in reality. However, in general, the model responses reflect the main dynamics and variation trends of the plant.

4.7 Summary:

The goal of this chapter is to explain the model parameters identification scheme and introduce some simulation results. Genetic Algorithms was adopted for optimal parameter solution which is much improved method over conventional optimization techniques. The data sets for once-through operation have been divided to four groups. One set of data has been used for identification which represents an increase in the electrical load from 35% to 100%. It is shown that the simplified nonlinear model unknown parameters selected by GA can simulate the main features of the real power station with obvious agreement between measured and simulated outputs. The others will be used for further model investigations in the next chapter to confirm the quality of the simplified model.

Chapter 5

A Complete Power Plant Process Model

5.1 Introduction

With the identified system parameter, this chapter will conduct further studies on the power plant model with different sets of data. The model will be extended to include the fuel grinding process model. The dynamic responses obtained using the model developed are compared with the real plant responses by using three sets of data in steady state and load change conditions. Then, the responses obtained from the model are compared with the result obtained using the software developed by Eutech for chemical reactions and thermodynamic process simulations. The simulation results, both static and dynamic, are in agreement with the real plant data for the various plant variables. A vertical spindle coal mill model which has been extensively validated in the published literature (Wei et al. 2007) is described and linked to the boiler-turbine-generator system. The mill model is an important subsystem that reflects approximate fuel source dynamics of the various variables inside the mill. Although the mill is not the most important part in the plant, by combining the mill to these sub-systems, the study of the influences of the mill grinding capability on the whole plant response is available. Unlike gas and/or oil firing plants, the coal fired plants are much slower in response to load changes and this will be clarified by step response test conducted at the end of this chapter.

5.2 Simulation Study using Different Sets of Data and Results Analysis

In this section, the simulation results for the remaining sets of data which have been used for the model investigation are reported. The five responses chosen in Chapter 4 are demonstrated through Figs 5.1 to 5.15 which show reasonable agreement between measured and simulated responses. Data set2: Figs 5.1 to 5.5 show the plant and model responses for load decrease from rated conditions to 55% of rated load. Data set3: Figs 5.6 to 5.10 demonstrate the results with small load variations around rated load conditions. Data set4: Figs 5.11 to 5.15 the results are reported for data set.4 which show increase in load conditions from 33% to 100% followed by small decrease to around 80%. In each virtual test, the models inputs were inserted from the corresponding plan inputs data and the model outputs are demonstrated on the same scope with the plant data output.

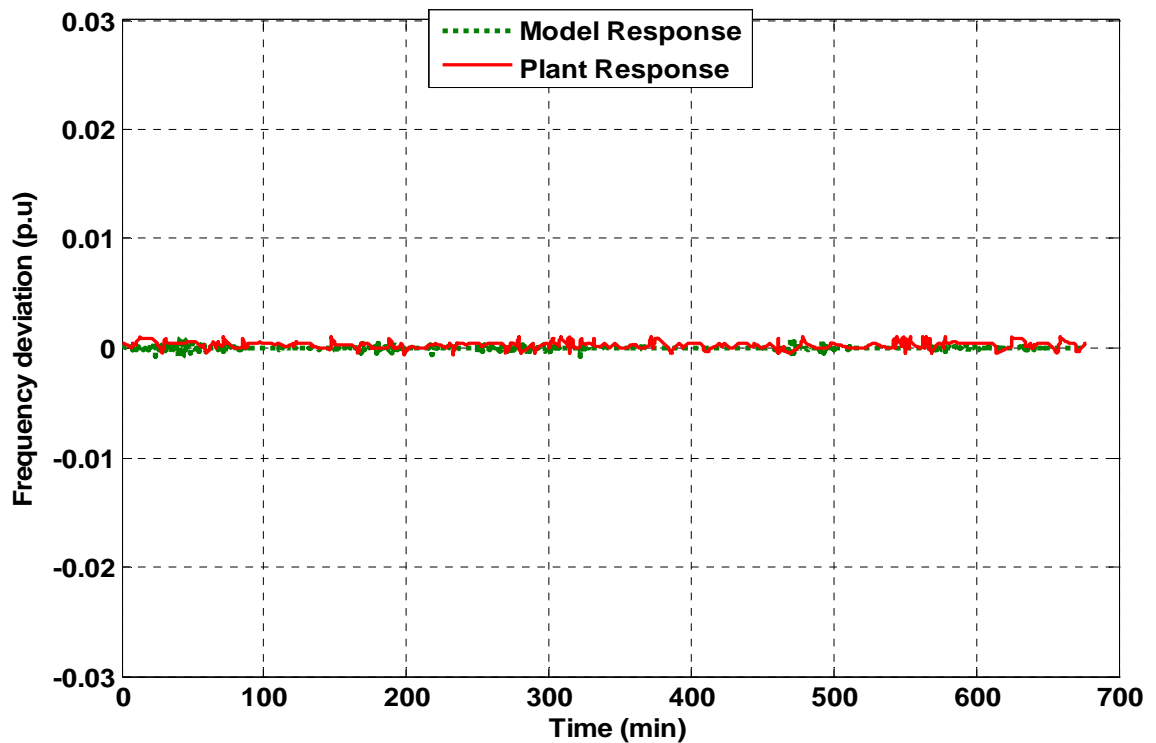


Fig5.1 Measured and simulated frequency deviation for data set.2

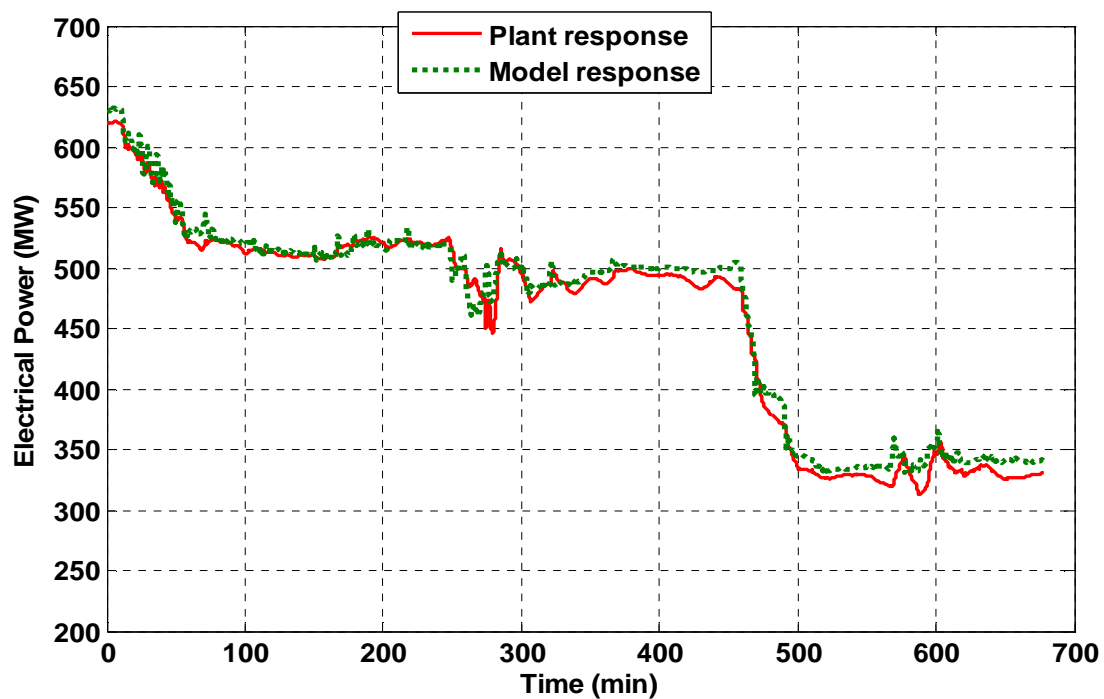


Fig5.2 Measured and simulated electrical power of the plant for data set.2

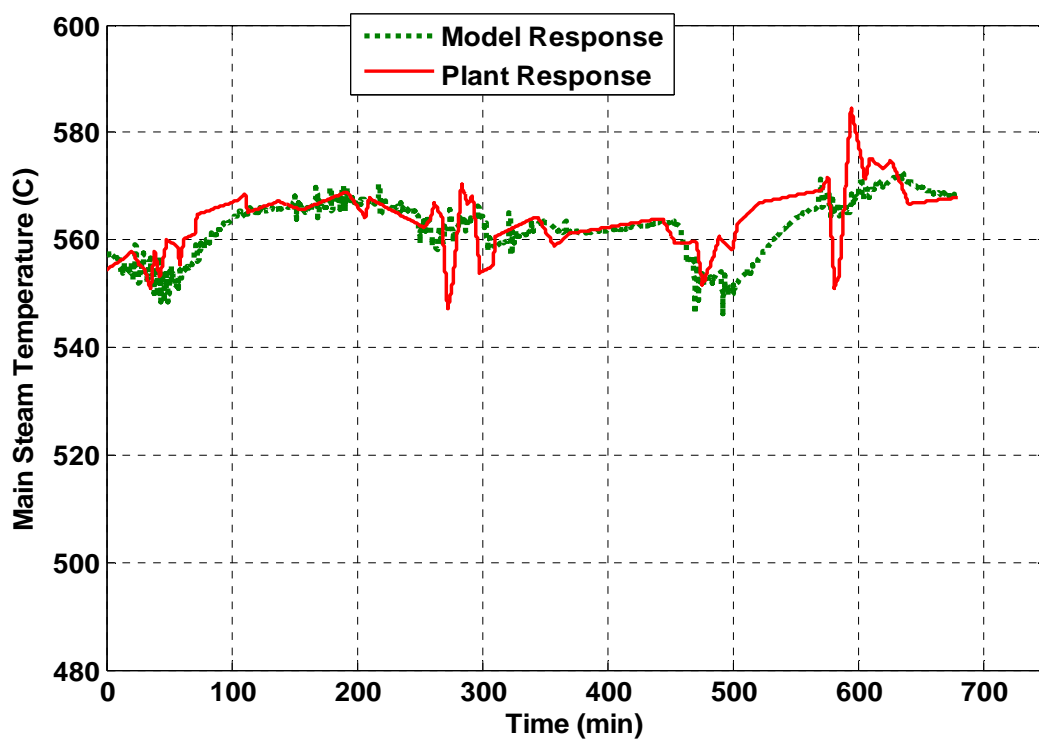


Fig 5.3 Measured and simulated main steam temperature for data set.2

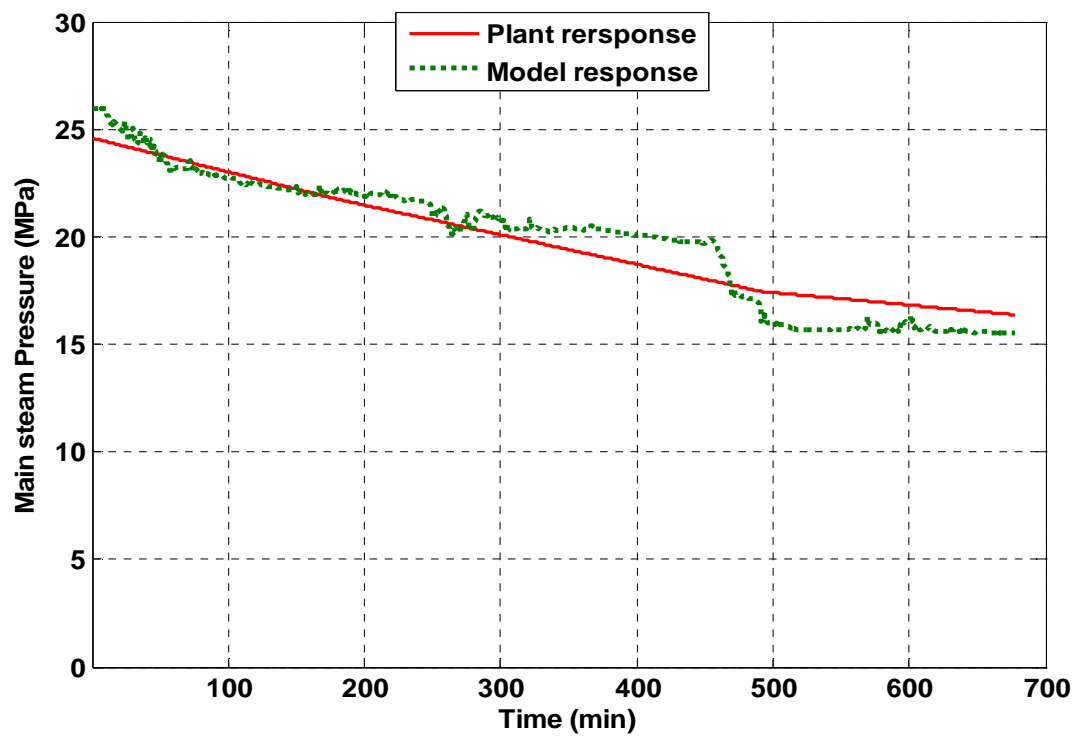


Fig5.4 Measured and simulated main steam pressure for data set.2

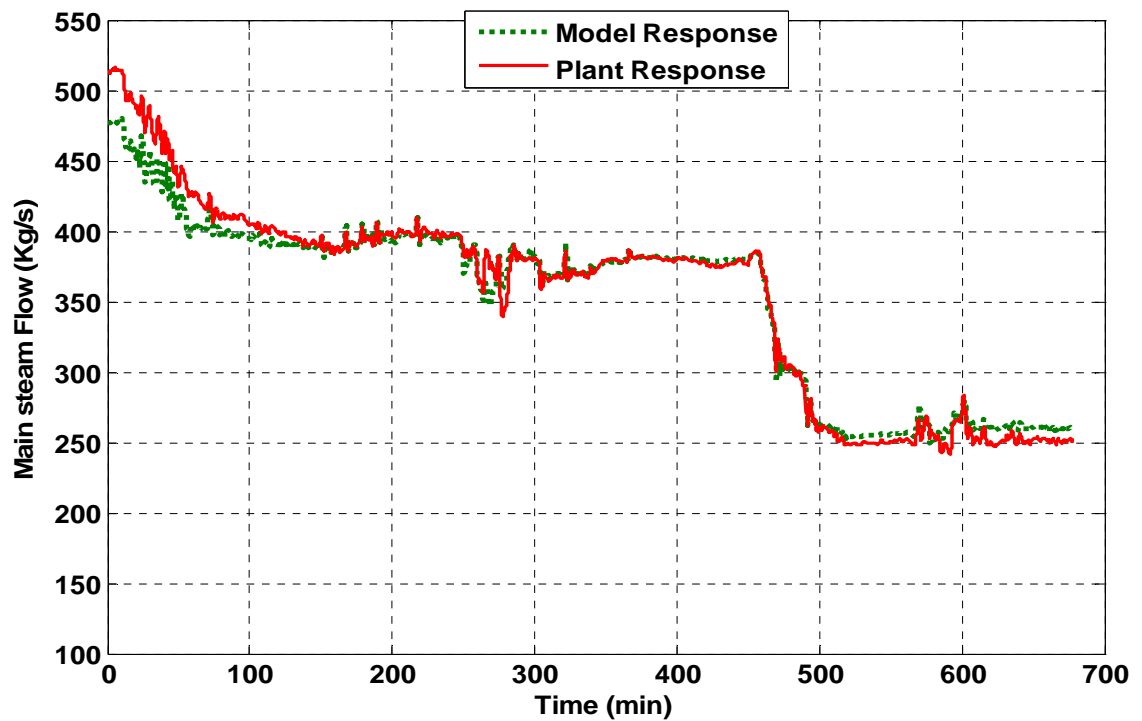


Fig5.5 Measured and simulated main steam flow for data set.2

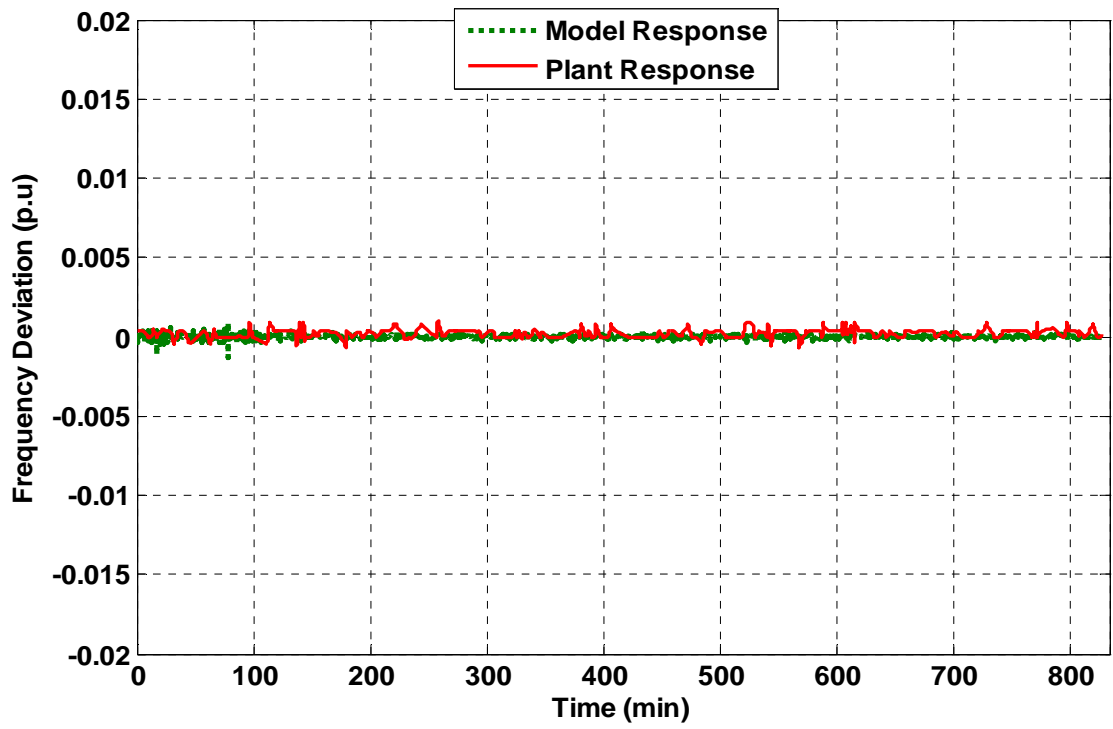


Fig5.6 Measured and simulated frequency deviation for data set.3

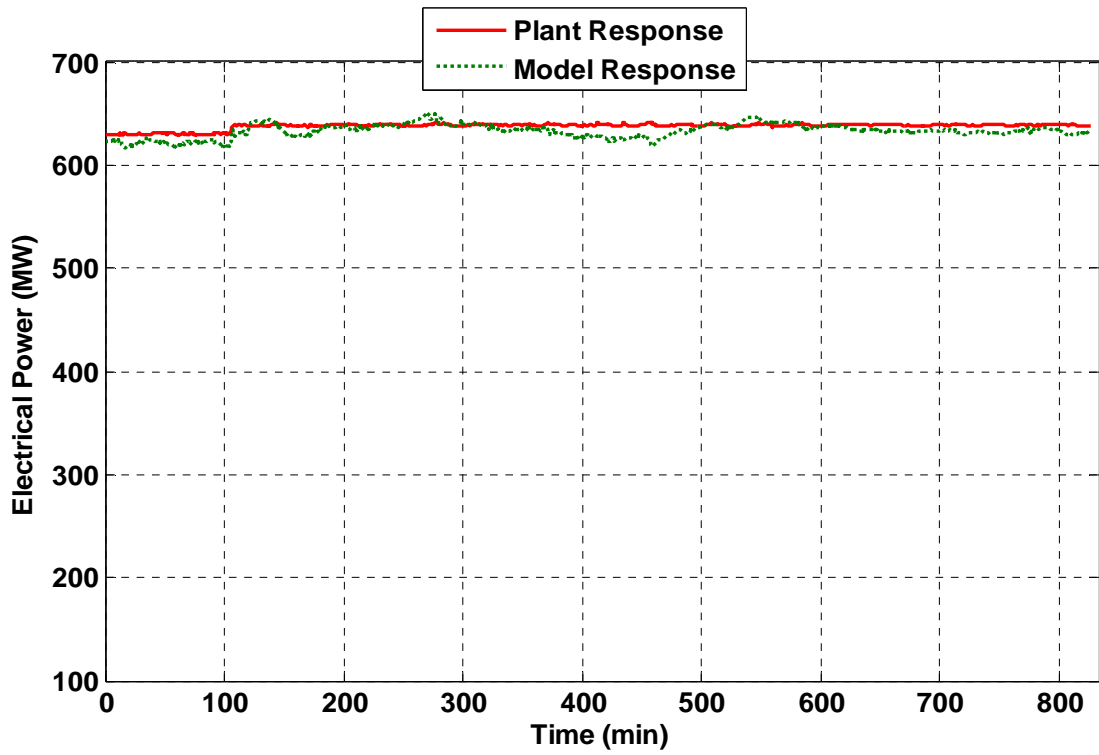


Fig5.7 Measured and simulated electrical power for data set.3

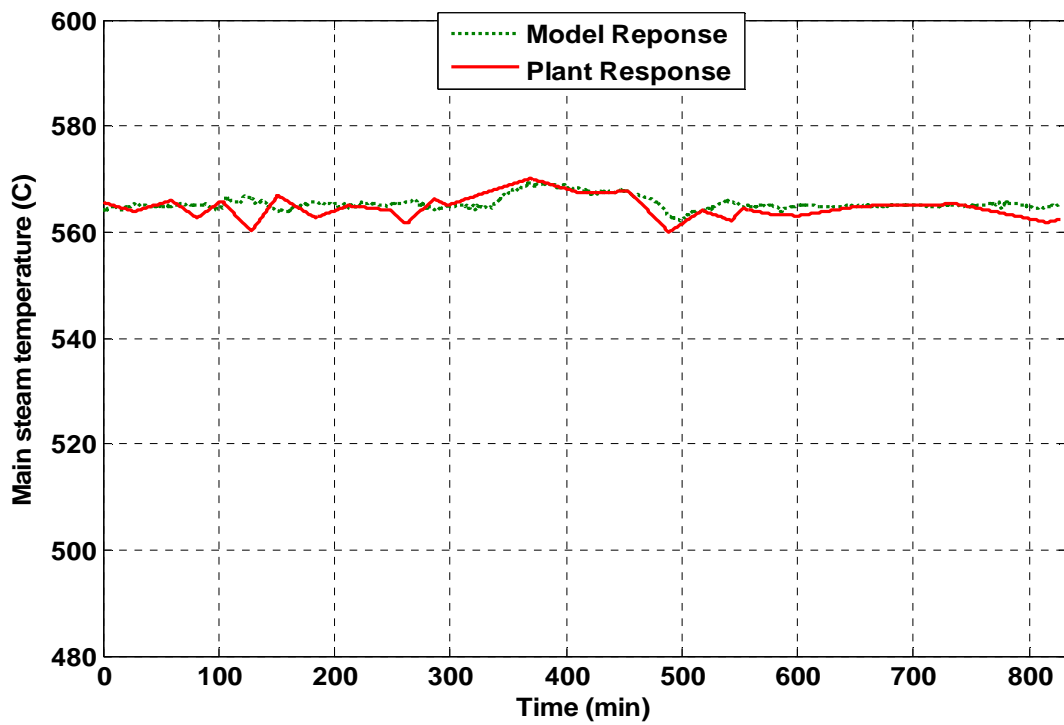


Fig 5.8 Measured and simulated main steam temperature for data set.3.

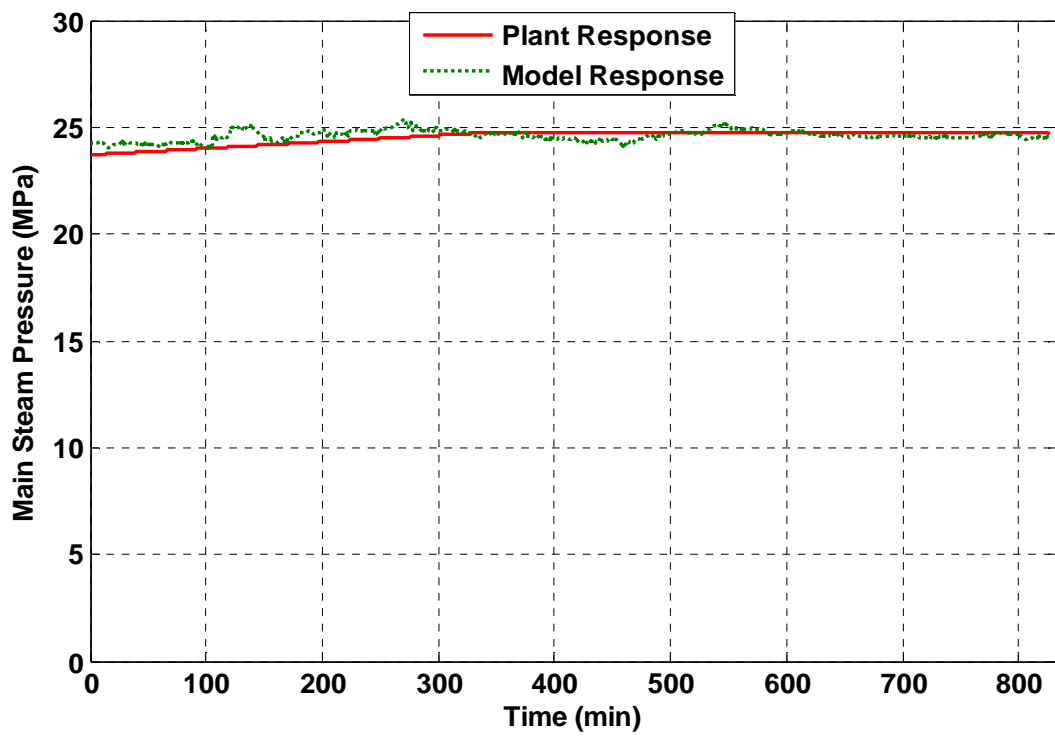


Fig5.9 Measured and simulated main steam pressure for data set.3

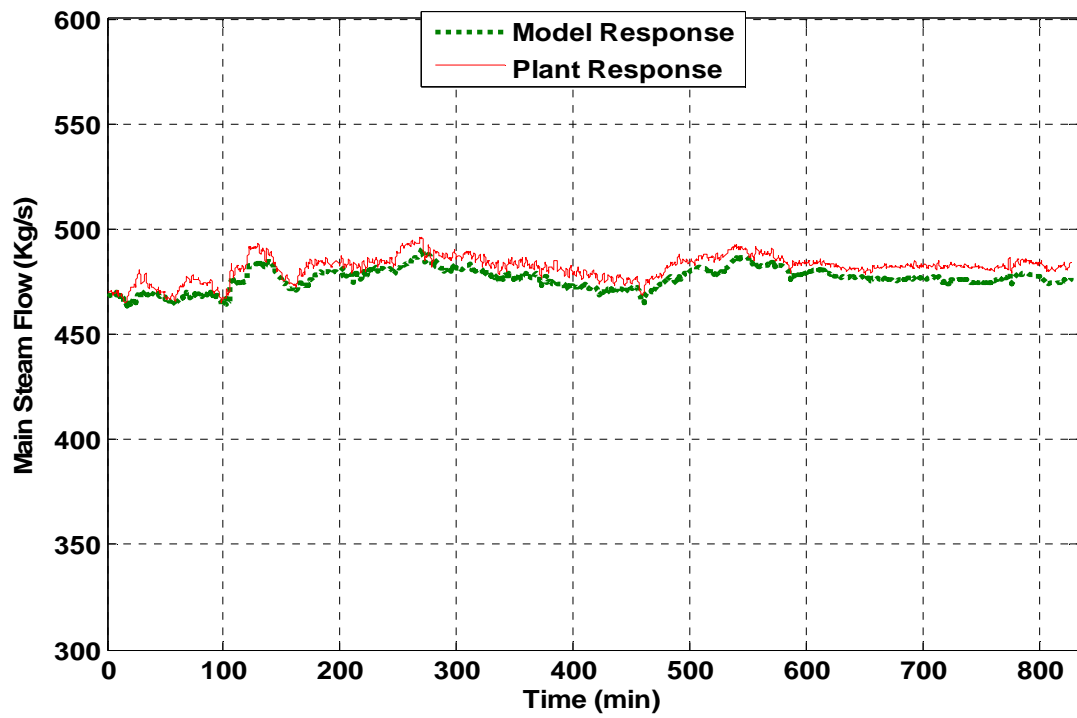


Fig5.10 Measured and simulated main steam flow for data set.3

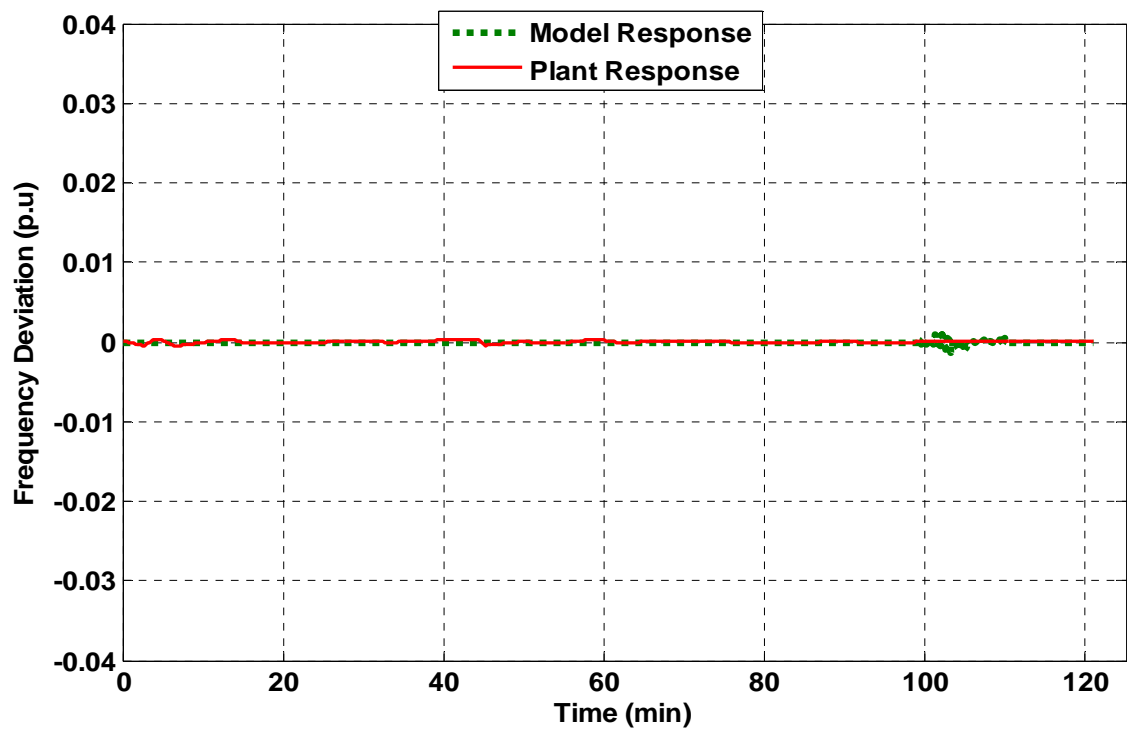


Fig5.11 Measured and simulated frequency deviation for data set.4

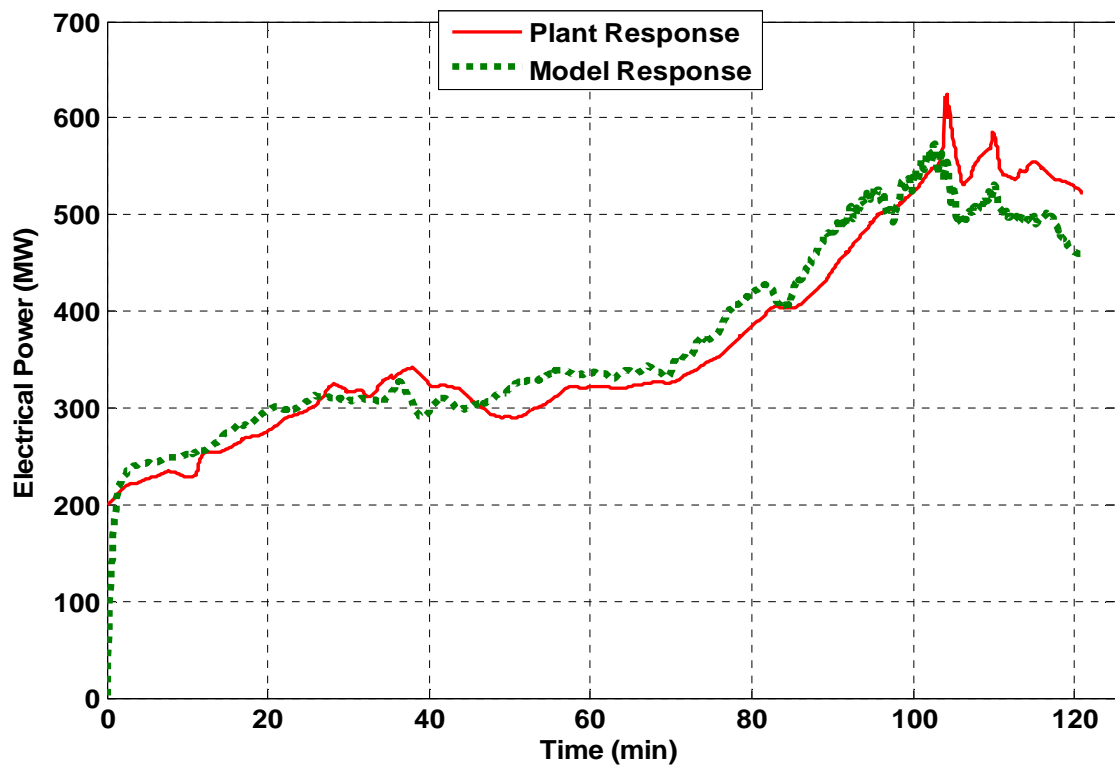


Fig5.12 Measured and simulated electrical power for data set.4

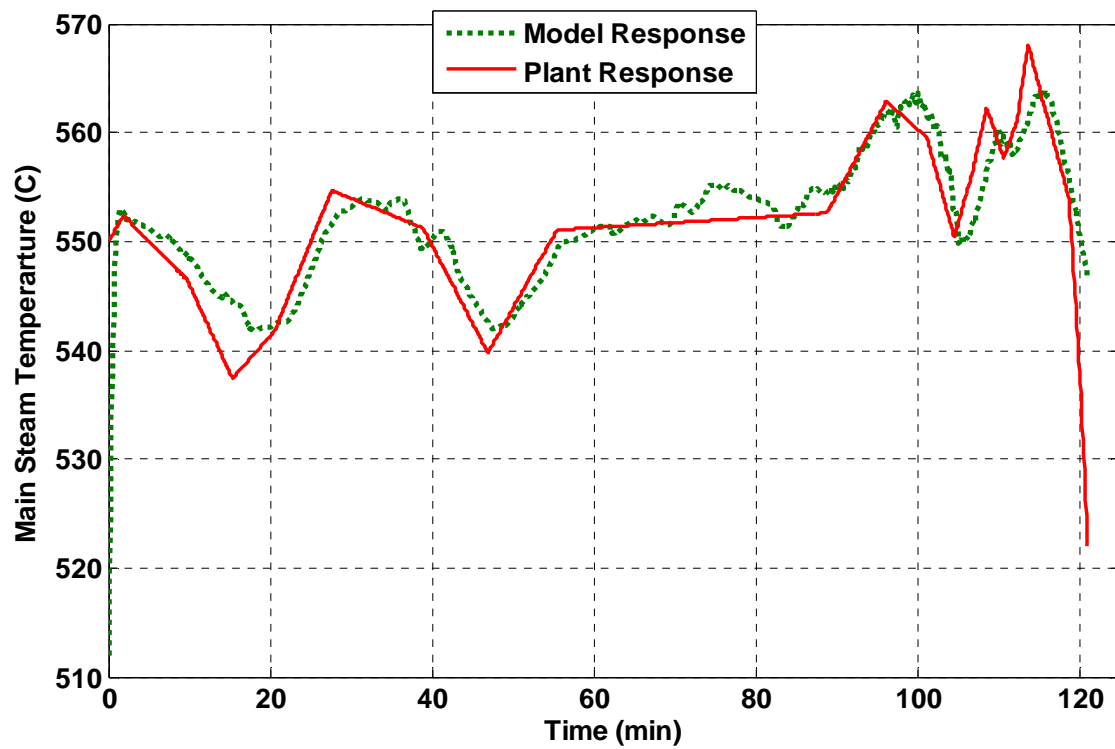


Fig5.13 Measured and simulated main steam temperature for data set.4

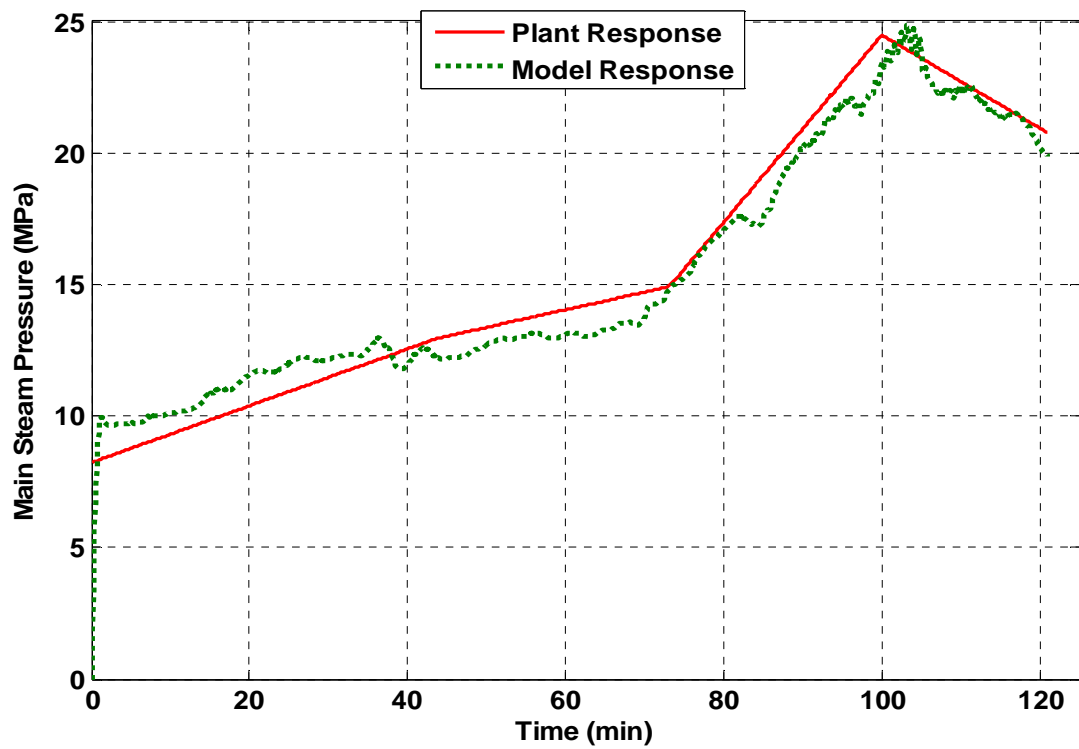


Fig 5.14 Measured and simulated main steam pressure for data set.4

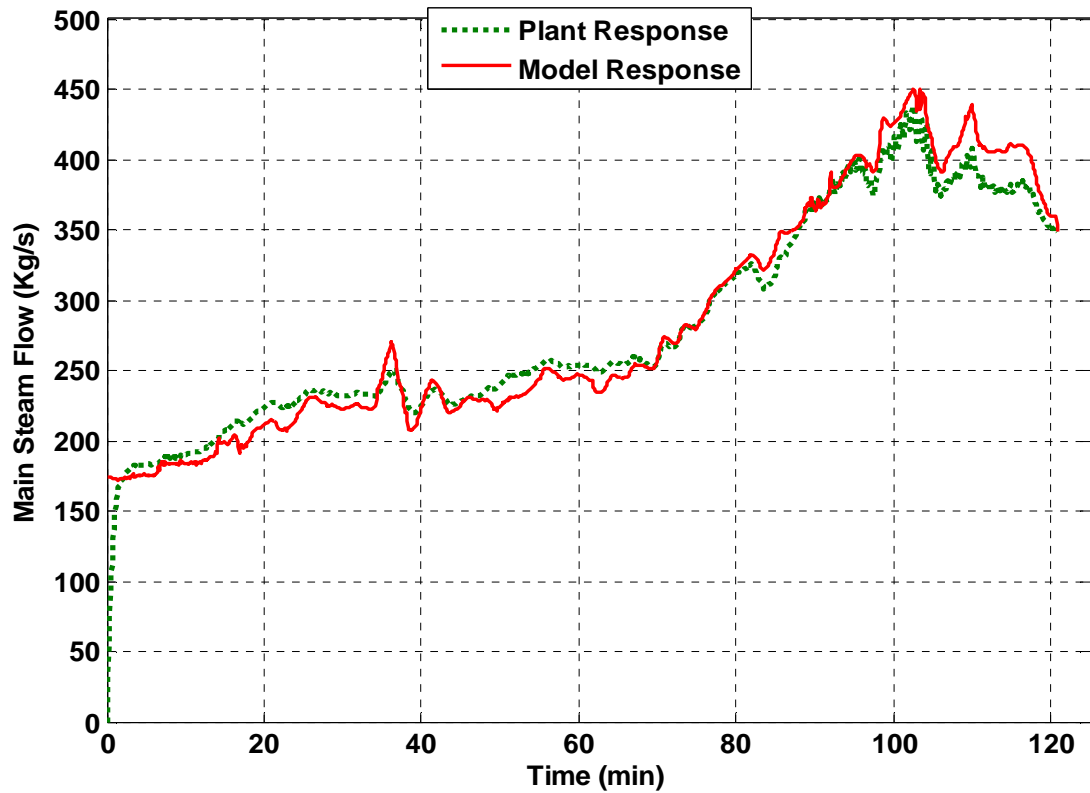


Fig 5.15 Measured and simulated main steam flow for data set.4

Nevertheless, it is quite visible that the model can simulate the main variation trends and dynamical features of the real plant and estimate the plant behaviour over a wide operating range with the optimal version of the parameters reported in Chapter 4. Thereby it has been confirmed that the nonlinear modeling and identification is preferable over linearized models which are valid only within small operating range. Although some assumptions were initially made to simplify the nonlinear modeling and identification procedure, the model is able to simulate the dynamic characteristics of the SCPP. Moreover, the results clearly confirm the robustness of GA as a parameter identification technique which handles optimization problems of nonlinear type and simultaneous multi-objective functions in smooth manner. However, there is a sudden slight drop/mismatch in the main steam pressure dynamics of the model response at approximately 460 min in Fig 4.5. This is because the data is gathered from real plant record, not from operator training simulator. In simulators which are based on physical principles, the trends of pressure are analogous to the trends of the power with different magnitudes. However, this is observed in the developed mathematical model in Fig 5.4 and Fig 5.2. Also, in the real power plant there may be different set points for the pressure which are sent to the initial pressure regulator of the DEH system. However, the pressure response for the other two sets of data validated the pressure response of the model in comparison to the pressure of the plant boiler. The model main steam temperature dynamics are in good agreement with the real temperature response. The validity is shown also on the power responses, main steam flow rate responses, and also for the frequency responses. The model has been investigated over a wide range of operation under steady state and transient load conditions. Some of these results are published and can be found on-line in our work (Mohamed *et al.* 2010, Mohamed *et al.* 2011a, and Mohamed *et al.* 2011b).

5.3 Comparison of static performances with the results obtained using Thermolib model

In this section, a comparative study between the mathematical model and another simulation tool is presented. Thermolib is a generic perfect tool for computer representation of thermodynamic systems. It was developed by Eutech in a SIMULINK environment with many functional blocks and fitted with a large thermodynamic database for some substances' properties. This package has been used to build a complete SC thermodynamic cycle of the SC plant and its output will be compared with the model output developed in Chapter 3 and 4. The thermolib blocks settings (like overall heat transfer rate of the boiler, the pump efficiency, pump outlet pressure, pressure loss coefficients, and turbine isentropic efficiency....etc) are adopted reasonably so that its output is tuned towards the model output at some operating conditions. Fig 5.16 shows the components of the plant thermolib model.

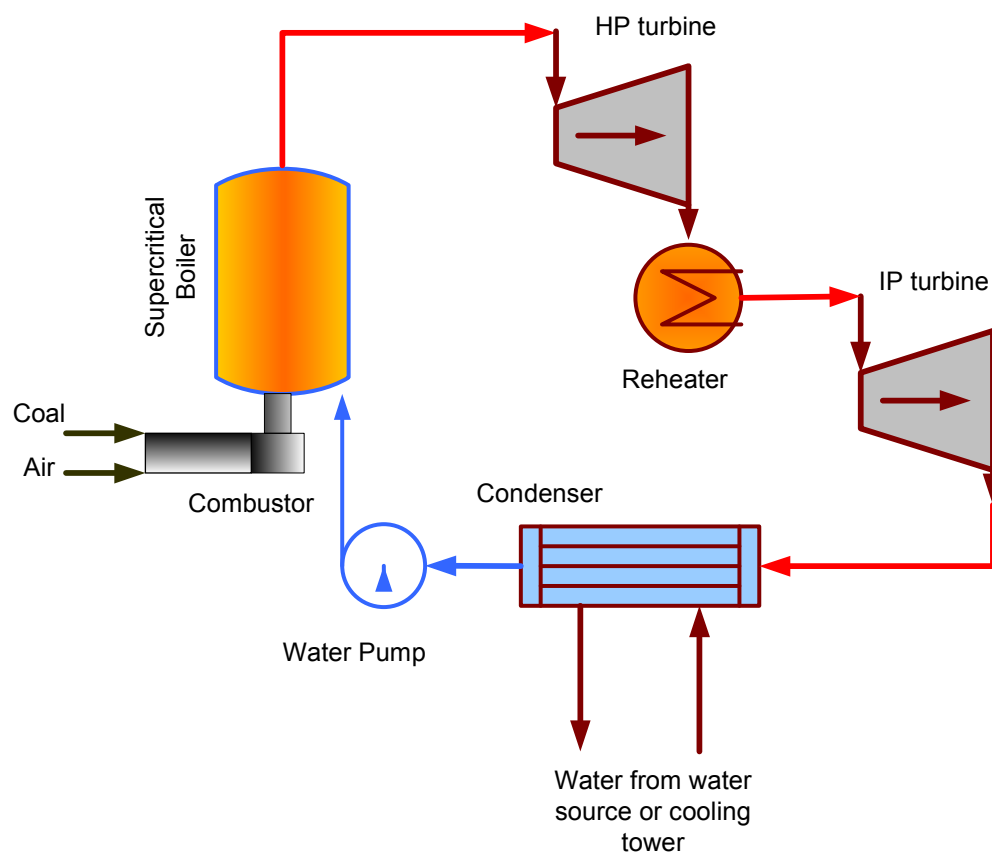


Fig. 5.16 The SC plant cycle's component used in thermolib model.

It also is noticeable that the thermolib model cannot represent the solid state of materials, only liquid and gaseous phases can be used. This will create problems in SC plant implementation on the side of the fuel flow because the coal must be discharged to the combustion furnace on its solid state. On the other hand, using natural gas flow to represent the fuel is not reasonable because the same amount of coal flow will not deliver the same amount of energy output or power. To overcome this difficulty, the thermodynamic data file, provided for Thermolib, has been expanded to include the coal properties on a gaseous phase on the basis of coal-gas or gasified coal concept that is used in thermal power plant. The coal properties in this case, which were recommended by Eutech, have been used to extend the thermolib substances data in Fig.5.17 in the right

hand side of the clipped view of the MSEExcel file of thermolib. This file has been converted to Matlab data file by one line command in the Matlab command window and stored in the Matlab directory in different file name.

New fuel insertion in Thermolib chemical data file

	A	B	C	D	E	F	W	X	Y	Z	AA	
1												
2												
3	Yes					Species	n-Propane	n-Butane	i-Pentane	R12	C	
4	No					formula		C4H10	C5H12	CCl2F2		
5	No					full_name			2-METHYLBUTANE	trichlorodifluoromethane	Coal	
9	Yes	A-element (high temp. range) [-]				NASA_A1_g	6.6678936300E+00	9.4453583400E+00	1.2327787000E+01	1.0708248000E+01	2.4926688800E+00	
10	Yes	B-element (high temp. range) [1/K]				NASA_B1_g	2.0612021400E-02	2.5785807300E-02	3.0613087000E-02	2.3232186000E-02	4.7988928400E-05	
11	Yes	C-element (high temp. range) [1/K^2]				NASA_C1_g	-7.3665302700E-06	-9.2361912200E-06	-9.8415785000E-06	-9.0073223000E-07	-7.2433502000E-08	
12	Yes	D-element (high temp. range) [1/K^3]				NASA_D1_g	1.1844076100E-09	1.4863275500E-09	1.3919776000E-09	1.5261702000E-10	3.7429102900E-11	
13	Yes	E-element (high temp. range) [1/K^4]				NASA_E1_g	-7.0695321000E-14	-8.8789715800E-14	-7.0337345000E-14	-9.4434958000E-15	-4.8727789300E-16	
14	Yes	F-element (high temp. range) [K]				NASA_F1_g	-1.6274852100E+04	-2.0138216500E+04	-2.5037492000E+04	-6.3102602000E+04	-1.4266117100E+04	
15	Yes	G-element (high temp. range) [-]				NASA_G1_g	-1.3185950300E+01	-2.6347007600E+01	-4.1133494000E+01	-2.6622876500E+01	6.0170979000E+00	
16	Yes	A-element (low temp. range) [-]				NASA_A2_g	4.2110262000E+00	6.1474680600E+00	1.0832882000E+00	3.8134966000E+00	3.579533470E+00	
17	Yes	B1-element (low temp. range) [1/K]				NASA_B2_g	1.7159980300E-03	1.5594738900E-04	4.4571076000E-02	2.0036835000E-02	-6.103536800E-04	
18	Yes	C1-element (low temp. range) [1/K^2]				NASA_C2_g	7.0618347200E-05	9.6791351700E-05	8.2389934000E-06	-9.8986693000E-06	1.016814330E-06	
19	Yes	D1-element (low temp. range) [1/K^3]				NASA_D2_g	-9.1959411600E-08	-1.2548391000E-07	-3.5258047000E-08	-8.7995353000E-08	9.070058840E-10	
20	Yes	E1-element (low temp. range) [1/K^4]				NASA_E2_g	3.6442137200E-11	4.9781655500E-11	1.5785762000E-11	7.1218552000E-12	-9.044244990E-13	
21	Yes	F1-element (low temp. range) [K]				NASA_F2_g	-1.4381210600E+04	-1.7599440200E+04	-2.0807535000E+04	-6.1253551000E+04	-1.434408600E+04	
22	Yes	G1-element (low temp. range) [-]				NASA_G2_g	5.6093049100E+00	-1.0940987900E+00	2.1795155000E+01	8.9909711000E+00	3.508409280E+00	
23												
24												
25												
26												
27												
28	Essential?	Chemical media data										
29	Yes	Molar Mass [kg/kmol]					M	44.0956	58.123	72.1498	120.914	12.01
30	Yes	Liquid density [g/m^3]					rho_liq	5.82E+05	5.79E+05	6.20E+05	1.75E+06	3.25E+06

Fig 5.17 Clipped view of the extended MS Excel file for chemical data of thermolib

Each subsystem in the mathematical model is represented by single or two blocks in thermolib model. For instance, chemical reaction block is used to represent the combustion chamber with simple chemical combustion equation. The condenser receives water from cooling tower which is implemented by water source and exchanges its heat with the steam exhausted from the turbine. The condensed sub-cooled water is re-delivered by the pump to the boiler to complete the cycle. For more details about each

block reference with system balancing blocks and other thermodynamic systems, refer to thermolib user's manual (Eutech. 2004).

The quantity of air required for coal combustion is chosen according to the stiochiometric ratio of bituminous coal (around 11.18) (British Electricity International. 1991). In practice, it is always necessary to supply more air to the combustion system than is theoretically necessary. The reason for this lies in the fuel-air mixing process in any combustion system, as it is not possible to ensure complete and intimate mixing of the fuel with the necessary oxygen at the point of injection (British Electricity International. 1991). This ratio has been estimated to be 20% (British Electricity International. 1991) of air mass and included in the source of mixed substances to be injected in the combustion chamber, and the total air is then resulted from excess air added to the theoretical air required.

The complete cycle has been built and both models' outputs are listed in Table 5.2. The results show good agreement for both models, especially for the power, pressure and main steam flow. A slight increase/deviation in the temperature of the SC boiler in thermolib model is observed in different loads. This is because of the high amount of temperature control parameters in the mathematical model that forces the SH temperature to be in fixed set point value.

Table 5.2. Mathematical model and Thermoilb results comparison

Percentages of Fuel & feedwater flows %	Main steam pressure MPa		Main steam temperature (K)		Turbine mechanical Power (MW)		SC Steam flow Kg/s	
	Themolib	model	Themolib	model	Themolib	model	Themolib	model
100	27.13	27.5	863.369	863	637.8	638	535.555	534.7
95	25.9	26.1	862.81	863	604.8	605.7	503.78	500
90	24.67	24.85	862.369	863	573.5	574	481.5	475
85	23.427	23.5	861.944	863	541.6	542	454.75	449.83
80	22.15	22.1	861.488	863	509.3	510	423.00	420
75	20.88	20.7	861.034	863	478.9	478	401.25	397.3
70	19.59	19.35	860.581	863	446.4	446	370.5	366.5
65	18.28	17.96	860.024	863	414.9	414.5	343.7	341
60	16.96	16.6	859.264	863	382.2	382.6	321.00	317.00
55	15.63	15.2	858.33	863	349.6	350.6	294.20	292.00

5.4 Coal mill model for normal grinding process

This section describes the coal grinding process that occurs inside the mill and the mathematical model of the mill which is combined with the rest of the plant. In coal fired power plants, a set of coal mills or pulverizers which have duty listed as (Rayaprolu, 2009):

- Grind the coal.
- Evaporate moisture to produce dry pulverized coal.

- Classify fines.
- Discharge acceptable fine powder pneumatically.

The most popular type of mills used for power plants is vertical spindle mills type.

Fig5.18 shows cross sectional view of vertical spindle mill.

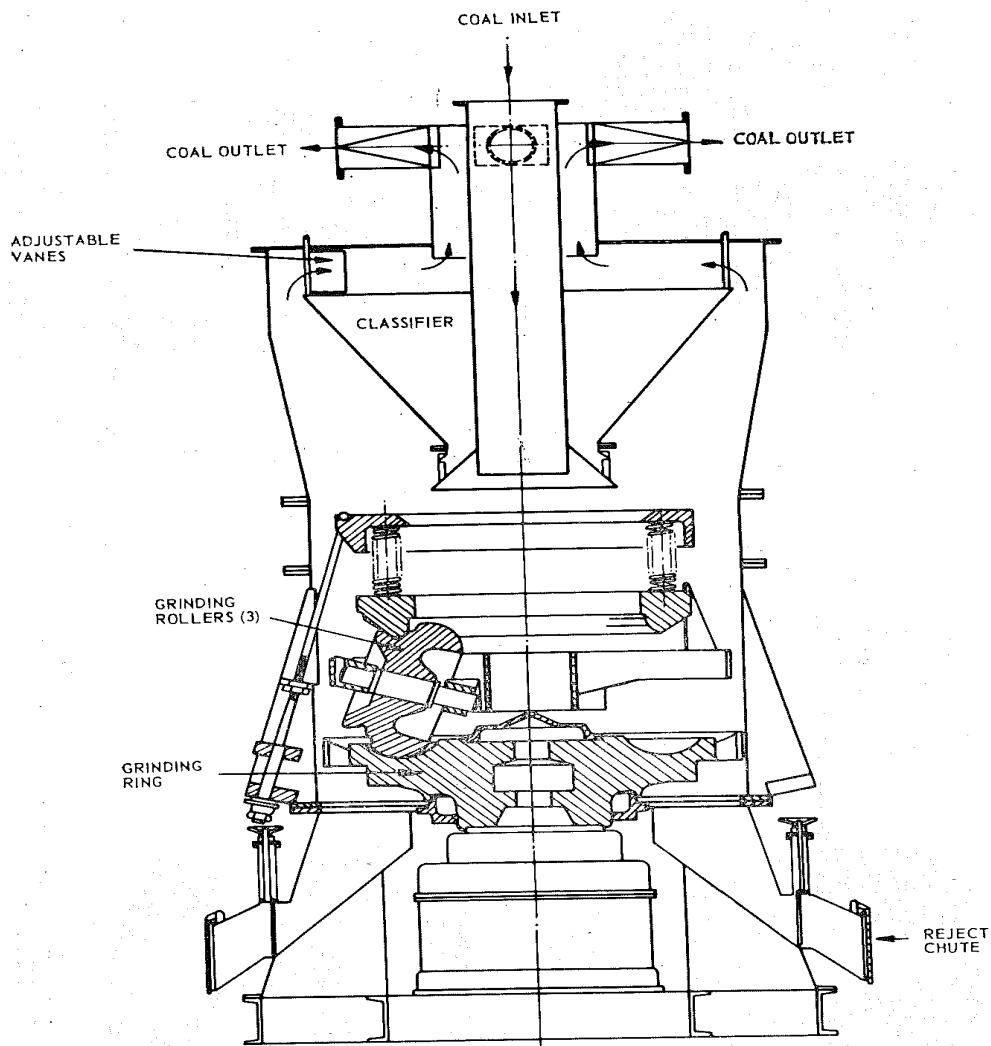


Fig 5.18 Cross sectional view for typical vertical spindle mill (Central Electricity Generation Board. 1971)

The feeder of the coal conveys the coal to the rotating table, while rotating, the coal is sent towards the outer edges where it is crushed by rollers or balls. The coal powder is carried

by hot primary air from the bottom to the classifiers which are located on the top of the mill. Heavier coal particles fall down to the grinding region and those that are acceptable fine powder continue their journey to the burners of the furnace.

The combination of mill with the boiler-turbine-generator system has two main purposes:

1. To study the influences of coal grinding and discharging capabilities on the power primary response that has been studied in more details yet.
2. According to the first point, there may be an opportunity to improve the load tracking performance or the plant MW response by improving response of the mills and grinding capability of the coal.

The main inputs to the mill are the primary air and raw coal. The quality of the model parameters are extensively verified in previous literature (Zhang et al. 2002, Wei et al. 2007). The model has been derived from thermodynamic principles with some simplifying assumptions and other engineering hypothesis. The concept of mass, and energy balances with some empirical equations are used to derive/formulate. It has been identified by GA and its parameters have been improved over a wide range of serious group work (Zhang et al. 2002, Wei et al. 2007). The model segment for normal operating conditions has been adopted for this research. Refer to (Zhang et al. 2002, Wei et al. 2007) for more details about the model for normal grinding and other operating conditions. The following model equations are implemented in SIMULINK:

$$\dot{M}_{rc} = w_{rc} - K_3 M_{rc}$$

$$\dot{M}_{pf} = K_3 M_{rc} - w_{pf}$$

$$\Delta \dot{p}_{mpd} = K_8 M_{pf} + K_9 M_{rc} - K_{10} \Delta p_{mpd}$$

$$\dot{T}_{out} = [K_{11}T_{in} + K_{12}] \cdot w_{air} - K_{13}w_{rc} - [K_{14}T_{out} + K_{15}] \cdot [w_{air} + w_{rc}] + K_{16}P_{mill} + K_{17}T_{out}$$

$$w_{rc} = K_1 \cdot F_s$$

$$w_{air} = 10 \cdot \sqrt{\Delta p_{pa} \cdot \frac{273}{273 + T_{in}} \times \frac{28.8}{22.4}}$$

$$w_{pf} = K_2 \cdot \Delta p_{pa} \cdot M_{pf}$$

$$P_{mill} = K_4 M_{pf} + K_5 M_{rc} + K_6$$

$$\Delta p_{mill} = K_7 \Delta p_{pa} + \Delta p_{mpd}$$

where

F_s : Feeder speed (m/s)

M_{rc} : Mass of raw coal in mill (Kg).

M_{pc} : Mass of pulverized coal in mill (Kg).

w_{rc} : Mass flow of raw coal (Kg/s)

w_{pf} : Mass flow of pulverized coal (Kg/s)

w_{air} : Primary air flow rate to the mill (Kg/s)

P_{mill} : Mill current (A)

Δp_{mill} : Differential pressure of the mill (mbar)

Δp_{pa} : Mill product differential pressure (mbar)

T_{in} : Inlet temperature (C°)

T_{out} : Outlet temperature (C°)

Inputs & outputs:

$$u_{mill} = [w_{rc} \quad \Delta p_{pa}]$$

$$y_{mill} = w_{pf}$$

With the optimal version of the parameters listed in Table 5.2.

Table 5.2 Optimal Parameters of the Mill (Zhang et al. 2002, Wei et al. 2007)

$K_1=0.16$	$K_8=0.001700$	$K_{13}=0.003837$
$K_2=0.002618$	$K_9=0.000565$	$K_{14}=0.001553$
$K_3=0.005133$	$K_{10}=0.08677$	$K_{15}=-0.086348$
$K_4=0.017125$	$K_{11}=0.000619$	$K_{16}=0.032505$
$K_5=0.002937$	$K_{12}=0.089614$	$K_{17}=-0.057244$
$K_6=30.173294$		
$K_7=5.549000$		

The coal mill model is simply linked to the furnace through the pulverized coal. In practice, there are multiple mills operating together to supply enough amount of coal. To account the operation of many mills, the pulverized coal output of the mill is multiplied by factor to produce the required pulverized coal supplied to the furnace which is equivalent to that discharged by the mills in service.

In 1969, Anderson and Woo from Westinghouse Company has performed manual step and ramp response tests on gas fired supercritical power plant power plant. A 20% increase in all manipulated inputs (Fuel, feedwater, and turbine valve) in 2min at the same time. It is interesting to perform this test virtually on the mathematical model to reassure the slowness of coal firing power plants in comparison with gas fired plants. Due to the fast combustion of gas the plant power has reached equilibrium after 8min of the step time. The outputs of their tests were recorded on high speed channel recorders (Normalized or in p.u). The same has been done on the model; by comparison, the coal fired plant power has

reached steady state or equilibrium after 18 min because of the coal volatile matter which affects burning rate and also the pulverized coal preparation inside the mill.

There is an initial rise in the pressure and temperature. However, the pressure has returned to its original position by the valve action and the temperature has decayed by the feedwater which cool the boiler tubes after firing. It is however shown that the coal fired power plants are slower in response to load changes because of the slower coal combustion in comparison with gas and also because of the coal mill slow dynamics.

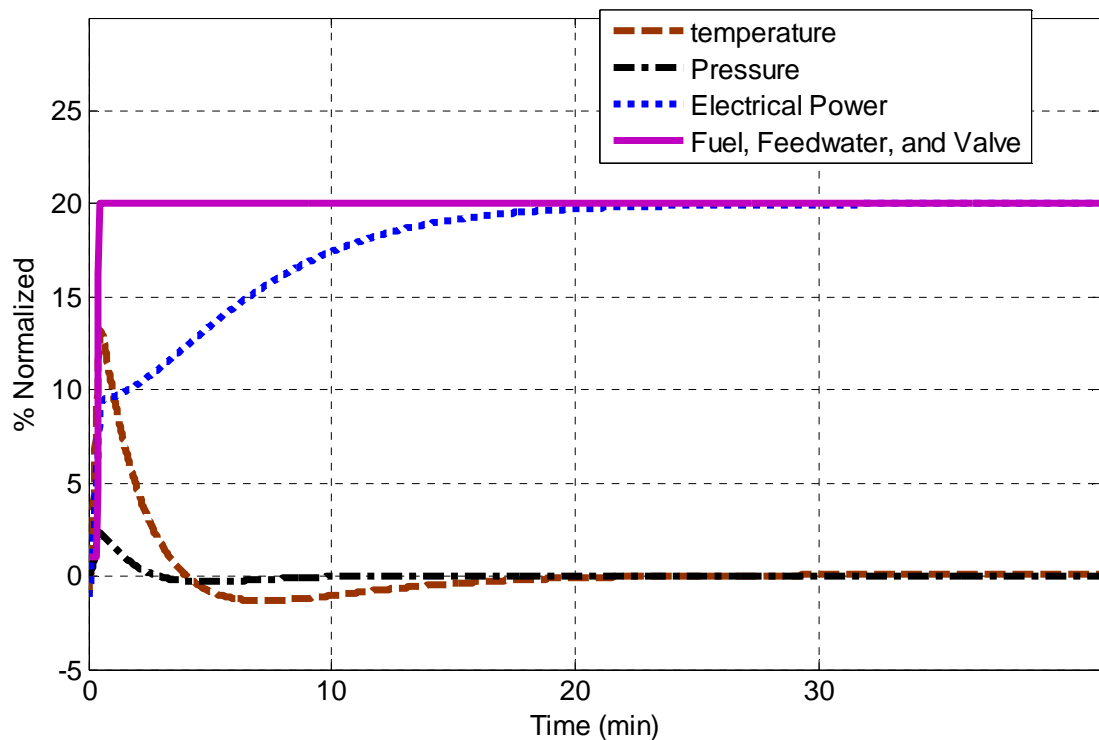


Fig 5.19 SC coal fired power plant response to simultaneous 20% change in 2min of fuel flow, feedwater flow, valve position.

Here it should be mentioned that the model is still based on actual quantities, not normalized, but only the variables mentioned in Fig 5.19 are converted to normalized values to present them on the same axes. They basically have been converted to normalize

per unit quantities by dividing the actual quantity of certain variable on the rated quantity of that variable.

The following main points are deduced from the previous three sections:

1. Although the mathematical model is not generic or perfect for all power plants, it simulates the main features for 600MW SC coal fired power plant.
2. The model accuracy is mainly affected by the parameters, the initial conditions of the integrators, and the operating conditions in which the data have been gathered.
3. The power plant capability is significantly affected by the pressure and temperature operating conditions of the various boiler's components, the inherent mill, also the fuel and its burning characteristics.
4. Coal fired power plants are much slower than gas fired power plants due to coal moisture, lower combustion speed, and slow mills dynamics.

5.5 Summary:

In this chapter, further study and investigations on the simplified model are reported. For the data gathered to present once-through mode, it is observed that the model response is matched to the real plant response over a wide operating range from 35% to above 100% of 600MW SC power plant. Moreover, the model has been compared with Thermolib software, both simulating the 600MW SCPP. The models show good agreement towards each other in different operating conditions. Finally, coal mill model that represents the dynamics of real vertical spindle mill is described. Thereby the model covers longer

process from fuel grinding to the electricity output. A study of feasible control strategy seems to be possible after this modeling study through the previous chapters. The next chapter discusses the theory of model predictive control and its applications to SCPP.

Chapter 6

Model predictive control theory and its applications to SCPP

6.1 Introduction

This chapter is to give an brief description of Model Predictive Control (MPC) which is widely used in control of thermal power plant industry and to review its applications to supercritical power plants up-to-date. MPC is considered as one of the well recognized control technologies for industrial process applications, especially, thermal power generation plants. MPC performs the optimization task which is based on minimizing certain objective function with pre-calculated output information and the pervious control information. One of the most significant advantages of this control algorithm is that it takes the operational constraints into consideration for control signals decisions which is very helpful for reliable and safe power plant operation. It is therefore necessary to understand the theoretical part of this control algorithm for successful / feasible implementation on the proposed model. First, a historical background that summarizes the current state-of-the-art of research is presented and discussed. Second, the principle of prediction and receding horizon control is presented and mathematically described. The optimization method used to decide the future control signals is reported. Finally, an example is given to illustrate applications of the MPC on a nonlinear paper machine headbox model is presented.

6.2 Historical Development on SCPP control:

Deregulation in the industry of electricity, and power stations in particular, have brought about a need for flexibility, increased automation, reliability and cost minimization in power plants (Oluwande 2001). Extensive research has been reported to incorporate model based predictive control and other control algorithms into subcritical and supercritical power generation stations to improve their dynamic response performances with emphasis on the aspects stated above as main target. It is well known that the SC power plant is a complex process and has a large thermal inertia which requires more sophisticated controls than conventional subcritical type of power plants. There is a need to evaluate such control strategies using a process model of a certain power plant that reasonably reflects the power station behaviour before the actual implementation on the operating unit. This helps in showing the control functions before actual plant operation, formulating a scientific conclusion to explain the observed results, and study what these results mean in the branches, theory and practice.

A research on linear quadratic regulator (LQR) of SC power plants was reported in 1978 with a state space model for identification and control optimization using a dynamic programming technique (Nakamura *et al.* 1981). Due to its simplicity, the controller has been applied on a 500MW oil-fired SC power plant and has been considered to be standard scheme for power plant steam temperature control in Japan on the long run (Nakamura *et al.* 1981, Ramirez *et al.* 2001).

In 1991, Dynamic matrix control (DMC), based on linear model based prediction, was developed and applied on gas fired SCPP process model to control the main steam temperature, main steam pressure, and electrical power of the plant. The model had been

identified by field tests and the control strategy was tested on simulator kit (SIMKIT) written in FORTRAN. Simulations results showed feasible controller performance (Rovnak et al. 1991).

Gibbs et al. 1991 reported the performance of nonlinear model predictive control (NMPC), based on reduced order nonlinear model, and implemented the controller on a gas fired SC operating unit. The controller was applied to control the main steam temperature and hot reheater temperature despite some load changes.

MPC was reported by (Trangbaek. 2008), based on linear state space model, for constrained control of once-through 400MW gas fired unit. Because the author intended to control the plant from 15% to 50% to include the mode of recirculation, the operation of the plant in SC conditions was not necessary. As in (Rovnak et al. 1991), the controller was applied on nonlinear process model that created in MATLAB[®] environment and simulation results show successful performance for some operating region without violating the plant operation restrictions and constraints.

(Lee. *et al* 2007, Lee. *et al* 2010) presented the performance of diagonal recurrent neural network (DRNN) for modeling and control of SC and USC coal fired power plants. In that research, the NN was used to model the plant subsystems individually and they were combined together to form the complete process of the stations (500MW and 1000MW operating units). Then, the authors designed what they called (modified optimal predictive control) also by NN and all set-points are nicely tracked.

In this thesis, the SCPP process model described in the previous chapters has been incorporated with discrete time MPC, based on an identified internal linear model for predication. The identified linear model is a low order state space model created by GA and tuned to match the original process model which is regarded as the plant to be controlled. In some research, it is called an “internal” because to it is the major part of MPC prediction algorithm. The control target is to control the electrical power, main steam temperature, and main steam pressure of the plant by the controllable variables (fuel flow, feedwater flow, and valve position). Two main contributions are newly added in this research:

- 1- Instead of direct control signal applications as in previous research of SCPP control, the optimal control signals are used as correction or adjuster to the reference of the plant local controls. One is sent to the mill local control system to improve the grinding capability, the second is sent to command the feedwater flow, and the third is sent to the reference of the turbine governor for optimal valve positioning. This idea is based on the fact that the model that is used to simulate SCPP responses has been initially identified with closed loop data so the signals of the MPC have to be sent to the reference of plant local controls. Also, there is no need to replace the existing controls and the fulfilment of the load requests while keeping optimal efficiency is the main target of the overall control system.
- 2- Because the mill has already been integrated to the rest part of the plant, it is found that the power primary response can be significantly improved through the primary air fan and feeder speed of the mill. If the amount of optimal coal flow is predicted in advance and the local control of the mill is properly adjusted, there will be more stored coal in the mill sufficient to give quicker response and pulverized coal

discharging. Thereby it shows that the milling conditions play an important role in satisfying the UK grid code demand. Unlike previous attempt reported in (Zindler *et al* 2008) which the condensate stoppage is proposed to speed-up the power response. The MPC fuel signal is used with the mill local control to speed-up the mill response and subsequently the power primary response.

The theory of MPC and its optimization technique is studied from detailed specialized texts (Fletcher. 1987, Maciejowski. 2002, Boyd *et al.* 2004, Wang. 2010). The MPC performance is tested with some load changes with consideration of output disturbance and measurement noises generalized from prediction algorithms and the MPC shows good performance results which are reported in separate section in the next chapter. Another control schematic is investigated which is based on three MPCs working to regulate three different operating regions of the plant. The switching mechanism from one MPC to another is based on the unit load demand. This provides wider range for controlling the plant and this version of results is also reported in the next chapter. Finally, another control scheme is investigated which employ a MIMO dynamic compensator with the MPC and tuned with GA to eliminate the error generated from such large load changes. The different three schematic of control and their performance results are reported in three different sections in the next chapter.

6.3 Introduction to Receding Horizon Principle

The principle of receding horizon is defined as “although the optimal trajectory of future control signal is completely described within the moving horizon window, the actual control input to the plant only takes the first sample of the control signal, while neglecting the rest of the trajectory”(Wang 2010). However, it is important to understand this concept

in more detail. Consider, for instance, Fig. 6.1 that demonstrates the basic predictive control principle. In theory, it is desired to consider single input- single output SISO system to understand the concept before extension to MIMO systems.

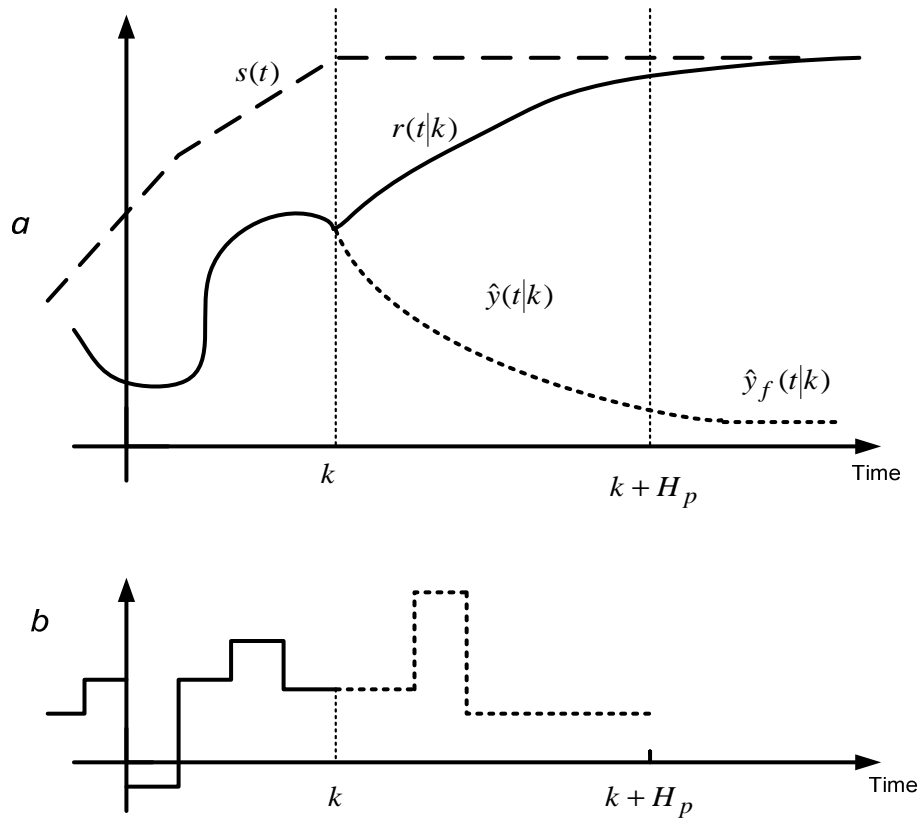


Fig. 6.1 The basic idea of predictive control (Maciejowski. 2002)

The MPC internal models, which are currently used in practice, are usually identified linear models for simplicity of predictive control (Maciejowski. 2002). The internal models are digitized or discretized for on-line implementation so it is desirable to assume discrete time with current time labelled as k .

The set-point trajectory is $s(t)$. The reference trajectory is distinct from the set point trajectory. This begins at the current output at k which is $y(k)$, and indicates a perfect trajectory which the system should return to the set-point trajectory, for example, after disturbance happens. The reference trajectory then defines a significant feature of the closed loop performance of the controlled plant. It is repeatedly assumed that the reference trajectory approaches the set-point exponentially from the current output amount, with the “time constant”, which we will denote T_{ref} , defines the speed of the response (Maciejowski. 2002).

That is, if the current error is:

$$\mathcal{E}(k) = s(k) - y(k) \quad (6.1)$$

then the current trajectory is chosen such that the error i steps later, if the output followed it exactly, would be

$$\mathcal{E}(k+i) = e^{-iT_s/T_{ref}} \mathcal{E}(k) \quad (6.2)$$

where T_s is the sampling interval and the reference trajectory is:

$$r(k+i|k) = s(k+i) - \mathcal{E}(k+i) \quad (6.3)$$

$$= s(k+i) - e^{-iT_s/T_{ref}} \mathcal{E}(k) \quad (6.4)$$

The notation $r(k+i|k)$ shows that the trajectory of the reference is dependent on the conditions at time k , in general. A straight line which starts from the current output reaches the set point trajectory after a certain time (Maciejowski. 2002).

Model predictive control has a local model which is used to predict the plant response for a specific horizon H_p . This predicted response depends on the assumed input trajectory $\hat{u}(k+i/k)$ ($i=0,1,\dots,H_p-1$) that is, to be applied over a horizon of prediction and the idea is to choose the input moves which give the optimal predicted behavior. The notation \hat{u} instead of u defines that at time k we only have the output a prediction of what the input at time k may be; the actual input $u(k+i)$, is likely to be not $\hat{u}(k+i/k)$ and the output $y(k)$ is given by the past control moves $u(k-1), u(k-2)\dots$, but not on the input $u(k)$ (Maciejowski. 2002).

As a simple case we can attempt to select the input trajectory such as to match the plant output to $r(k+H_p)$ at H_p . There are many input trajectories which perform this, and we could select one of them, for instance, the one which needs the lowest input energy. Fig 6.1 the diagram labelled with b shows the input assumed to change over the first three samples of the prediction horizon, but remain fixed thereafter: $\hat{u}(k+2/k) = \hat{u}(k+3/k) = \dots, \hat{u}(k+H_p-1/k)$. Once the input trajectory is selected, only the first element of that trajectory is used as input control signal to the plant. Then the process of output measurement, prediction, and input trajectory determined is repeated, one sampling later: a recent output measurement is given $y(k+1)$; a reference trajectory $r(k+i|k+1)$ ($i=2,3,\dots$) is defined; a prediction is performed for a horizon $k+1+i$ with $i=1,2,\dots,H_p$. a new input trajectory $\hat{u}(k+i|k+1)$, with $i=1,2,\dots,H_p-1$ is chosen, and the next input is sent to the plant $u(k+1) = \hat{u}(k+1|k+1)$, this approach of controlling a system or process is usually called receding horizon control (Maciejowski. 2002).

6.4 Prediction

The most understandable model structure that is widely used to formulate the prediction algorithms is discrete-time state space format (Maciejowski 2002) (Wang 2010). So we have;

$$x(k+1) = Ax(k) + Bu(k) \quad (6.7)$$

$$y(k) = Cx(k) \quad (6.8)$$

If $C=I$ and the whole state vector is measurable, i.e. $\hat{x}(k) = x(k) = y(k)$. By iterating (6.7) and (6.8) we have;

$$\hat{x}(k+1|k) = Ax(k) + B\hat{u}(k|k) \quad (6.9)$$

$$\begin{aligned} \hat{x}(k+2|k) &= Ax(k+1|k) + B\hat{u}(k+1|k) \\ &= A^2x(k) + AB\hat{u}(k) + B\hat{u}(k+1|k) \\ &\vdots \\ \hat{x}(k+H_p|k) &= A^{H_p}x(k) + A^{H_p-1}B\hat{u}(k|k) + \dots + B\hat{u}(k+H_p-1|k) \end{aligned} \quad (6.10)$$

Since $\Delta\hat{u}(k+i|k) = \hat{u}(k+i|k) - \hat{u}(k+i-1|k)$. Then we have:

$$\begin{aligned} \hat{u}(k|k) &= \Delta\hat{u}(k|k) + u(k-1) \\ \hat{u}(k+1|k) &= \Delta\hat{u}(k+1|k) + \Delta\hat{u}(k|k) + u(k-1) \\ &\vdots \\ \hat{u}(k+H_u-1|k) &= \Delta\hat{u}(k+H_u-1|k) + \dots + \Delta\hat{u}(k|k) + u(k-1) \end{aligned}$$

Substituting these input equations to (6.9) to (6.10) to have the prediction format expressed in terms of $\Delta\hat{u}(k+i|k)$ rather than $\hat{u}(k+i|k)$ we get;

$$\hat{x}(k+1|k) = Ax(k) + B[\Delta\hat{u}(k|k) + u(k-1)]$$

$$\hat{x}(k+2|k) = A^2x(k) + AB[\Delta\hat{u}(k|k) + u(k-1)] + \underbrace{B[\Delta\hat{u}(k+1|k) + \Delta\hat{u}(k|k) + u(k-1)]}_{\hat{u}(k+i|k)}$$

$$= A^2x(k) + (A+I)B\Delta\hat{u}(k|k) + B\Delta\hat{u}(k+1|k) + (A+I)Bu(k-1)$$

$$\begin{aligned}\hat{x}(k+H_u|k) &= A^{H_u}x(k) + (A^{H_u-1} + \dots + A + I)B\Delta\hat{u}(k|k) + \dots + B\Delta\hat{u}(k+H_u-1|k) \\ &\quad + (A^{H_u-1} + \dots + A + I)Bu(k-1)\end{aligned}$$

$$\begin{aligned}\hat{x}(k+H_u+1|k) &= A^{H_u+1}x(k) + (A^{H_u} + \dots + A + I)B\Delta\hat{u}(k|k) + \dots + (A+I)B\Delta\hat{u}(k+H_u-1|k) \\ &\quad + (A^{H_u} + \dots + A + I)Bu(k-1)\end{aligned}$$

\vdots

$$\begin{aligned}\hat{x}(k+H_p|k) &= A^{H_p}x(k) + (A^{H_p-1} + \dots + A + I)B\Delta\hat{u}(k|k) + \dots + \\ &\quad \dots (A^{H_p-H_u} + \dots + A + I)B\Delta\hat{u}(k+H_u-1|k) \\ &\quad + (A^{H_u} + \dots + A + I)Bu(k-1)\end{aligned}$$

Finally the prediction equation in matrix format;

$$\begin{aligned}
\begin{bmatrix} \hat{x}(k+1|k) \\ \vdots \\ \hat{x}(k+H_u|k) \\ \hat{x}(k+H_u+1|k) \\ \vdots \\ \hat{x}(k+H_p|k) \end{bmatrix} &= \underbrace{\begin{bmatrix} A \\ \vdots \\ A^{H_u} \\ A^{H_u+1} \\ \vdots \\ A^{H_p} \end{bmatrix} x(k) + \begin{bmatrix} B \\ \vdots \\ \sum_{i=0}^{H_u-1} A^i B \\ \sum_{i=0}^{H_u} A^i B \\ \vdots \\ \sum_{i=0}^{H_p-1} A^i B \end{bmatrix} u(k-1)}_{\text{past}} + \\
\underbrace{\begin{bmatrix} B & \cdots & 0 \\ AB+B & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \sum_{i=0}^{H_u-1} A^i B & \cdots & B \\ \sum_{i=0}^{H_u} A^i B & \cdots & AB+B \\ \vdots & \vdots & \vdots \\ \sum_{i=0}^{H_p-1} A^i B & \cdots & \sum_{i=0}^{H_p-H_u} A^i B \end{bmatrix}}_{\text{future}} \begin{bmatrix} \Delta \hat{u}(k|k) \\ \vdots \\ \Delta \hat{u}(k+H_u-1|k) \end{bmatrix} & \quad (6.11)
\end{aligned}$$

Or

$$X = Fx(k) + Gu(k-1) + \Phi \Delta U \quad (6.12)$$

However, there are other factors that may influence the controller's decision. In practical applications and industry, unpredicted restrictions, disturbances, or process nonlinearity are able to amend the values that are actually used in the plant. If the actual values are known and fed back to the controller, its predictions will be enhanced. With consideration of disturbances acting on the plant outputs which formulate any unexpected events that may occur on the plant output. Then the internal model prediction should be augmented by the disturbance model. It might be considered as constant over a prediction horizon or can be considered as collection of integrators driven by white noise. As a result of this, the

disturbances due to, for example, gain nonlinearity, are safely rejected (Trangbaek. 2008 , Bemporad 2010, Lee. 2010). Also, the measured output can be assumed to be corrupted by random Gaussian noise that satisfies the noisy nature of thermal power plant. These impacts can be easily formulated by the MPC tool in MATLAB[®] through the tab of estimation which includes output disturbance and measurement noises on the plant output. Though the consideration of such states is optional, the internal state space model used to formulate the predictive control algorithm is then amended as (Ricker. 1990, Poncia et al. 2001, Bemporad *et al.* 2010):

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + B_u\mathbf{u}(k) + B_v\mathbf{v}(k) + B_w\mathbf{w}(k)$$

$$\begin{aligned} \mathbf{y}(k) &= \mathbf{y}(k) + \mathbf{z}(k) \\ &= C\mathbf{x}(k) + D_u\mathbf{u}(k) + D_v\mathbf{v}(k) + D_w\mathbf{w}(k) + \mathbf{z}(k) \end{aligned}$$

where \mathbf{x} is a vector of states. \mathbf{u} is the inputs vector, \mathbf{v} is the measured disturbance and \mathbf{w} is the unmeasured disturbance vector, \mathbf{z} is the measurement noise. By adding these extra states, the quality of prediction and control will be improved. They can be easily amended/modified by the provided MPC tool. This subject is addressed in more detail in the literature (Bemporad *et al.* 2010, Morari *et al.* 1998) as this section and the whole chapter only covers the theoretical parts which are related to the main research objectives.

6.5 Optimization of control signals

The control task is basically translated into a computation of the best control signals such that the objective function or error function between the plant output and set point signal is minimized (Wang 2010). The solution of this problem is found by quadratic programming (QP) procedure. This problem has been studied in detail in the literature of mathematical

optimization (Fletcher. 1987, Boyd et al. 2004). This section gives the related theory and algorithms of this optimization problem. The control task is to minimize;

$$\xi(k) = \sum_{i=H_w}^{H_p} \left\| \hat{\mathbf{y}}(k+i|k) - \mathbf{r}(k+i|k) \right\|^2 \mathbf{Q}(i) + \sum_{i=0}^{H_c-1} \left\| \Delta \hat{\mathbf{u}}(k+i|k) \right\|^2 \mathbf{R}(i) \quad (6.13)$$

Subject to,

$$\mathbf{u}_{min} \leq \mathbf{u} \leq \mathbf{u}_{max} \quad (6.14)$$

$$\Delta \mathbf{u}_{min} \leq \Delta \mathbf{u} \leq \Delta \mathbf{u}_{max} \quad (6.15)$$

The weighting coefficient matrices (\mathbf{Q} and \mathbf{R}) are vectors which affects the optimization routine and input penalties, the control interval (H_w), the prediction and control horizons (H_p , H_c), all these parameters are used to tune the MPC and they mainly affect the performance of the controller and computation time demands. They can be decided by trying to simulate different scenarios or events during controller implementation (Rovnak et al. 1991, Trangbaek. 2008). Here, \mathbf{u} and \mathbf{y} are the input and output vectors respectively, The term \mathbf{r} is a vector represents the demand outputs as references for MPC. The input/output constraints are determined according to the plant operation restrictions, which are expressed as the maximum and the minimum allowable inputs. The recent QP formula is not as (6.13), but rather it should be expressed in one variable for feasible and simplified optimization. The error vector can be expressed in terms of the input or input moves as

detailed in (Maciejowski 2002); the input or input moves are the changed in such a way to minimize the objective function in (6.13) which can be written more generally as:

$$\min_{\theta} \frac{1}{2} \theta^T \Phi \theta + \Phi^T \theta \quad (6.16)$$

Subject to

$$\Omega \theta \leq \Theta \quad (6.17)$$

and

$$H \theta = h$$

which is the conventional form of QP optimization. θ plays the role of input or input moves Δu and (6.15) is the constraints which are gathered from the plant operating restrictions. It is apparent that Φ depends mainly on the values of vectors \mathbf{Q} and \mathbf{R} in (6.13). If Φ is positive definite, the convexity of the optimization problem, and consequently the termination of optimization problem, is guaranteed. Thereby the enough conditions for θ to have a unique optimum solution are given by Kraush-Kuhn-Tucker (KKT) conditions, Lagrange multipliers vectors must be existed $\lambda \geq 0$, and ζ and $t \geq 0$ (Fletcher. 1987, Maciejowski 2002, Wang. 2010) so that

$$\Phi \theta + H^T \zeta + \Omega^T \lambda = -\Phi \quad (6.16)$$

$$-H \theta = -h \quad (6.17)$$

$$-\Omega \theta - t = -\Theta \quad (6.18)$$

$$t^T \lambda = 0 \quad (6.19)$$

Solving this optimization problem is strait forward then by setting the gradient of the cost functions to zero and find the control inputs numerically. There are two methods which are currently used active set method and interior point method.

6.5.1 Active set method:

Most QP optimization problems include inequality constraint and therefore they can be formulated in the structure (6.14), (6.15) (Fletcher. 1987). This section is to briefly describe this method of solving QP problems. The concept of active set approach is to show at each iterative step of an algorithm a set of constraints, which is to be treated as the active set or working subset (Wang. 2010). The active constraints are regarded as equality $\Omega_a \theta = \Theta_a$ subset. Assume that there is a feasible solution θ_r at the iteration r . The active set method provides the better (i.e. more converged) solution $\theta_r + \Delta\theta$ which minimizes (6.14) while the constraints ($H\theta = h$ and $\Omega_a \theta = \Theta_a$) are of course satisfied. If the current point is feasible (i.e. $\Omega (\theta_r + \Delta\theta) \leq \Theta$), then it is approved as next iterative step. If not, the search is performed in $\Delta\theta$ to find the point in which the inequality inactive constraints should be active. The current found point is regarded to be the next iteration and so on (Fletcher. 1987, Maciejowski 2002). Solving the equality constrained optimization problem is by Lagrangian methods. As stated in (6.16)-(6.19) and computing the Lagrange multipliers in each step until termination occurs when $\theta^{op} = \theta_r$ and that the KKT conditions are satisfied. Some illustrative examples are mentioned in (Fletcher. 1987, Wang. 2010) for those who are more interested in more detail.

6.5.2 Interior point method

Interior point method is an alternative method of solving convex optimization problems. Unlike the active set method which searches the points on the bounds of the feasible region from one iteration to another, this method makes its search on the interior of the feasible region. Assume that the function $V(x)$ is the objective function to be minimized and subjected to the constrain $Ax \leq b$. the interior point method modifies the cost function to be minimized to the function

$$f(x, \gamma) = \gamma \cdot V(x) - \underbrace{\sum_i \log(b_i - a_i^T x)}_{\text{barrier function}} \quad (6.20)$$

In (6.20), γ is positive scalar, a_i^T is the i th row of the matrix A , and b_i is the i th element of the vector b . The addition of logarithmic term in (6.20) ensures that the search is in the feasible region. In other words, it prevents the search from going away from the feasible region because it will be infinite in the boundaries of the feasible region. Suppose that x_γ is the optimal solution of $f(x, \gamma)$ and x^* is the optimal solution of the original objective function $V(x)$ with constraints satisfaction. x_0 lies on the interior of the feasible region and should be independent of the objective function $V(x)$. If an initial feasible iteration is around x_0 , it can be converged to the optimal solution continuously by increasing γ and minimizing $f(x, \gamma)$ until x^* has no significant mismatch with x_0 (Maciejowski 2002).

It is however found that the optimization algorithms used in predictive control is simple enough to be used on-line or applied in practice as it is compatible with real-time operation of power plant. For those who are interested in applications of MPC, based on an linear models, in subcritical and supercritical power plants, please refer to the literature which are available online (Rossiter *et al.* 1991 , Rovnak *et al.* 1991, Lu *et al.* 1997, Poncia *et al.* 2001, Li *et al.* 2006 , Trangbaek. 2008, Choi *et al* 2010, Moon *et al.* 2010).

6.6 Illustration example

It is desirable to show the performance of MPC before applying it to the SCPP model. The example which has been adopted in this thesis is the paper machine model which is found in model predictive control user's guide and widely used in the literature (Morari *et al.* 1998 , Maciejowski 2002 , Bemporad *et al.* 2010). This shall be discussed in this section with some simulation results and findings/conclusions that are deduced from the performance results.

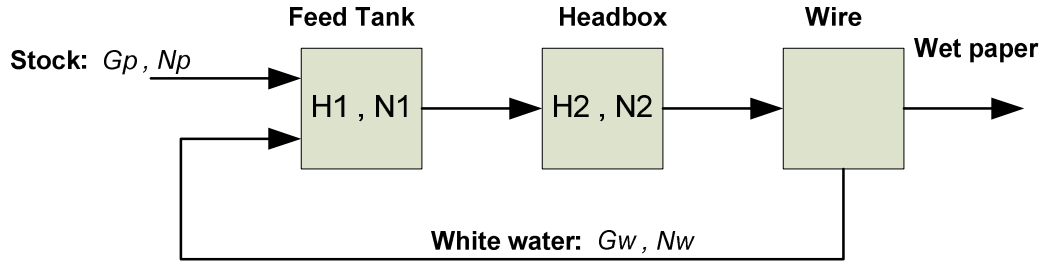


Fig 6.2 Paper Machine Headbox

The paper machine headbox is shown in Fig. 6.2, the model has two manipulated variable and three outputs to be controlled. The model states are:

$$x = [H_1 \quad H_2 \quad N_1 \quad N_2]^T$$

where H_1 is the level of the liquid in the feed tank, H_2 is the liquid level in the headbox, N_1 is the consistency of the feed tank, and N_2 is the headbox consistency. The system measurable outputs are:

$$y = [H_2 \quad N_1 \quad N_2]^T$$

The main control task is to maintain H_2 and N_2 at their reference set points. The model manipulated variables or inputs:

$$u = [G_p \quad G_w]^T$$

where G_p is the stock flow rate into the feed tank, and G_w is the recycled flow rate of white water. The stock consistency flowing into the feed tank, N_p , is a measured disturbance and the consistency of the white water N_w is unmeasured disturbance.

All system variables are normalized; all of them are zero at steady state nominal conditions. In MATLAB® the nonlinear model is implemented in SIMULINK® S-function (See the appendix) and prepared for controller implementation.

The linearized model:

$$A = \begin{bmatrix} -1.93 & 0 & 0 & 0 \\ 0.394 & -0.426 & 0 & 0 \\ 0 & 0.63 & 0 & 0 \\ 0.82 & -0.78 & 0.413 & -0.426 \end{bmatrix}, B = \begin{bmatrix} 1.274 & 1.274 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1.34 & -0.65 & 0.203 & 0.406 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, D = \text{Zeros}(3,4)$$

In order to show that all manipulated variables are affecting all outputs, the step response test has been made on the model (the same as that applied on SCPP model in the Chapter.5), the results are demonstrated in Fig 6.3 and 6.4.

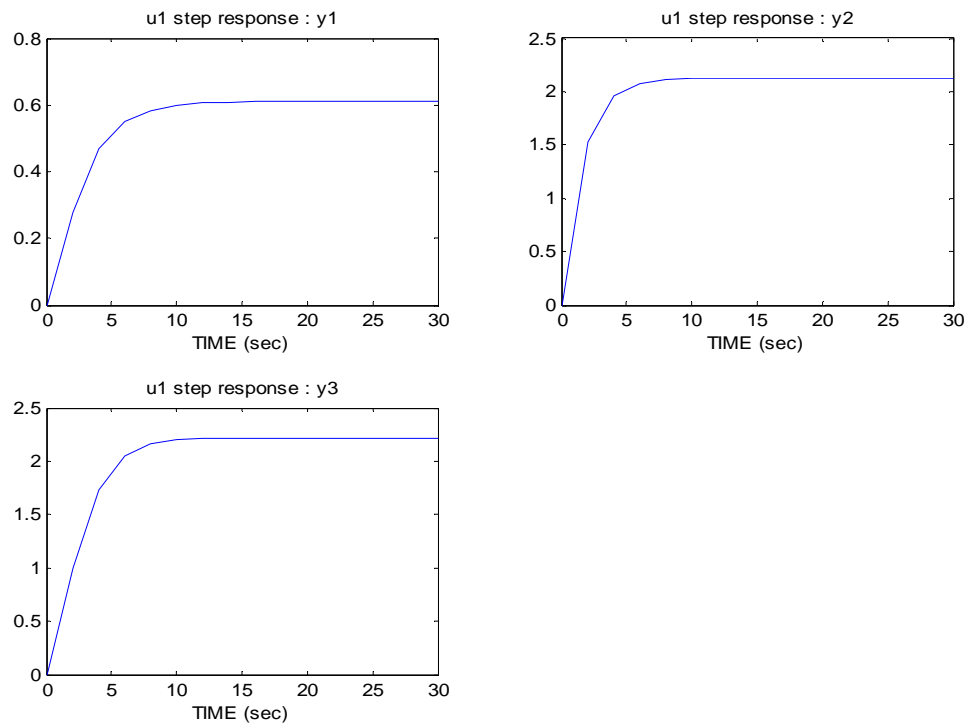


Fig 6.3 The impact of the 1st input on the all system outputs

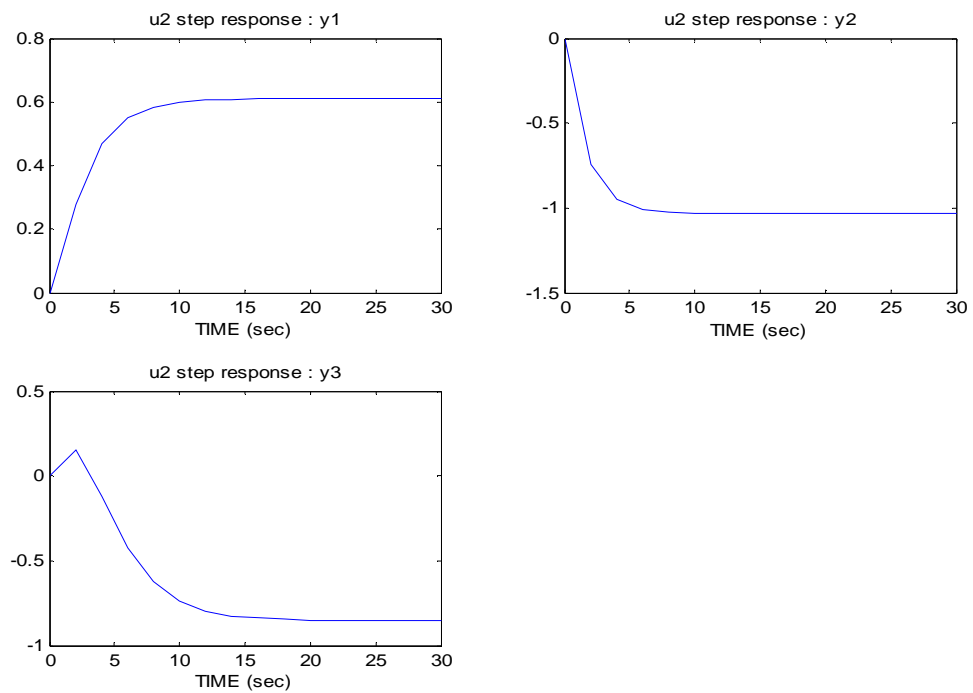


Fig 6.4 The impact of the 2nd input on the all system outputs

6.6.1 Controller design and application on paper machine nonlinear model as plant

This subsection shows the controller performance on the nonlinear model which is more important and closer to the real applications. The prediction horizon was chosen to be 10 sampling intervals for reasonable computation burden, the control horizon is 2. The MPC initial parameters are in Matlab workspace as:

Sampling time: 1

Prediction horizon: 10

Control horizon: 2

The nonlinear model is created in M-File S-Function type called `mpc_pmmode1.m`. and already embedded in MATLAB[®] directory for this study. The M-File has been reported in the appendix to avoid too much information here. The SIMULINK[®] diagram which includes the plant and its controller is shown in Fig 6.5.

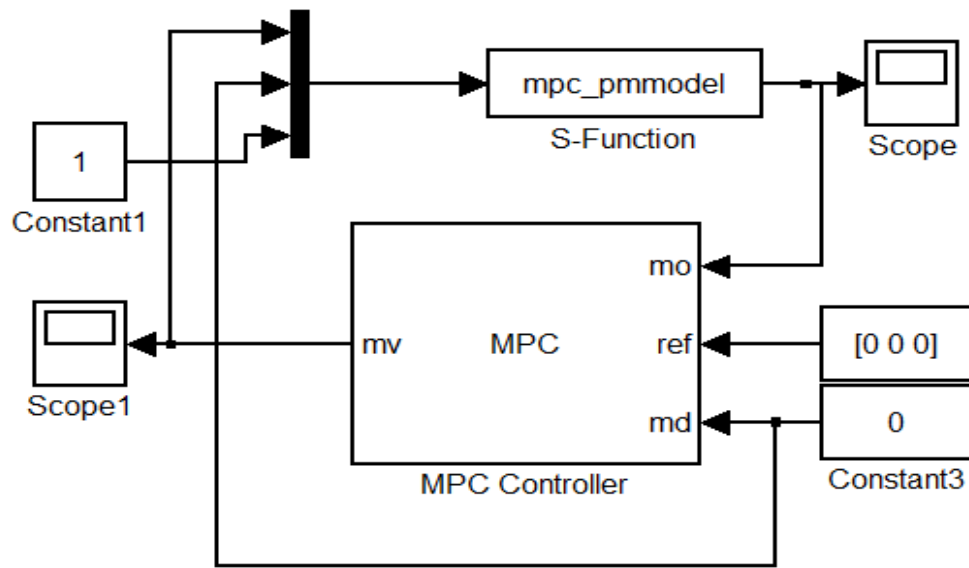


Fig. 6.5 Model-based predictive control applied on paper machine nonlinear model

In some tests, the MPC provide good ability for tracking the set point with zero steady state error (Fig 6.6 and 6.7). The performance is still acceptable with small changes in the set points (see Fig 6.8 and 6.9) or small disturbances (see Fig 6.10 and 6.11). As the reference magnitude increases or the unmeasured disturbance increases, a small offset starts to appear between the set point and process model output response (See Fig 6.12 and 6.13 for disturbance size of 9). It is believed that this is due to the process nonlinearity and also because the number of manipulated variables is less than the output variables to be controlled. The MPC tool is found to be effective tool for regulating many processes including SCPP control which indicates that the dynamic response of SCPP can be further studied, investigated, and improved through this controller theory and its associated computer tool.

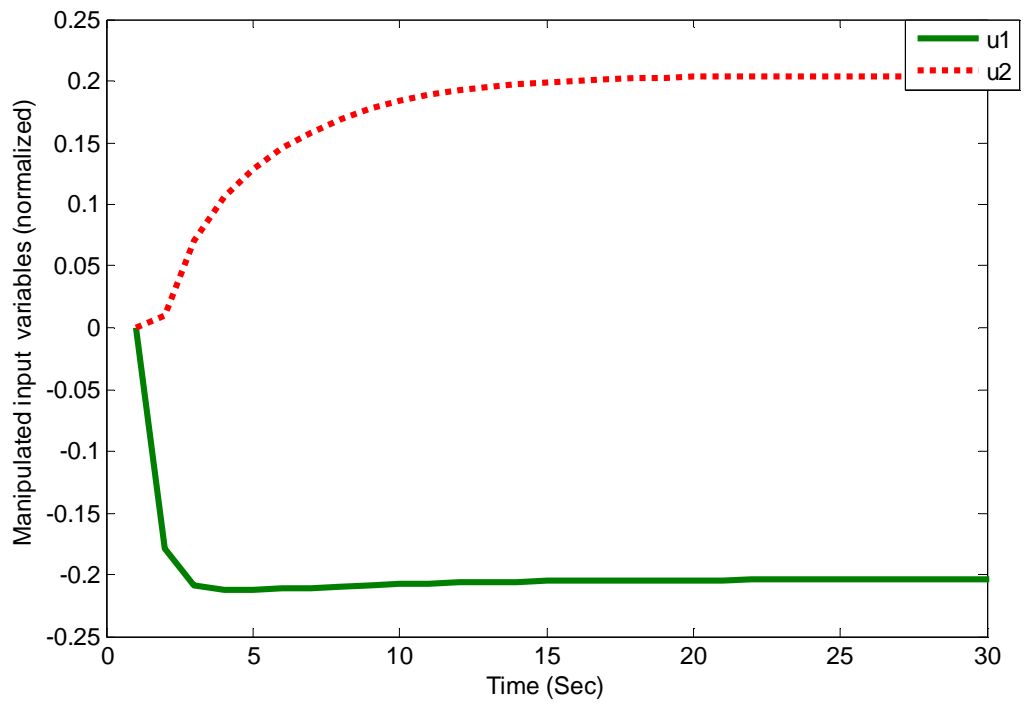


Fig 6.6 Manipulated inputs for set point $[0 \ 0 \ 0]$ disturbance size=1

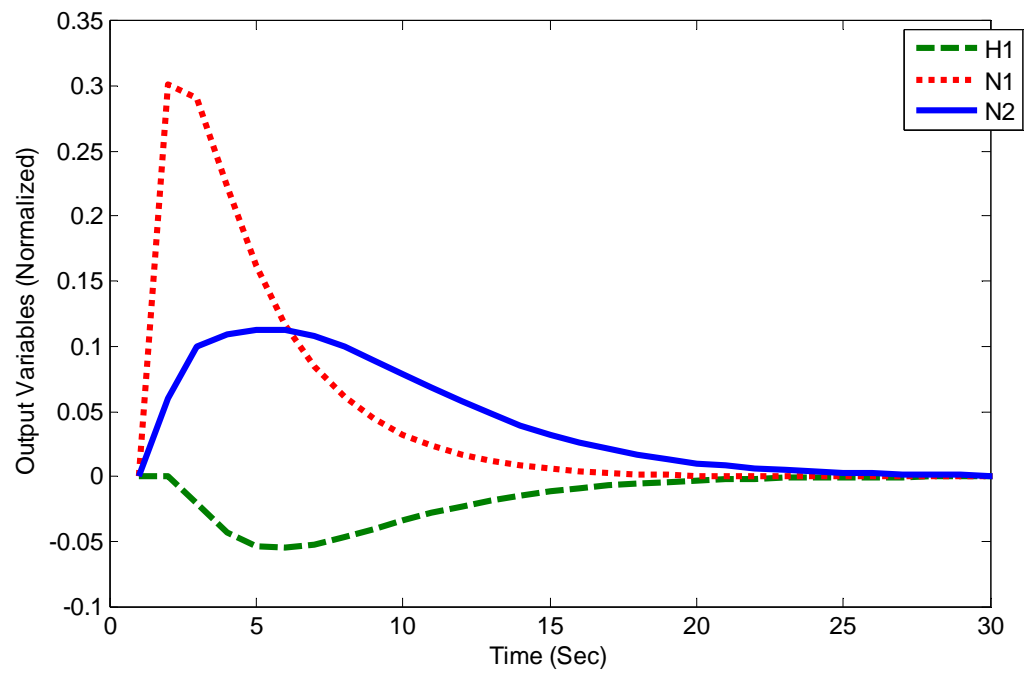


Fig 6.7 Output variables (Controlled variables) $[0 \ 0 \ 0]$ disturbance size=1

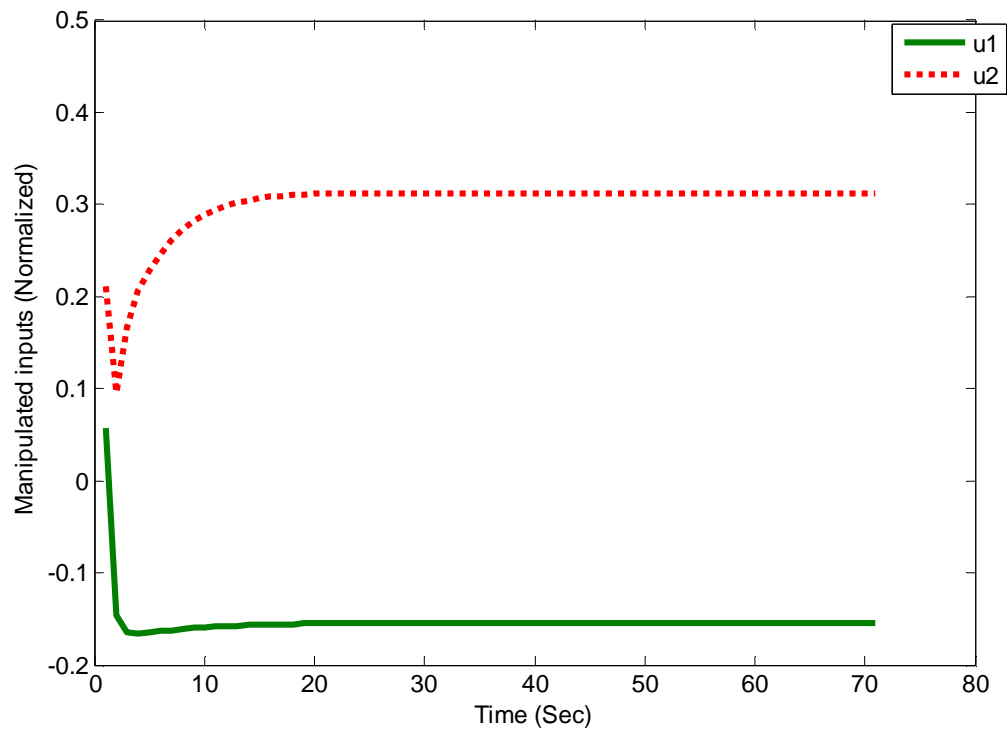


Fig 6.8 Manipulated inputs for set points of [0.1 0 0.02] disturbance size=1

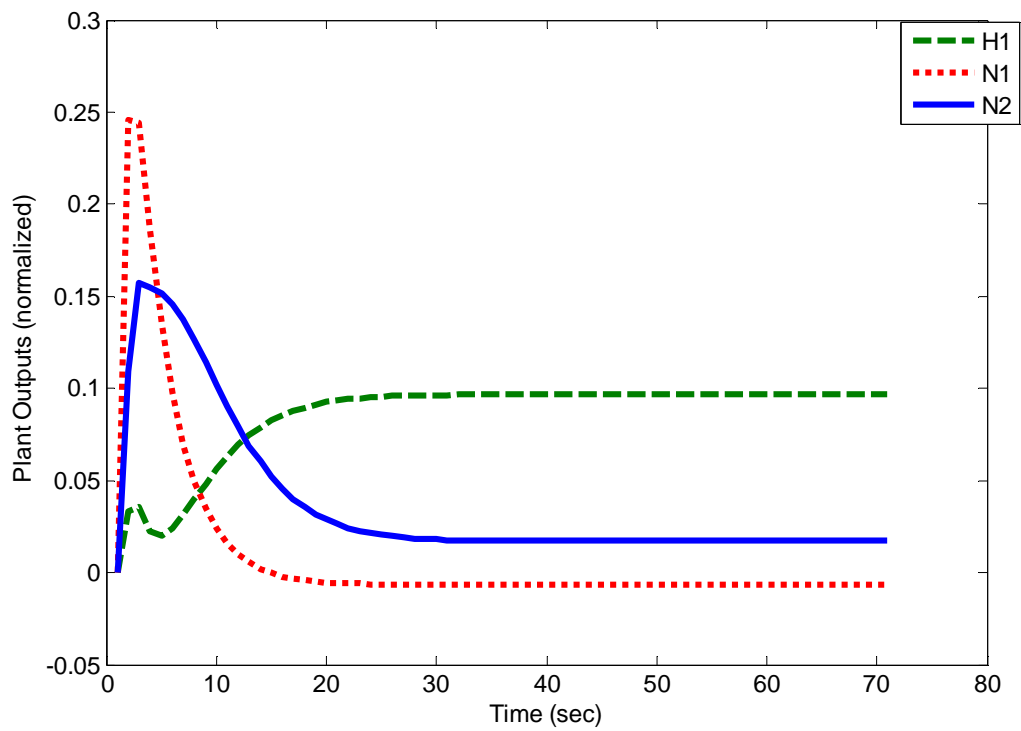


Fig 6.8 Output Variables for set points of [0.1 0 0.02] disturbance size=1

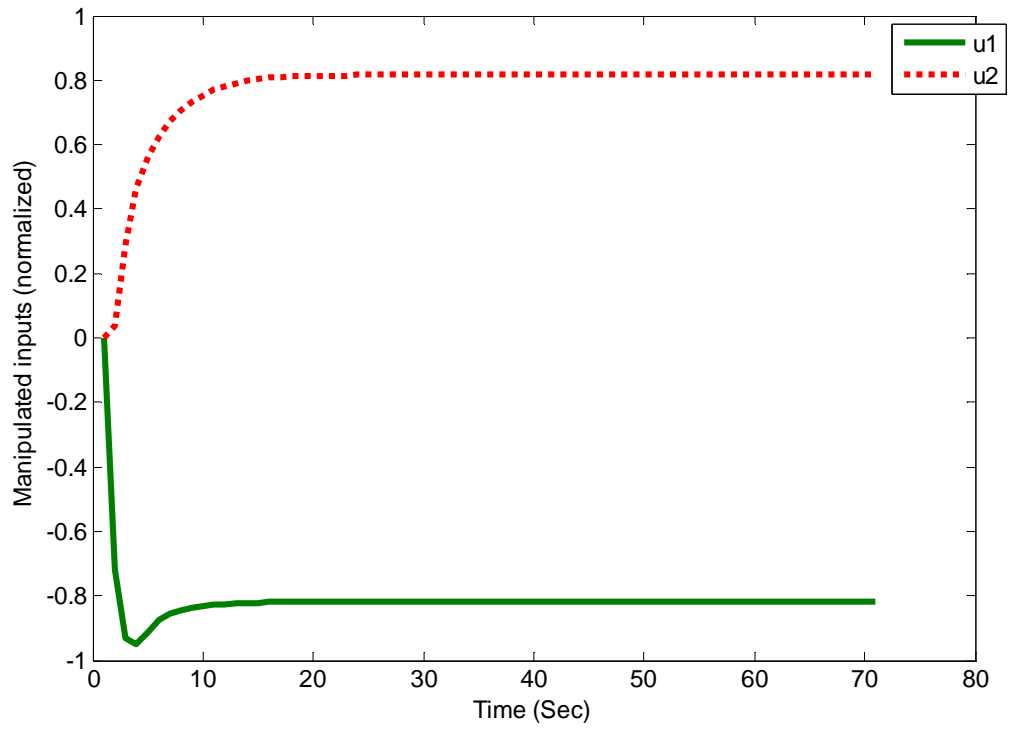


Fig 6.10 Manipulated inputs for set points $[0 \ 0 \ 0]$ and disturbance size of 4

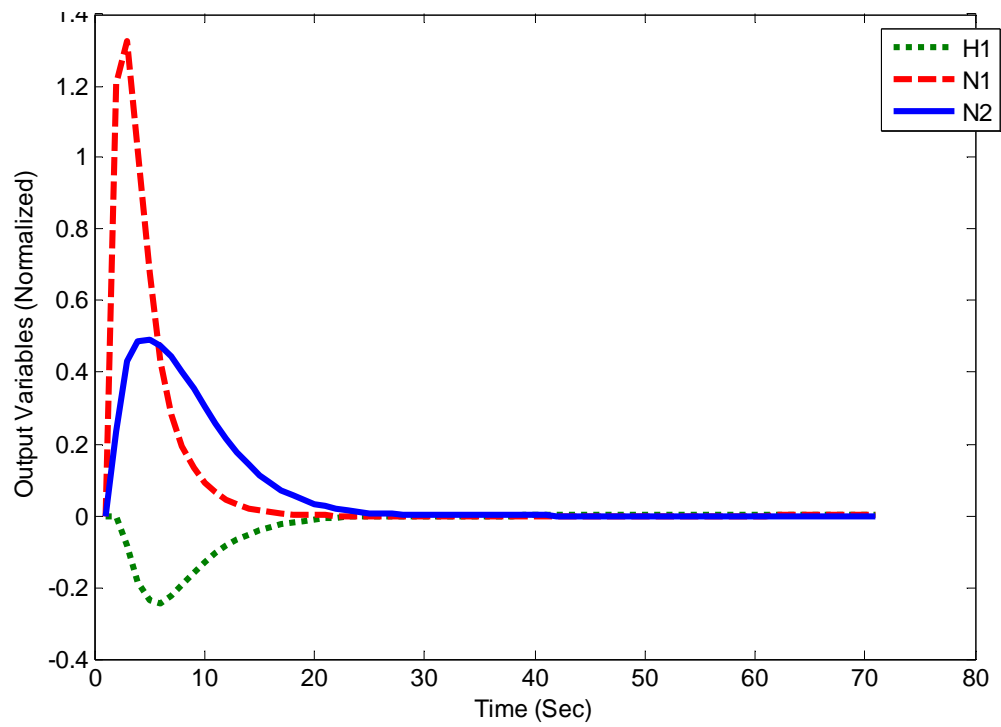


Fig 6.11 Output variables for set points $[0 \ 0 \ 0]$ and disturbance size of 4

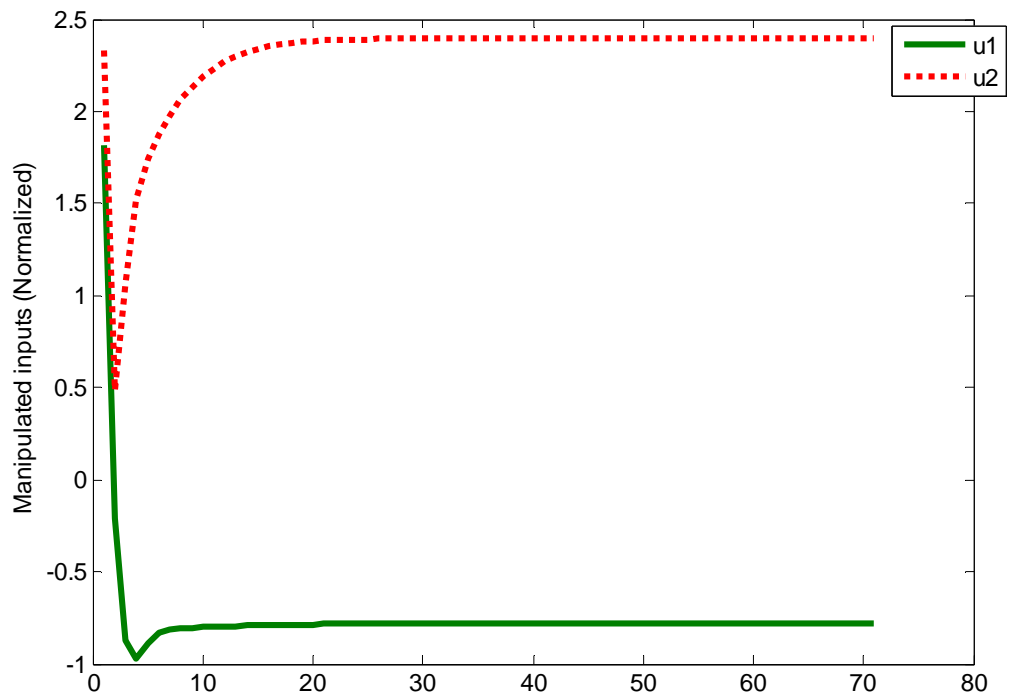


Fig 6.12 Manipulated Inputs for set points [1 1 1] and disturbance size of 9

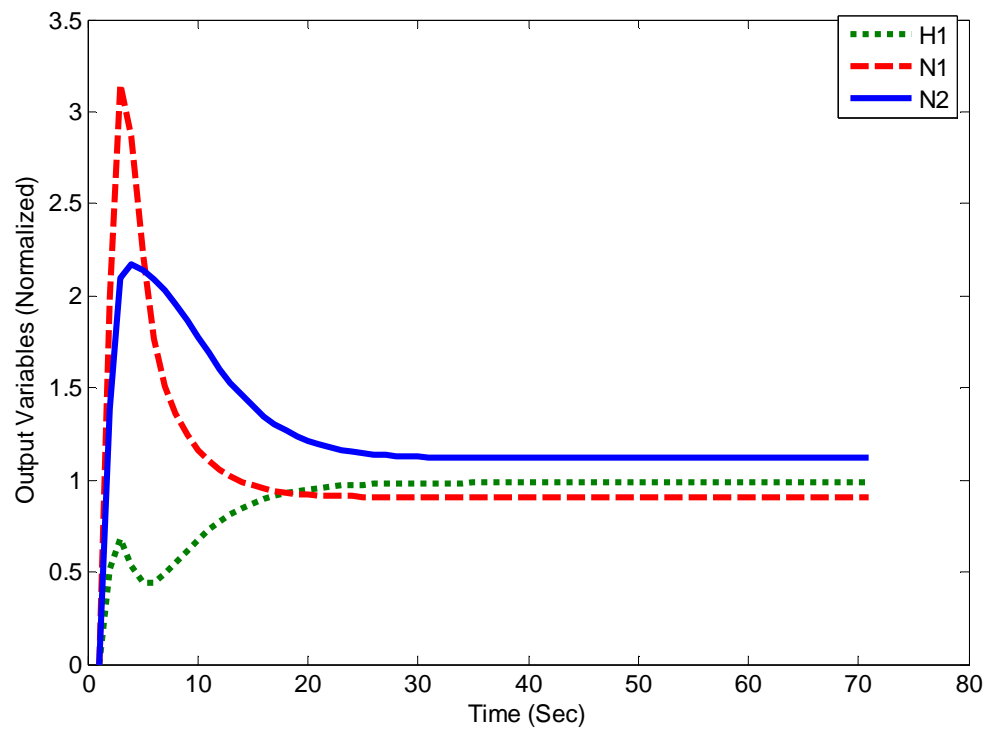


Fig 6.13 Output variables for set points [1 1 1] and disturbance size of 9.

6.7 Summary

This chapter introduces the principles of model-based predictive control strategy. The choice of this strategy is due to its simplicity, applicability in practice and successful performance from the history of SCPP control. Among many published research the contribution of this research work is reported. The concepts of receding horizon idea, prediction, are discussed very briefly. The future optimization is reported for two well recognized methods which are currently used to solve the QP problem. As an example for applications of MPC, its performance is tested on nonlinear paper machine headbox model. This is actually regarded as preparation to the next chapter which include many simulation results of SCPP dynamic responses to many load change demands and results discussion.

Chapter 7

MPC Control of a Supercritical Power Plant and Simulation Study

7.1 Introduction

This chapter presents MPC control and simulation study of a supercritical coal fired power plant control. The developed process model has been adopted to simulate the power plant responses. Generally, Coal firing power plant is a complex process that contains multi-inputs multi-outputs and high nonlinearity due to thermal and chemical processes. The challenges in control of supercritical power plants are still available because of their complexity and the difference in power grid codes and regulations from country to another. The chapter is divided as follows: First, the predictive control described in chapter 6 has been implemented on the plant process model. However, it is found that the MPC performance are acceptable within small and medium load changes. The predictive control has been extended to include three switchable MPCs to control the plant behaviour over a wider operating range and large amounts of load demand changes. Each MPC is designed to control certain operating region by three different unmeasured disturbances and internal augmented models for the three MPCs. Simulations show good controller performance for small and large load changes. Finally, another controller scheme is tested which is based on using parallel compensator with the MPC and again the simulation results are conducted. In all controller schemes, the simulation results are conducted in different control settings of the local control of the mill to show their influences on the plant output responses. From

these simulations it is deduced that the coal milling capabilities play an important role in improving the SSCP dynamic responses.

7.2 Configuration of the control strategy

As mentioned in Chapter 6, the signals of the multivariable controller or MPC are used to adjust the reference of the plant local control. This section describes how the MPC is implemented in the control strategy proposed. Fig 7.1 shows the controller block diagram and its signals are labeled to show how each control inputs is related to the current plant process. The fuel control signal is sent to the mill local control as reference adjuster. In particular, the milling process is regulated by three controllers. A controller regulates the coal feeder speed based on the demand value. One controller is used to control the primary fan speed or power output, which will in turn tune the Pulverized coal (fuel) flow rate to the furnace. Another controller is the temperature controller, which regulates the hot air flow input to control the mill temperature. Then the MPC coal flow signal is used as reference adjuster signal to these controllers for regulating the pulverized coal flow (the mill output).

The other two control signals from the MPC are sent to the feedwater flow reference of the boiler and the turbine valve governor. The use of feedwater flow as the additional input is found to be useful in regulating the boiler pressure and temperature when the fuel firing is raised or lowered. The final input to the plant is the turbine valve. The plant turbine governor is a digital-electro-hydraulic (DEH) governor which is the most popular scheme of governors for large scale power plant. The DEH actuator simplified model, which is adopted in the process model, can be found in (Kundur.1994, IEEE Committee. 1991). The MPC third signal is then used as optimal valve setting to the turbine control valves.

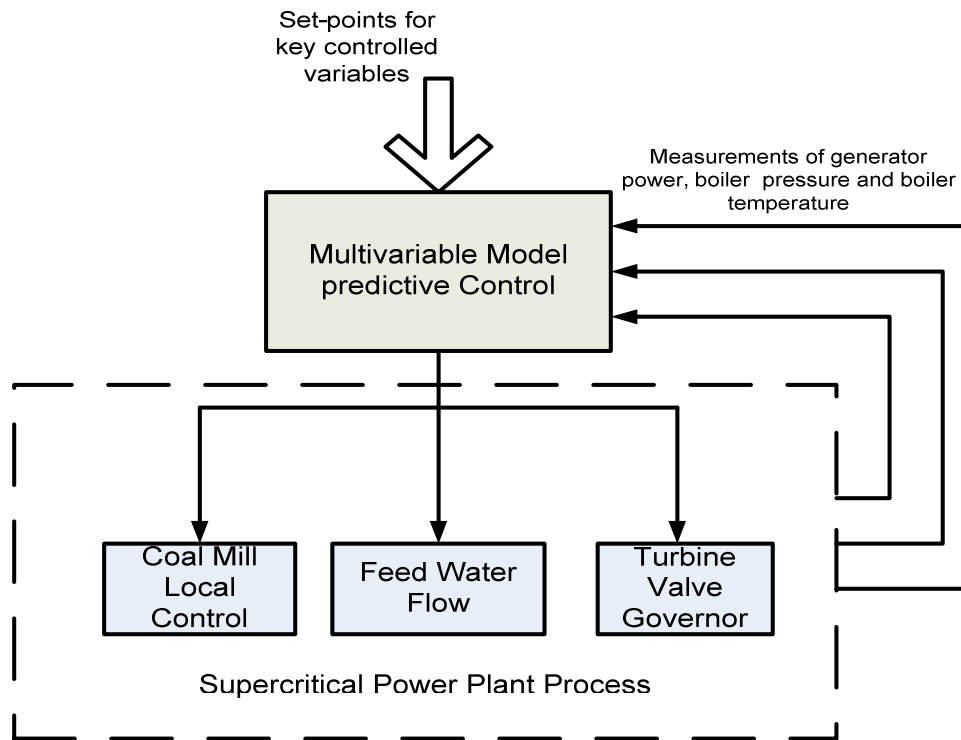


Fig 7.1 Schematic diagram for the multivariable predictive control and the SCPP process

The MPC has an internal model which is regarded as a predictor to the plant controlled outputs which are the electrical power, the main steam pressure, and main steam temperature. Table7.1 summarises the controller inputs/outputs and their associated subsystems.

Table7.1 Control inputs and plant outputs

Manipulated inputs	Controlled outputs
u_1 : Feed water Flow (Kg/s)	Main Steam pressure (MPa)
u_2 : Coal flow demand (Kg/s)	Electrical Power (MW)
u_3 : Valve position reference (p.u)	Main steam temperature (C°)

The next section presents different scenarios for the first control scheme which is a predictive controller based on an identified state space model.

7.3 The 1st Scheme of control: Model based predictive control strategy

In this scheme, the multivariable control system is based on MPC with identified state space model for prediction. It has been tested with two simulation scenarios. According to the inputs/outputs listed in Table 7.1, a linear internal model has been developed by GA to match the response of the process model. It is however impossible for linear time-invariant model to cover the whole range of power plant process. The process model which is regarded as a plant has some nonlinear feature resulting from nonlinear differential and algebraic equations that represents the thermal and chemical processes. It is likely that the plant is working around nominal (supercritical) conditions so the state space model has been identified with a portion of data that represents rated conditions. Figs 7.2 and 7.3 show the identification results which represent a portion of more than 200min 1st and 2nd sets of data. The responses of linear model and nonlinear plant model pressure, power, and temperature have shown good accuracy towards each other. The temperature of the linear model is more matched with nonlinear plant model when the spray attemperator is de-activated and this has been confirmed in Poncia *et al.* 2001. However, it has been decided to leave as it is in this scheme so that the temperature will be regulated by the spray attemperator and also by the MPC action. has been done in The model has four states $[x_1 \ x_2 \ x_3 \ x_4]^T$, three inputs $[\dot{w}_{fw} \ \dot{w}_f \ \mathbf{x}_{hp}]^T$, and three outputs. $[y_1 \ y_2 \ y_3]^T = [x_2 \ x_3 \ x_4]^T = [P_e \ p_{ms} \ T_{ms}]^T$. The use of low order identified linear models is useful for simplified prediction and optimization algorithms as justified in many research articles (Rossiter *et al.* 1991, Rovnak *et al.* 1991, Lu *et al.* 2000, Poncia *et al.* 2001, Choi *et al.*

2010, Trangbaek. 2008, Mohamed *et al.* 2012*a*, Mohamed *et al.* 2012*b*). In addition, it is intended to identify the model with data sets around rated condition which the plant is likely to operate. The linear model has the following parameters in discrete time format:

$$A = \begin{bmatrix} 0.7687 & 0.05486 & 0 & 0 \\ 0.7537 & 0.05379 & 0 & 0 \\ -0.003729 & -0.0002662 & 4.041e-018 & 0 \\ 18.94 & -23.78 & 0 & 1.0001 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.008409 & 0.01259 & -0.3041 \\ 0.008181 & 0.01243 & -0.3318 \\ 0.9934 & 1.249 & 21.75 \\ 0.2056 & 0.3123 & -8.338 \end{bmatrix}, C = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, D = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

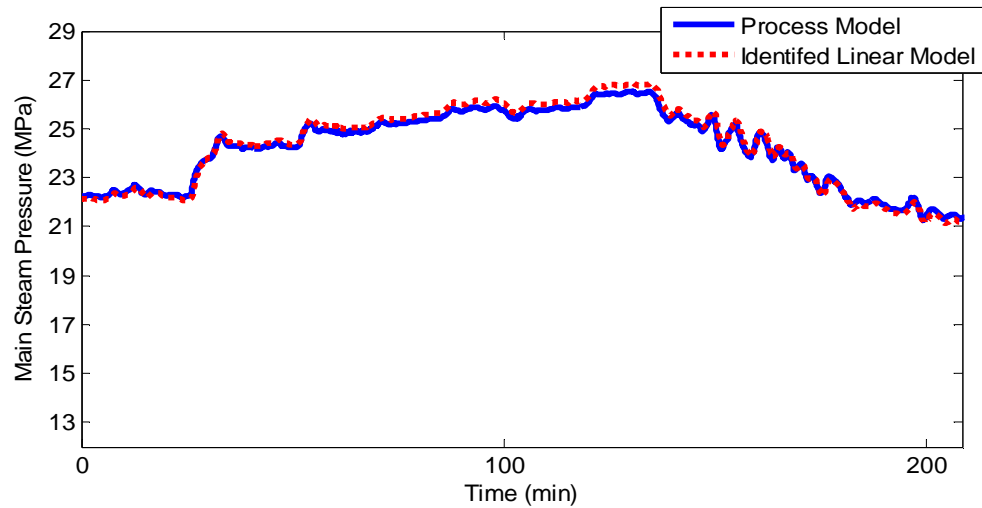


Fig7.2 Main steam pressure response

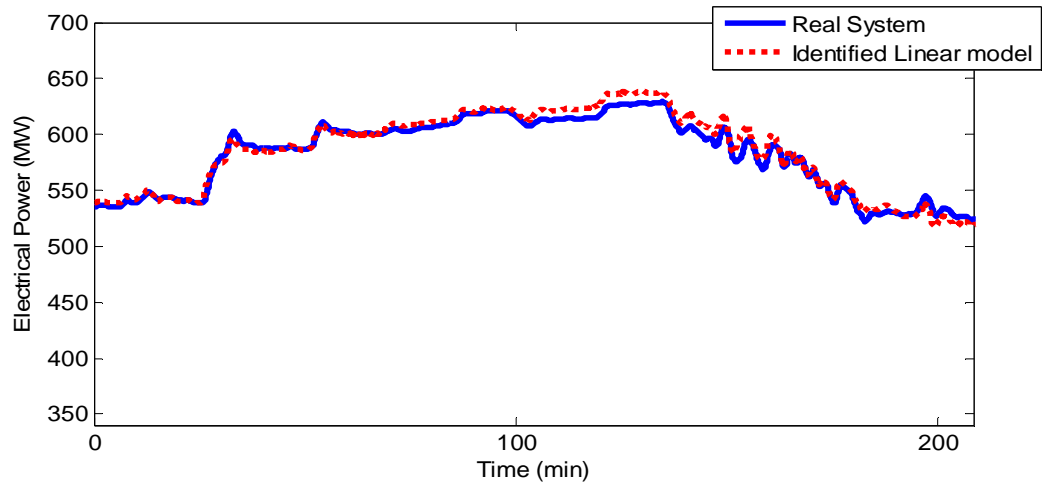


Fig7.3 Electrical Power response

The model predictive control tool is used to design the controller. First, the internal model parameters have been imported to the tool for designing the controller. The control inputs constraints have been selected according to the operating restrictions of once through mode of the plant. Inside the tool, the linear model is appended with the unmeasured disturbance compensation and integrated measurement noises to formulate generalized algorithm of predictive control. The weighting matrices, prediction and control horizons have been determined through simulating different scenarios and adopting the ones which give satisfied performance while keeping manageable computation demands. The control interval is 1 sample, the prediction horizon is set to be 20 samples and control horizon of 5 samples. $\mathbf{Q} = [1 \ 1 \ 1]$ and $\mathbf{R} = [0.1 \ 0.1 \ 0.1]$. A unit load demand change from 600MW to 620MW is assumed as setpoint. The pressure setpoint is re-scheduled using look-up table. The temperature setpoint is set to 570C° which is the same setpoint already existed in the water attemperator of the superheater, With the whole package described in Section 7.1 simulation results are conducted. The results are presented below in Figs 7.4, 7.5, 7.6 and 7.7. Case. A is the new strategy and Case. B is the existing one.

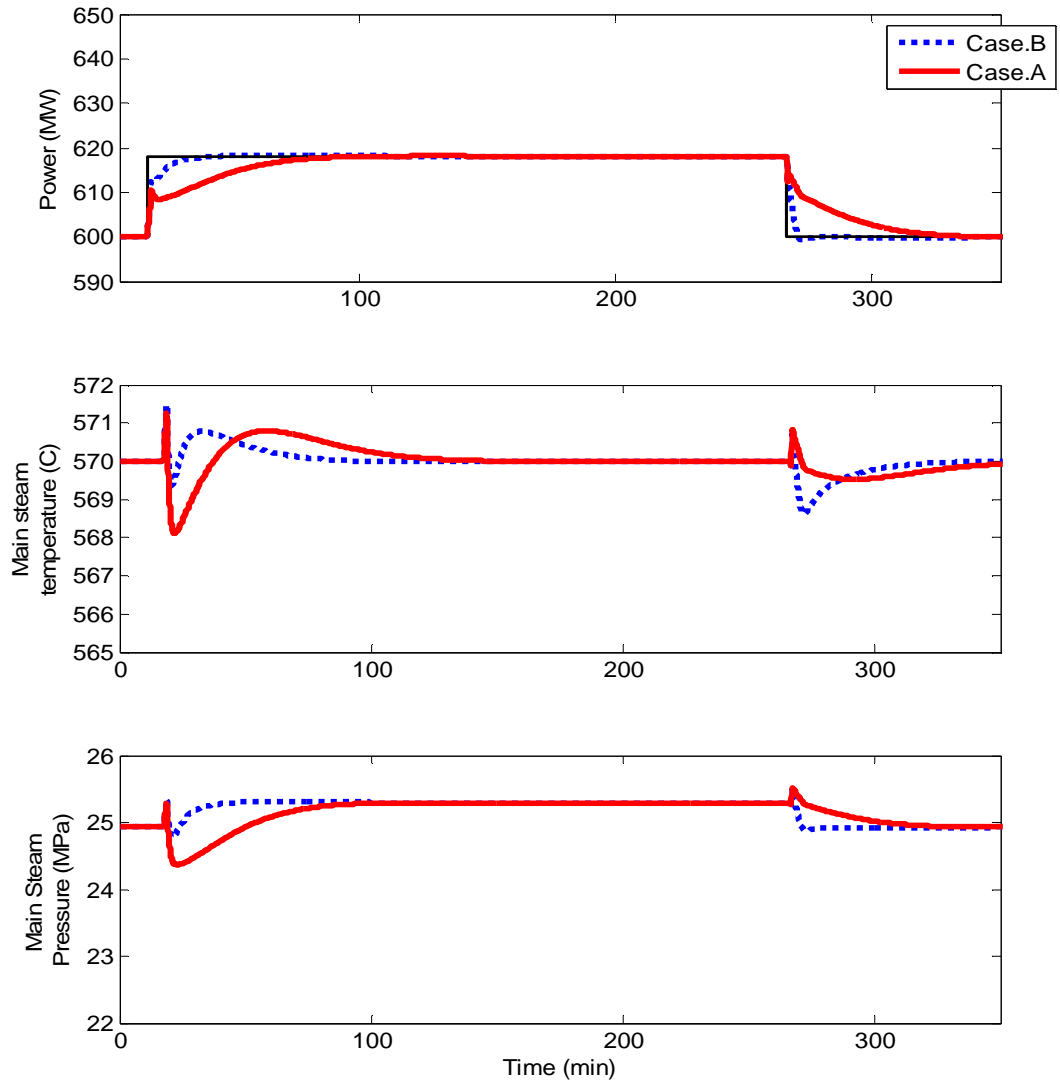


Fig7.4 Controlled variables of the plant

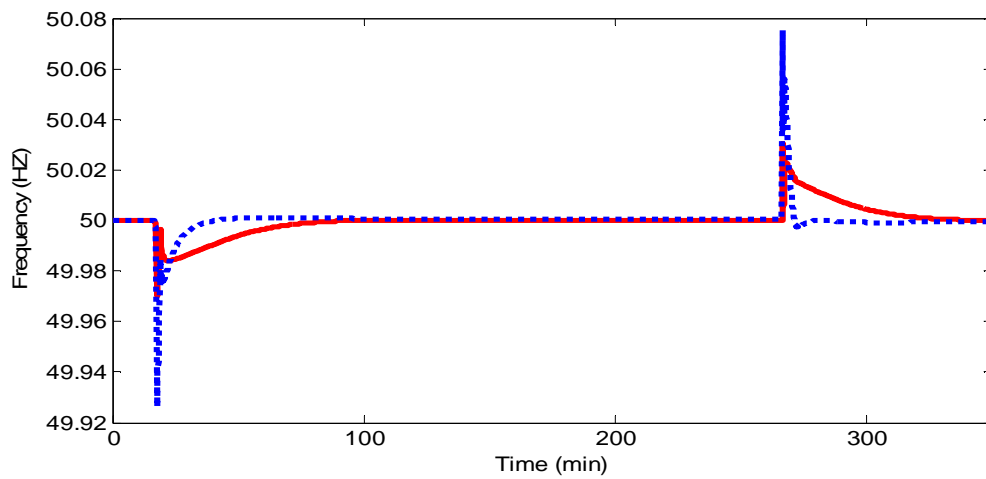


Fig7.5 Frequency

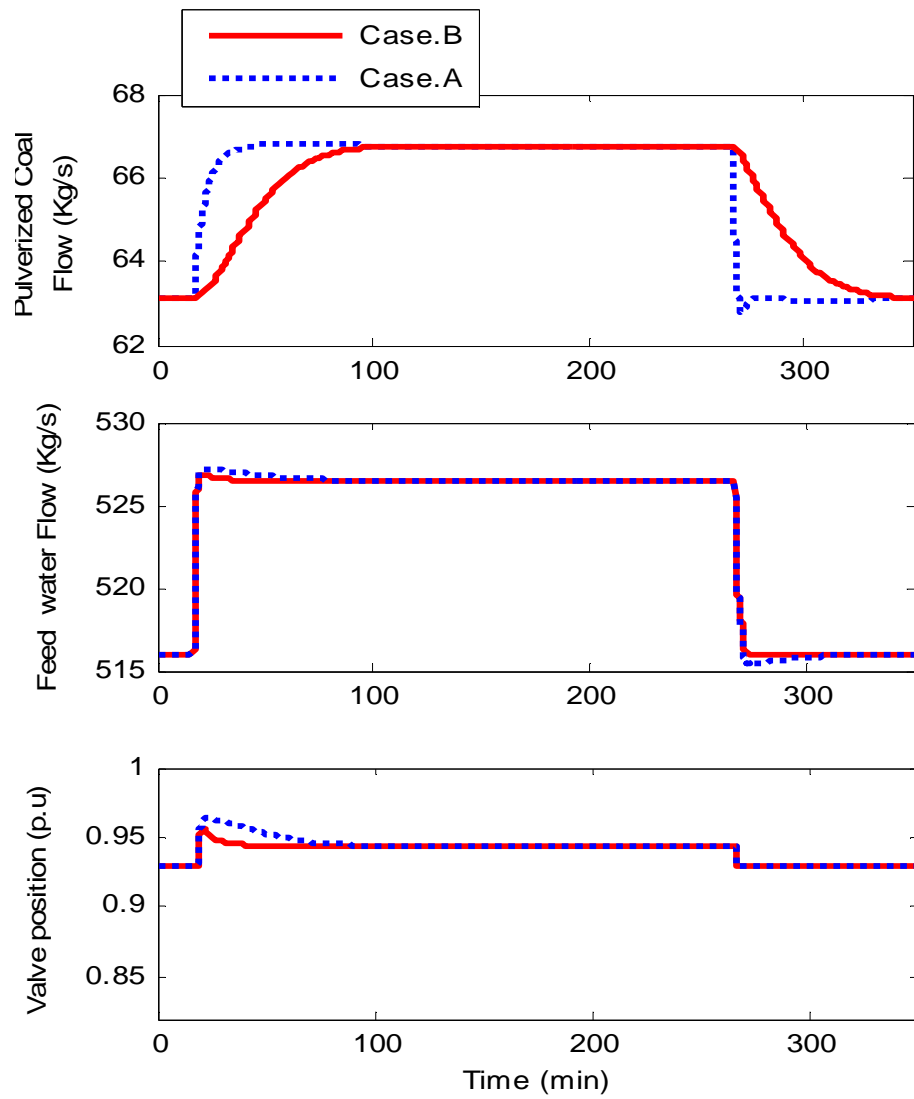


Fig7.6 Manipulated inputs to the plant

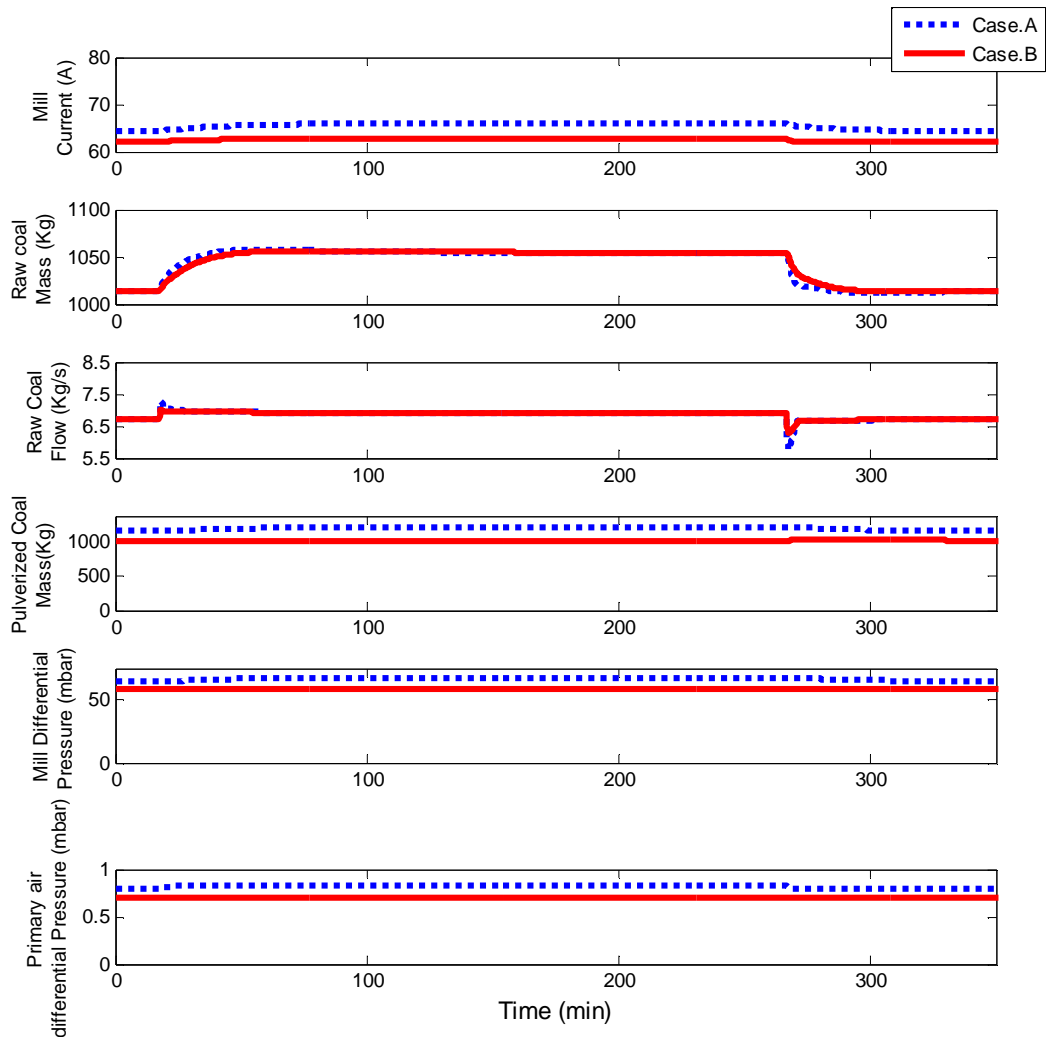


Fig7.7 Major variables of one mill.

Further to the previous small step change in the unit load demand, the control strategy has been tested with ramp load change from 610 MW down to 590MW and the temperature setpoint is kept as in scenario.1 which is 570C°. The pressure setpoint is rescheduled

according to the unit load demand using look-up table. The plant various responses are reported below in Figs 7.8 to 7.11.

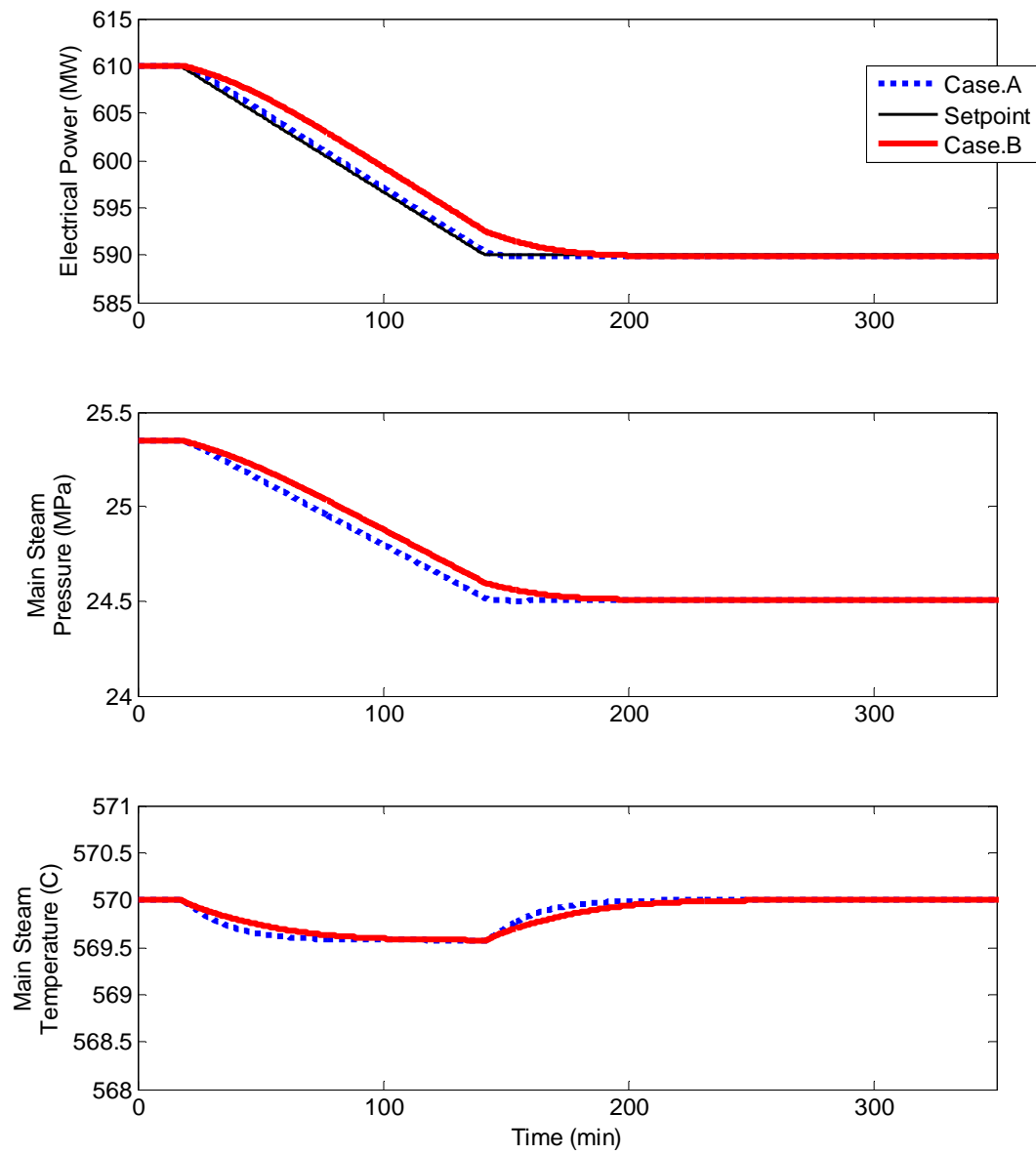


Fig.7.8 Manipulated inputs

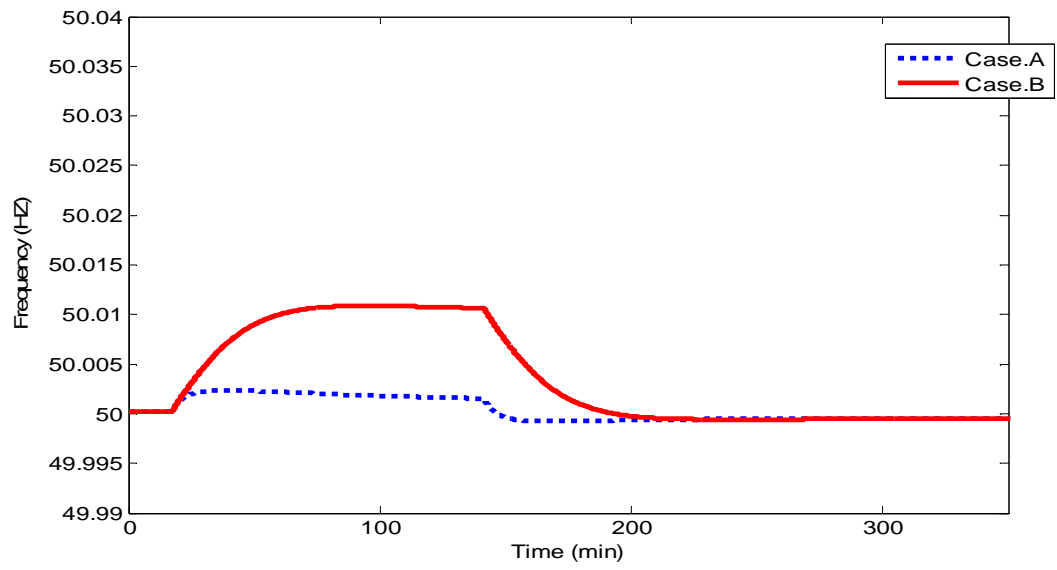


Fig. 7.9 Frequency

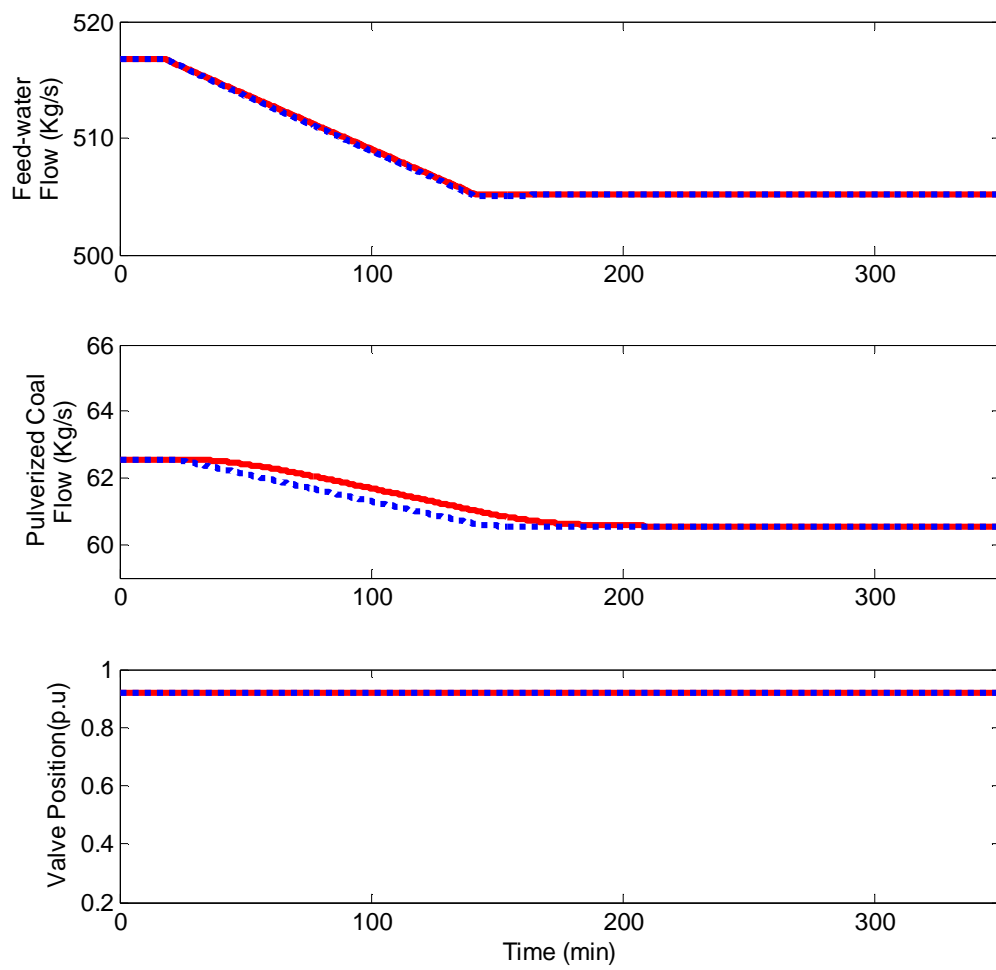


Fig7.10 Controlled Variables

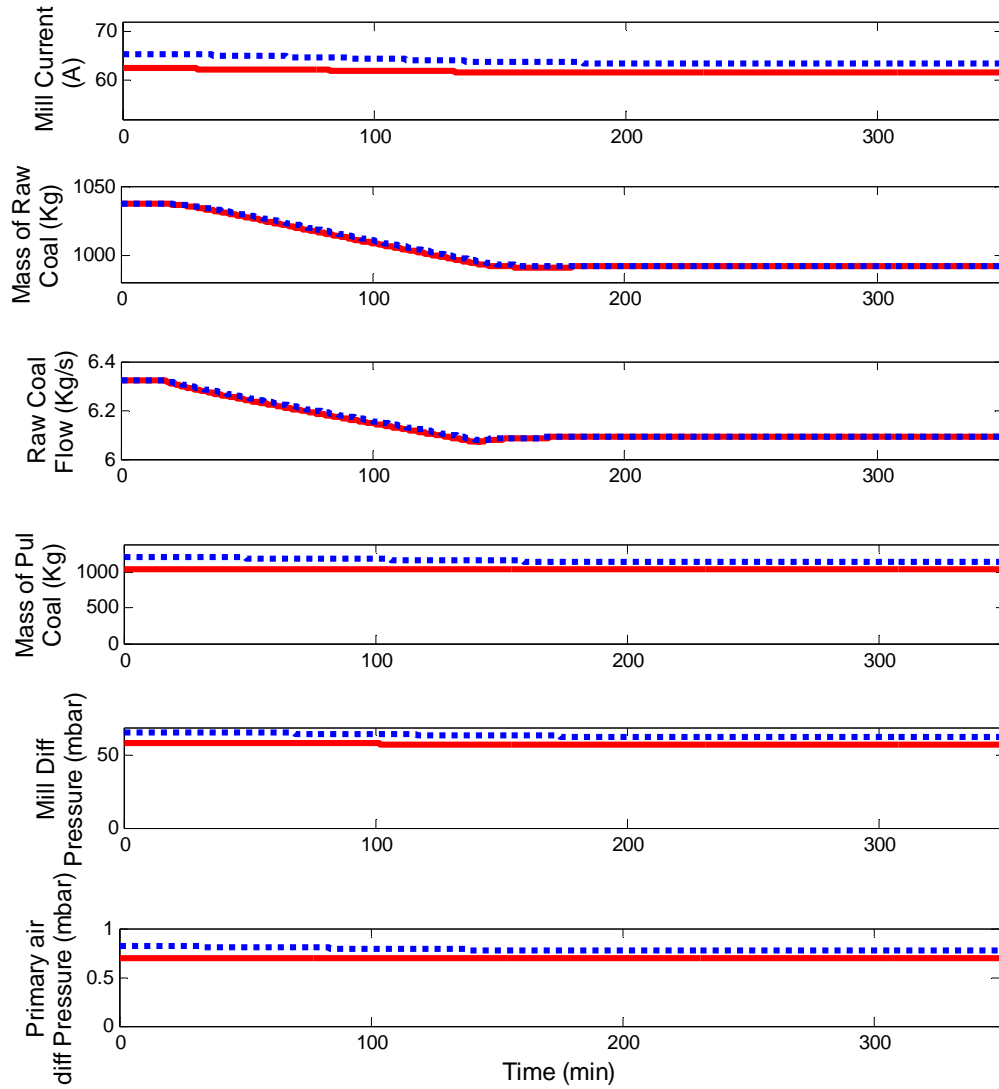


Fig7.11 Major Variables of one mill.

7.3.1 Results analysis and discussion 1:

From the 1st scenario of previous simulation study, it is observed that the control strategy using MPC is much improved the over existing control strategy. The response of output power in the improved case has reached equilibrium faster than the case without using the

proposed control strategy. It is believed that the main reason behind that is the improved coal grinding and discharging capability of the mills in service, which in turn, are resulting from the MPC optimal coal flow reference signal and the tuned feeder-speed and primary air fan regulators. More pulverized coal is discharged from the mills and more will be burnt in the furnace per unit time.

The other two controlled input variables (i.e. the boiler main steam pressure and temperature) are kept to maintain the supercritical conditions with smaller fluctuation around the set-point despite load variations. In addition, the frequency response in the improved case is so fast compared to the one without using the proposed controller. Fig 7.7 shows the variations of the major coal mill variables which confirmed the improved performance of power plant output. In the improved control strategy, (Case. A), higher mill and primary air differential pressures are created to carry more pulverized coal to the burners. More pulverized coal is ready inside the mill to be transmitted to the furnace in Case A; this will result in faster responses. In the 2nd scenario, less improvements has been seen because the plant was tested with gradual ramp load change, not a sudden step change as used in the 1st scenario. This is obvious also in the frequency deviations responses in the two scenarios where the second scenario has smaller deviation.

It is however found that the MPC is valid within small load changes around supercritical conditions. The deterioration of MPC performance in large load changes is due to using one local linear model for MPC predictions and constant disturbance model for a specific prediction horizon. To cover wider operating range and test the SCPP responses against larger load changes, MPC with three local models is proposed (Multiple MPC) which is described in the next scheme.

7.4 The 2nd Scheme: Multi-Model based predictive control strategy:

This section describes the 2nd controller scheme which is slightly different from the 1st one. The main difference is that three switchable MPCs are designed to regulate the plant behaviour instead of one. Each MPC is designed to control the plant in a certain load conditions. The switching mechanism between one MPC to another is decided by the unit load demand or power set-point. The multi-variable multi-model predictive controller simple scheme is shown in Fig 7.12.

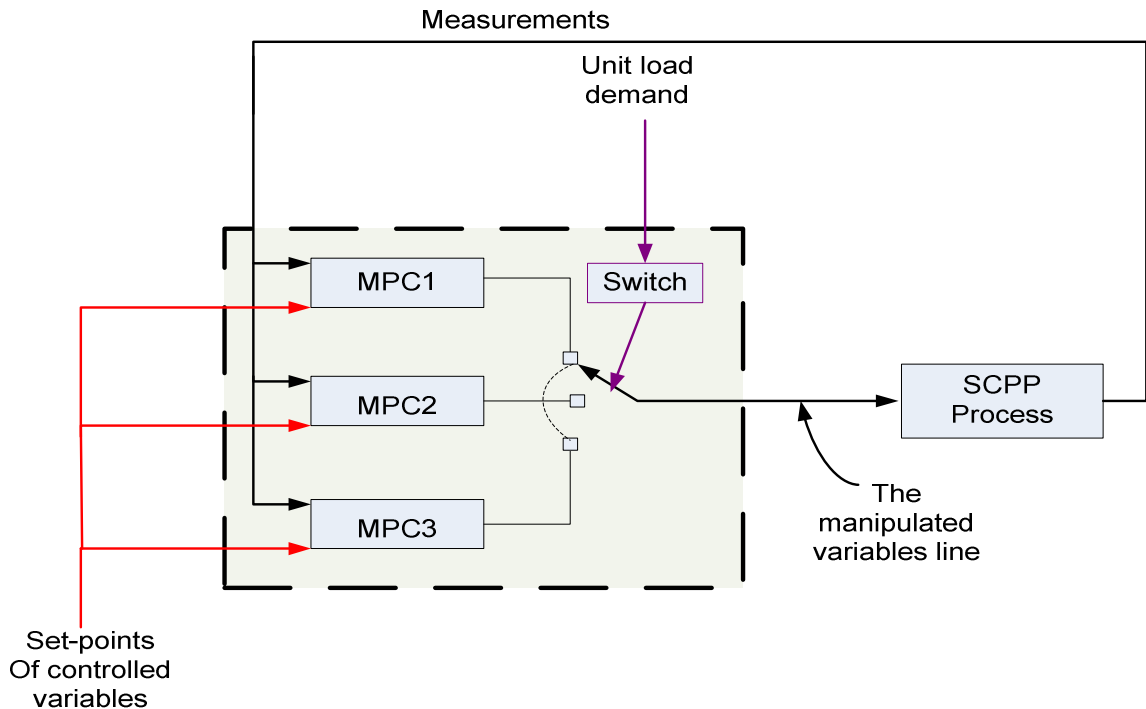


Fig 7.12 Multi-Model Predictive Controller scheme

One of the local models is the same as the one described in Section 7.2.1. Only a few parameters of the 1st linear model have been modified to get the other two models which work on lower subcritical conditions (extracted from Data set 2 and 4). Also, each model is augmented with different disturbance models in the prediction algorithm to handle the disturbance variations as a function of operating conditions which is likely to be unknown

from one operating region to another. The MPCs' transfer functions are mentioned in the Appendix. From 600MW to 480MW the controller has been tested and shown similar and improved results compared with the results obtained using control scheme 1. In this test a big load change of 620MW to 480MW then to 640MW is introduced to the plant reference input. The temperature set-point is kept constant to 570°C and the pressure reference is changeable and rescheduled as a function of the unit load demand. The control interval, prediction and control horizons are 1, 40, and 5s respectively for the three MPCs. Simulations have been conducted and the results are reported in Figs 7.13 to 7.15.

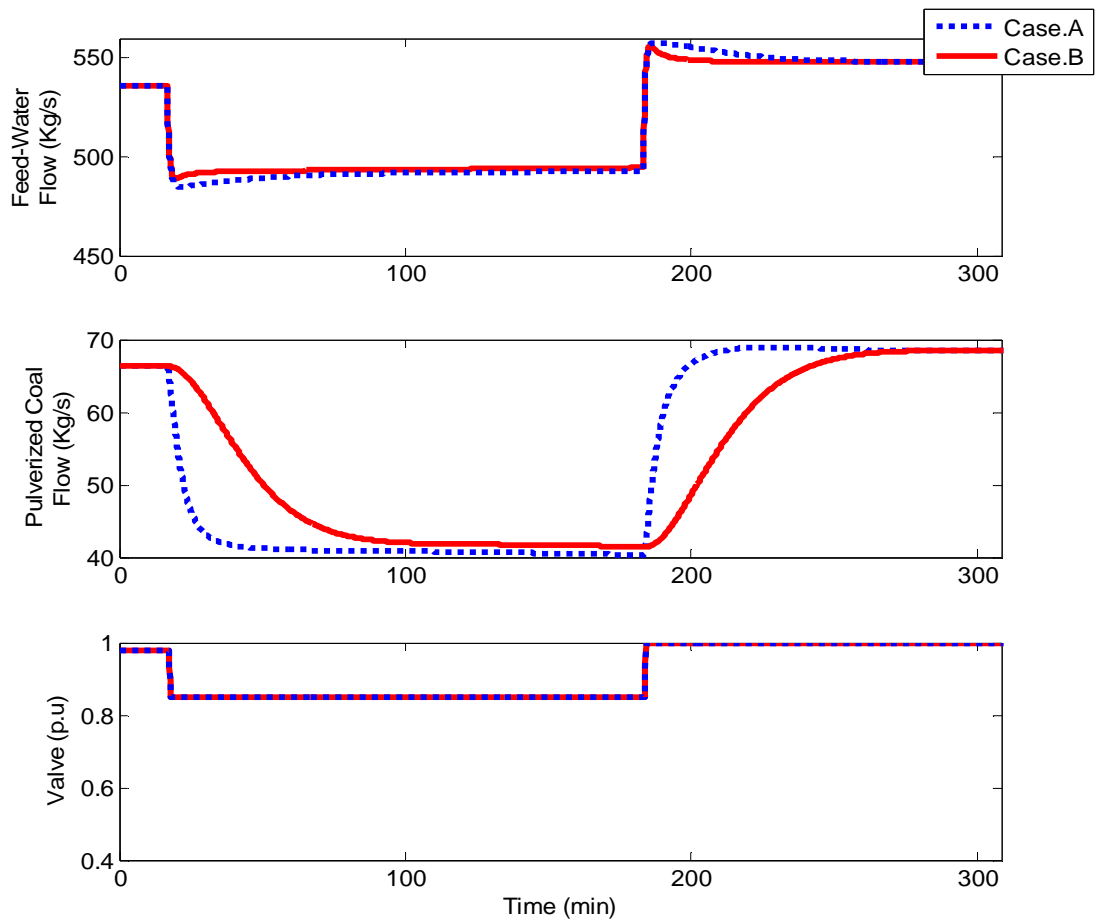


Fig 7.13 Manipulated inputs

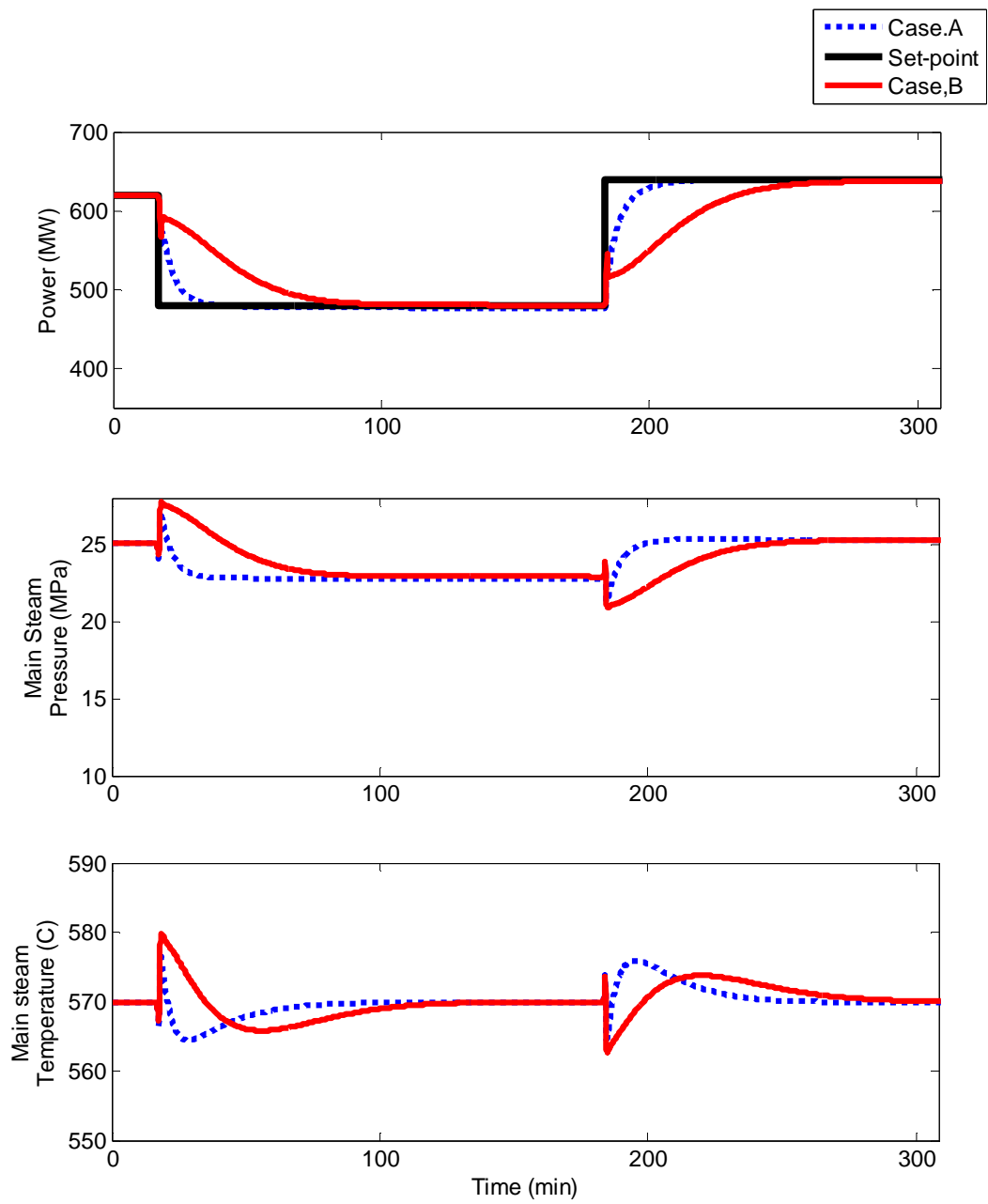


Fig7.14 Controlled variables of the plant

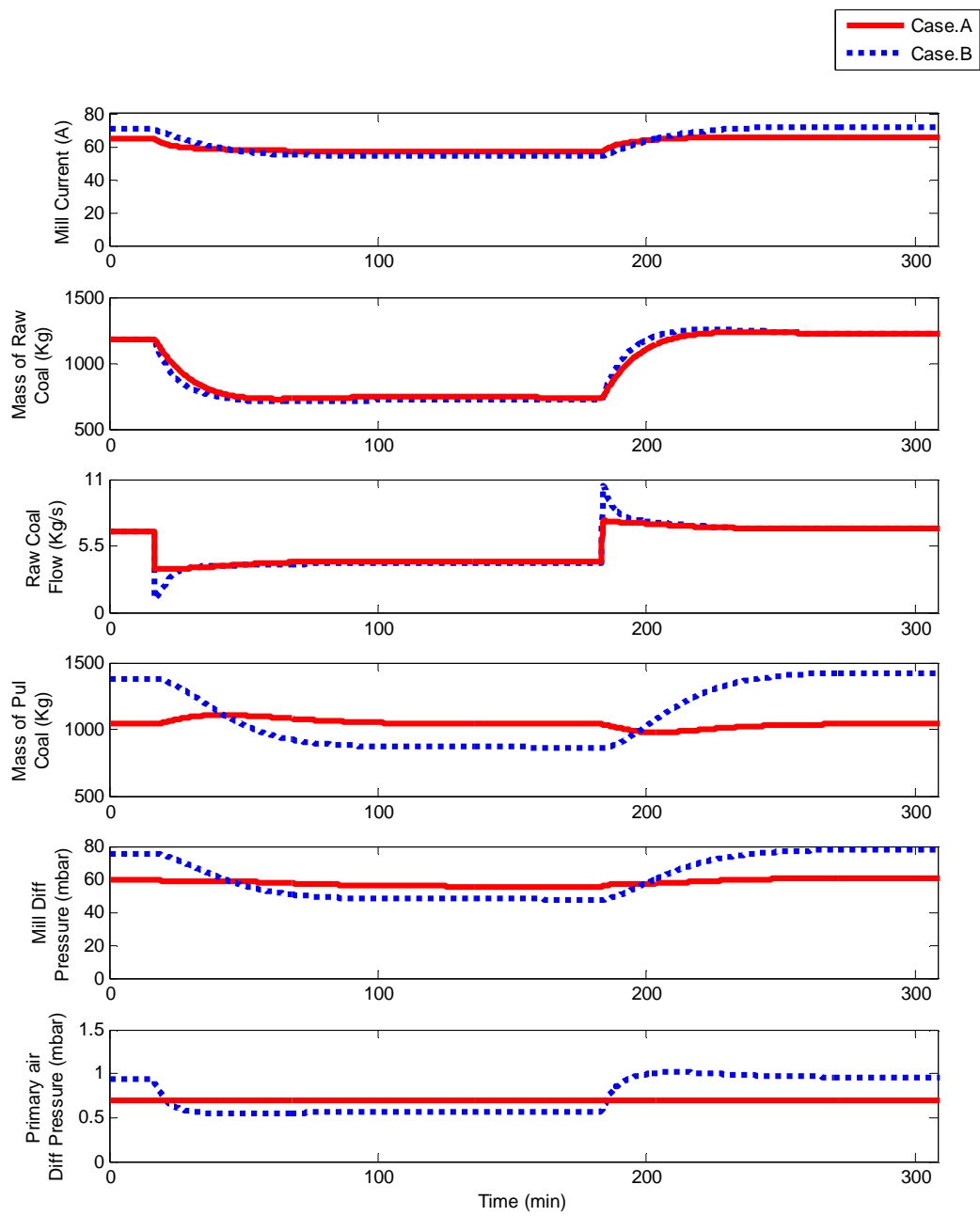


Fig7.15 Mill major variables

The second scenario is a ramp load change request from 530MW to 600MW (shown as solid black line in the Fig 7.17). The simulations are recorded from Fig 7.16 to 7.18. The MPCs prediction and control horizons are the same. Ramp load change has less impact on the plant dynamics than sudden step changes.

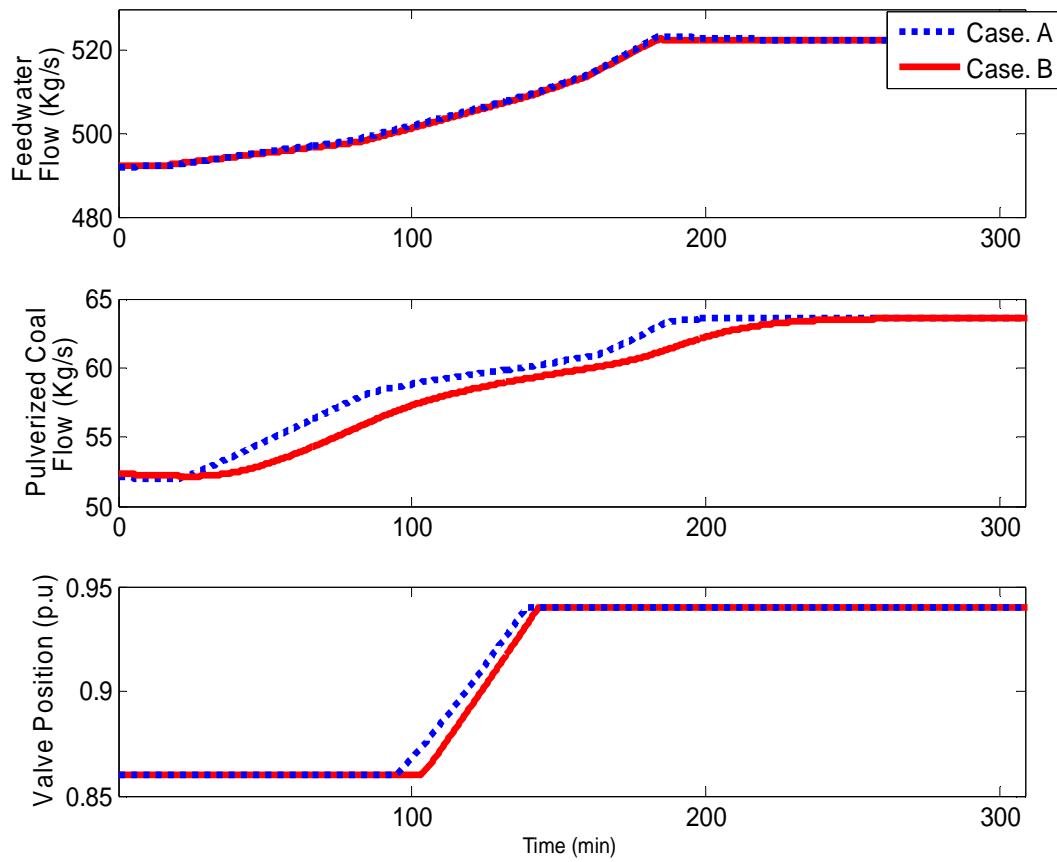


Fig 7.16 Manipulated inputs for both cases

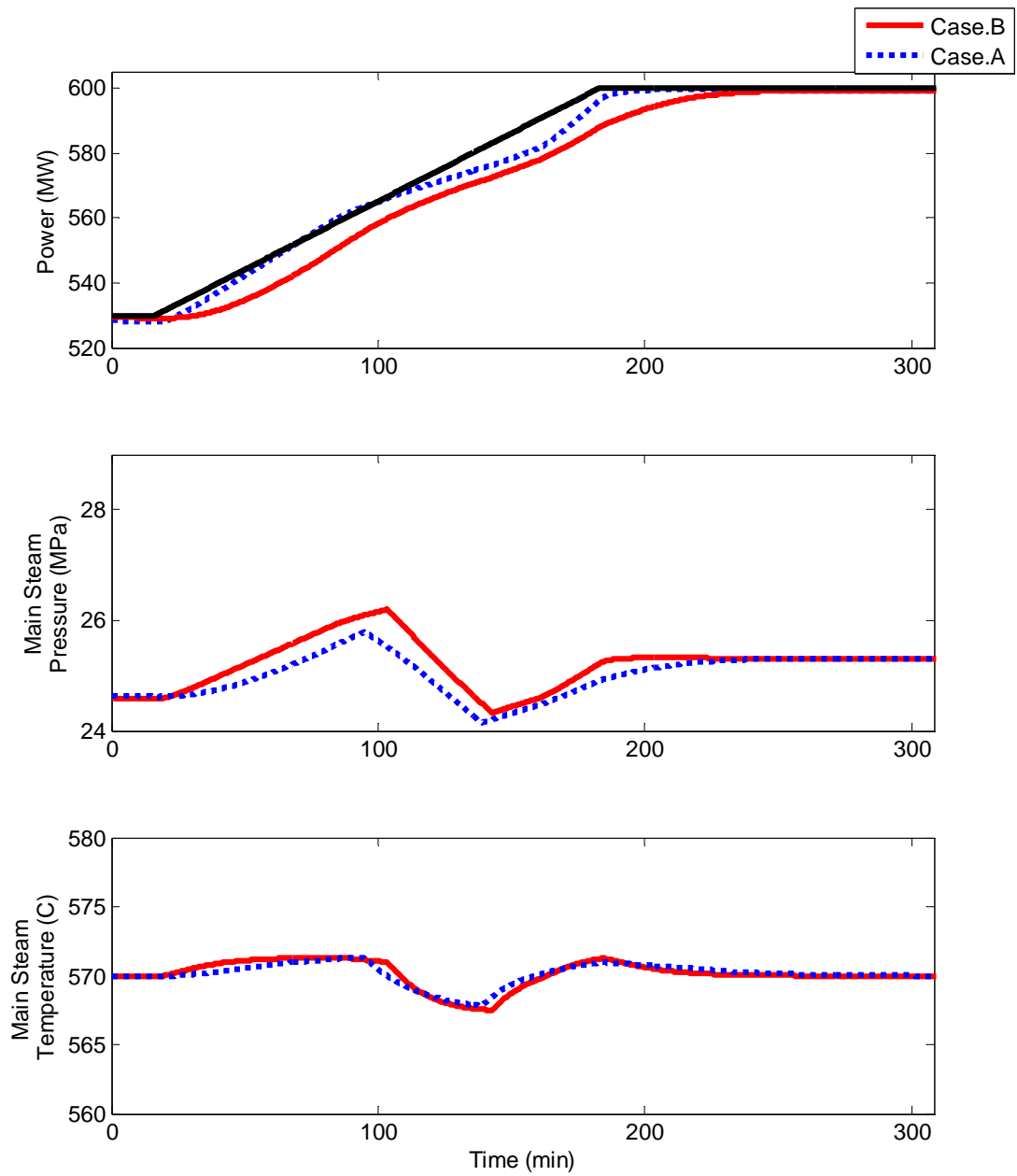


Fig 7.17 Controlled variables.

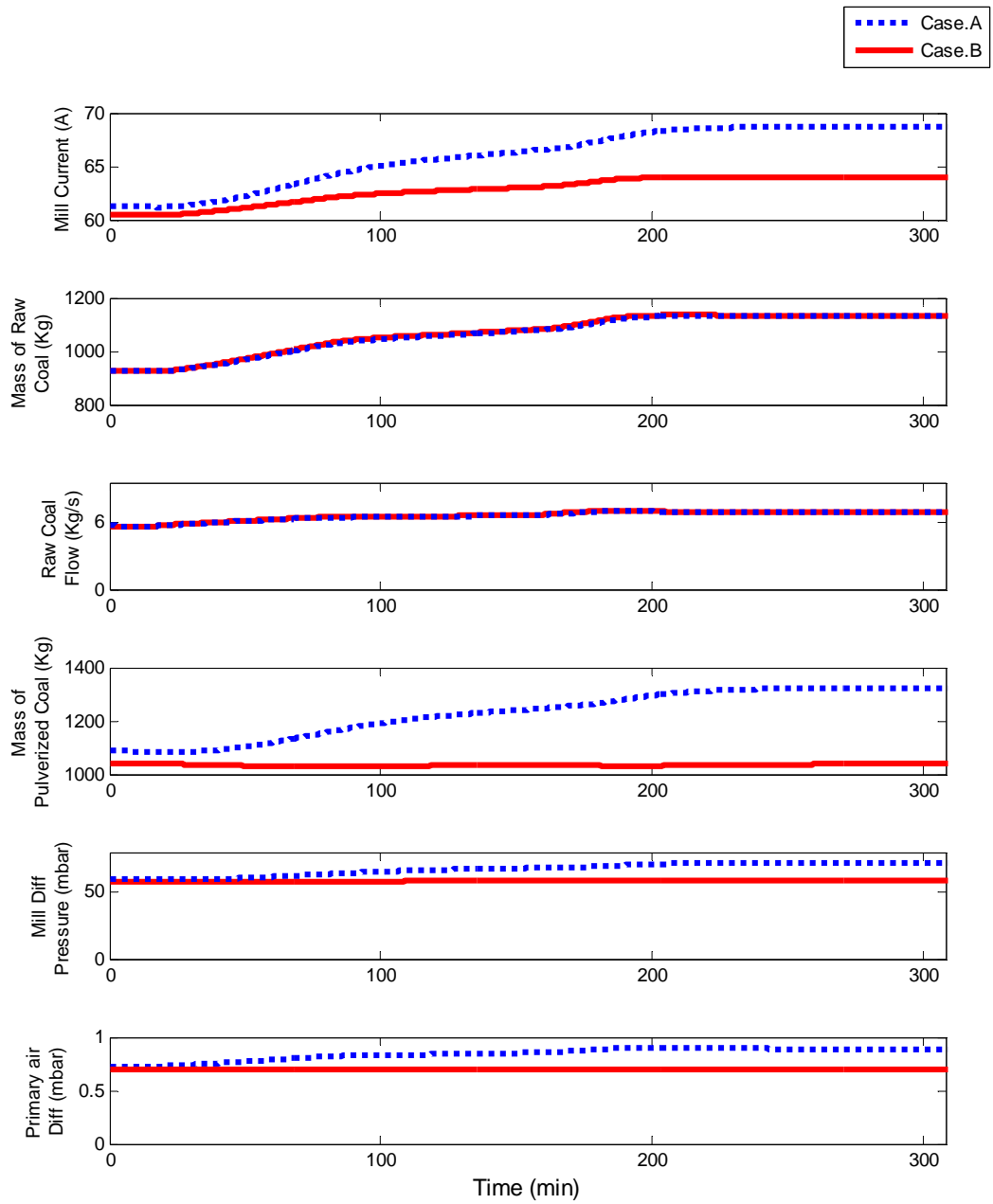


Fig 7.18 Variables per mill in service

7.4.1 Simulation results analysis and discussion 2

The simulation results for this extended controller have shown consistence with the previous scheme, but with larger load requests (20% partial load rejection/application, and ramp load change). Also the simulation results have been compared with the previously

reported related research; the various responses are generally in agreement with the controlled once-through OT plant responses in (Rovnak *et al.*1991, Poncia *et al.*2001, and Lee. 2010). The results proved that predictive control using three local models with different unmeasured disturbances for compensation is able to cover wider range for control than only one MPC (Mohamed *et al.* 2012c). Again the results show that with increased grinding capability, the plant responses are improved. This is obvious in the improved load following capability, less pressure and temperature fluctuations.

The next section shows the 3rd control scheme which is composed of MPC in parallel with dynamic compensator optimally tuned by GA. The hybrid structure offers advantages of wide-range load tracking and handling constraints which is suitable for simulating large partial load rejections. As in the previous sections, under the controller structure, the influences of milling performance are studied and discussed.

7.5 The 3rd Scheme of Multivariable Optimal Controller

In this section, a dynamic compensator has been installed in parallel with MPC the 1st scheme structure and optimally tuned with GA with the data to cover the whole once-through mode of the plant. Accordingly, there will be two objective functions to be minimized not only one as in the two schemes. One is minimized by the MPC QP algorithm and the other is minimized by GA which represents the steady state error resulting from any mismatches between the MPC internal models and the process plant. Recalling the 1st objective function to be minimized by the MPC which is described in Chapter 6:

$$\xi(k) = \sum_{i=H_w}^{H_p} \left\| \hat{y}(k+i|k) - r(k+i|k) \right\|^2 \mathbf{Q}(i) + \sum_{i=0}^{H_c-1} \left\| \Delta \hat{u}(k+i|k) \right\|^2 \mathbf{R}(i) \quad (7.1)$$

The dynamic compensator is MIMO PID with a coupled structure. It can be designed by GA and reported in many research articles (Wei-Der *et al.* 2007, Herreros *et al.* 2002 and Dimeo *et al.* 1995); the generalized form for $n \times n$ system is then described by:

$$\mathbf{K} = \begin{bmatrix} C_{11}(s) & \cdots & C_{1n}(s) \\ \vdots & \ddots & \vdots \\ C_{n1}(s) & & C_{nn}(s) \end{bmatrix} \quad (7.2)$$

in which the input to this matrix is the errors vector, the output is the signal required for compensation. Each s function in the matrix has the normalized proportional, integral and differential parameters which can be written as:

$$C_{ab}(s) = k_p + \frac{k_i}{s} + k_d s \quad (7.3)$$

The multivariable controller \mathbf{K} is implemented by SIMULINK[®] and with control blocks and linked in parallel with the MPC in an analogy to the implementation reported in Dimeo *et al.* (1995). The second performance index minimized by GA is selected to have the following structure

$$\mathcal{E} = \sum_{t=0}^N w_1 |e_p(t)| + w_2 |e_P(t)| + w_3 |e_T(t)| \quad (7.2)$$

Then, the final optimal control law for robust solutions becomes:

$$\mathbf{u} = \underbrace{\mathbf{u}_{mpc}}_{\text{minimizes } \xi} + \underbrace{\mathbf{u}_{co}}_{\text{minimizes } \mathcal{E}} \quad (7.3)$$

where e is the error remaining from plant severe nonlinearity and the subscripts to indicate the outputs responses of pressure, Power, and Temperature, respectively. w_1 , w_2 and w_3 are the weighting coefficients used in optimization. In our work, the matrix \mathbf{K} is only 3×3

matrix. The major steps performed by GA to reach the optimal solution should be referred back to Chapter 3. The dynamic compensator parameters are listed in Table III and the control system scheme is demonstrated in Fig 7.19.

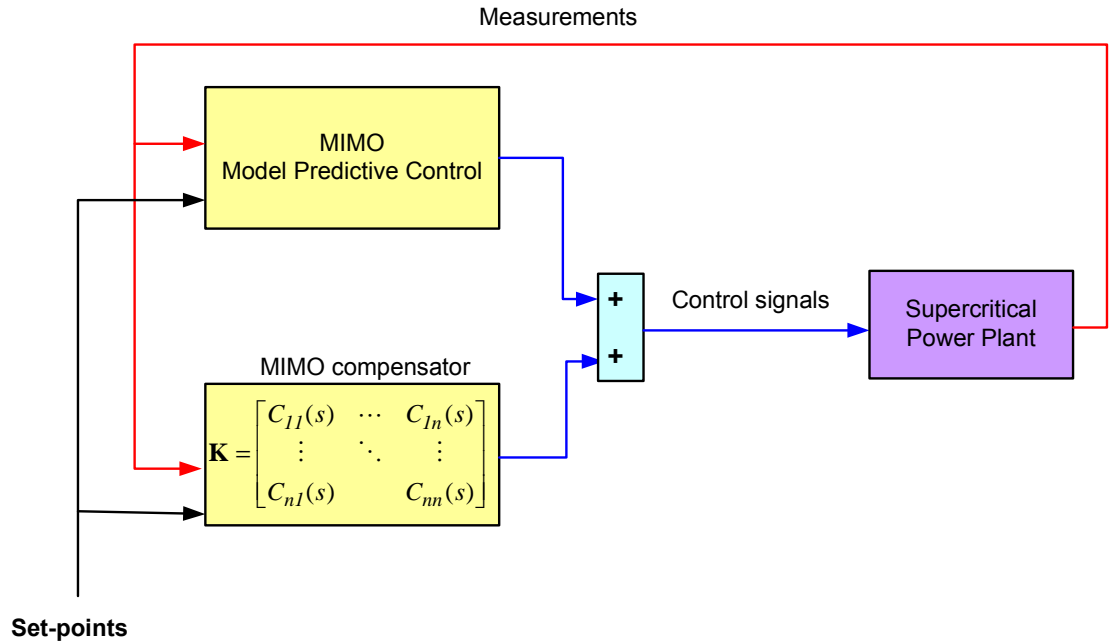


Fig 7.19 Parallel cooperative controllers of MPC and MIMO compensator

Table 7.2 MIMO compensator parameters

C_{ab}	k_p	k_i	k_d
C_{11}	2.88	0.0393	0
C_{12}	0.074	0	0
C_{13}	0.0041	0	0
C_{21}	0.0209	0	0
C_{22}	0.0054	2.8×10^{-8}	0
C_{23}	0.0054	0	0
C_{31}	0.0862	0	0
C_{32}	7.74×10^{-8}	0	0
C_{33}	0.0054	7.1571×10^{-8}	0

There are other parallel schemes reported in the literature of chemical process control and thermal plant control (Po-Feng *et al.* 2003, Peng *et al.* 2005, Simon *et al.* 2010, Mohamed *et al.* 2011). Po-Feng *et al.* (2002) implemented an adaptive neuro controller in parallel with MPC to increase the controller robustness while in Peng *et al.* (2005) extra PID scheduled loops are installed in parallel with MPC to cope with the plant nonlinearity and control the plant as it would be in practice. The use of parallel cooperative controllers is justified.

Partial load rejections are rare events that happen in power systems due to tripping faulty lines or loads for protection or other system disturbances which occur accidentally in the power grid (deMello *et al.* 1983). This section reports a simulation study of partial load rejection to investigate the ability of SCPP to withstand partial load rejection. From a survey of utility experience for power plant responses to partial load rejection, it is reported that Super-critical units would probably not be able to reject more than 50% load due to the boiler pressure sensitivity (Kundur. 1983).

Drum type units are more reliable which can safely reject up to 60% partial load rejection (Abdenmour. 2000). This limitation in SCPP in comparison to drum type units has been studied by two simulation scenarios: 33% load rejection and 66% load rejection. The plant various responses to 33% load rejection is reported in Fig.7.19. Case .A and B means two different cases of mill controller settings: existing and improved one..

The load dropped suddenly by 33% from 600MW to 400MW and the plant output follows the load instruction with zero steady state error in both cases. The pressure dropped to subcritical level which indicates the existence of water level in the water wall. However, it doesn't really matter because once-through boilers are designed to work in both subcritical and supercritical conditions. Furthermore, from the plant practical data, the pressure is subcritical when the plant supplying 400MW. The temperature has decayed for few minutes before it has been returned to its original position by control action.

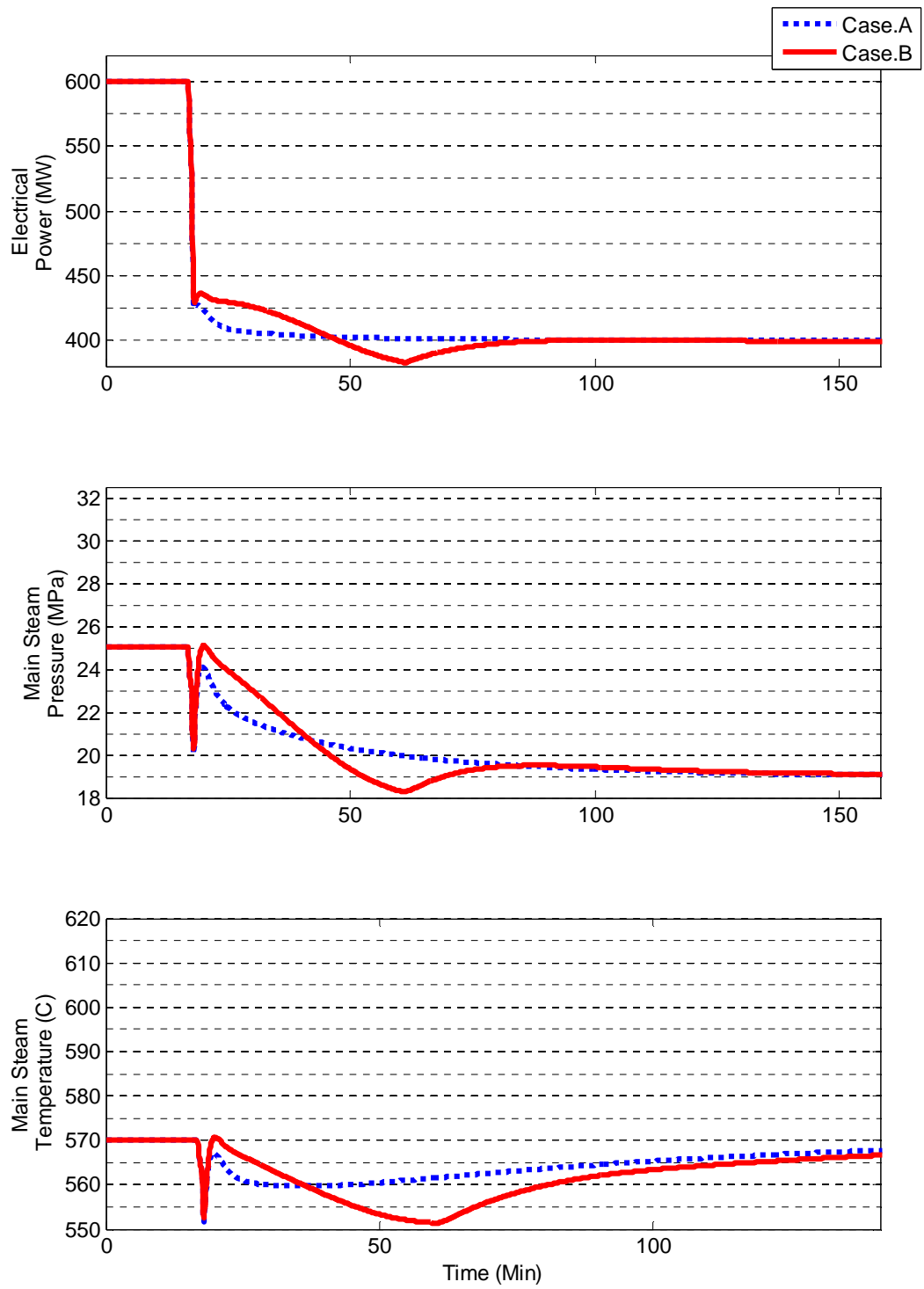


Fig 7.20 SCPP responses to 33% partial load rejection (output variables)

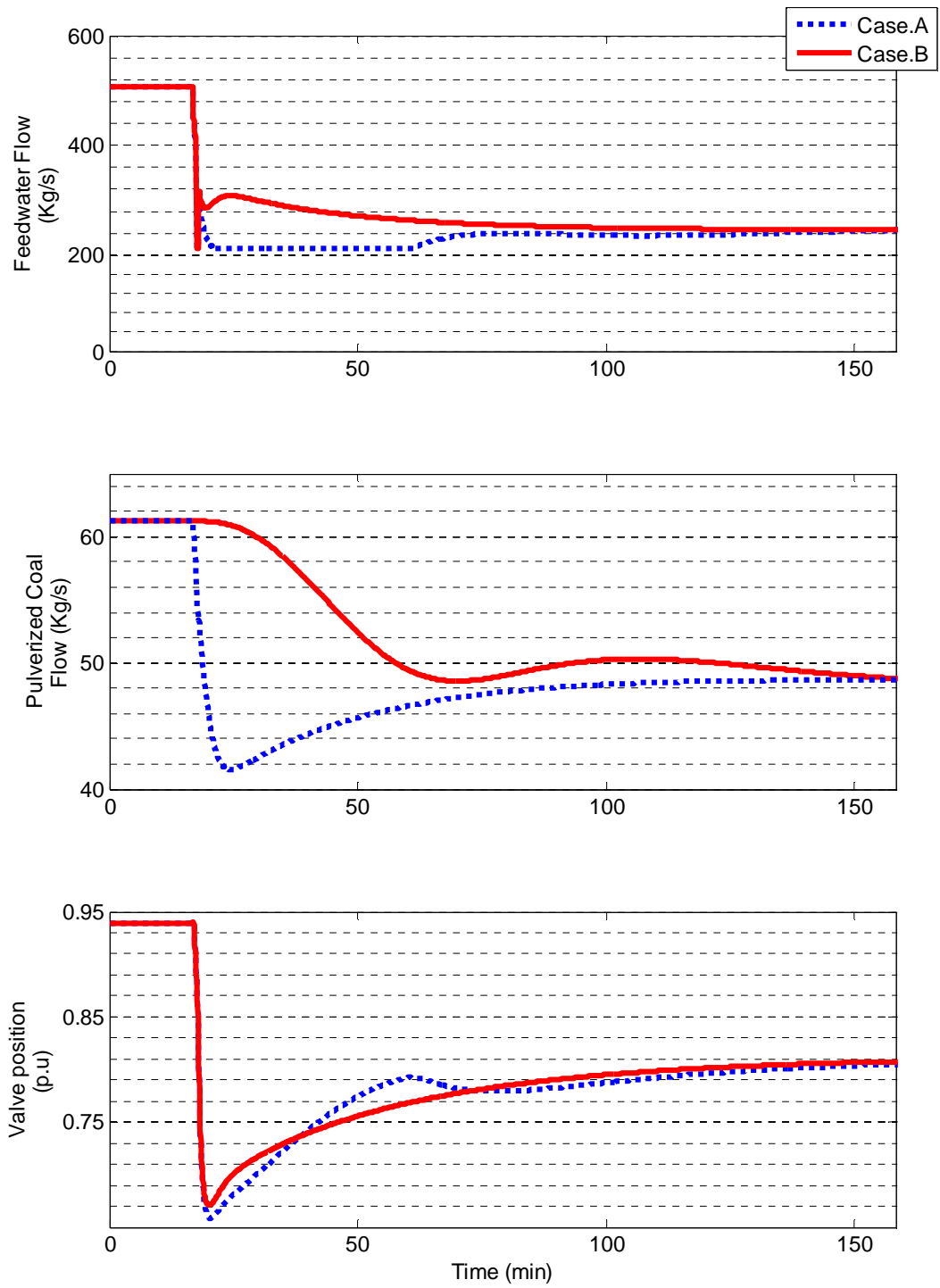


Fig 7.21 SCPP responses to 33% partial load rejection (input variables)

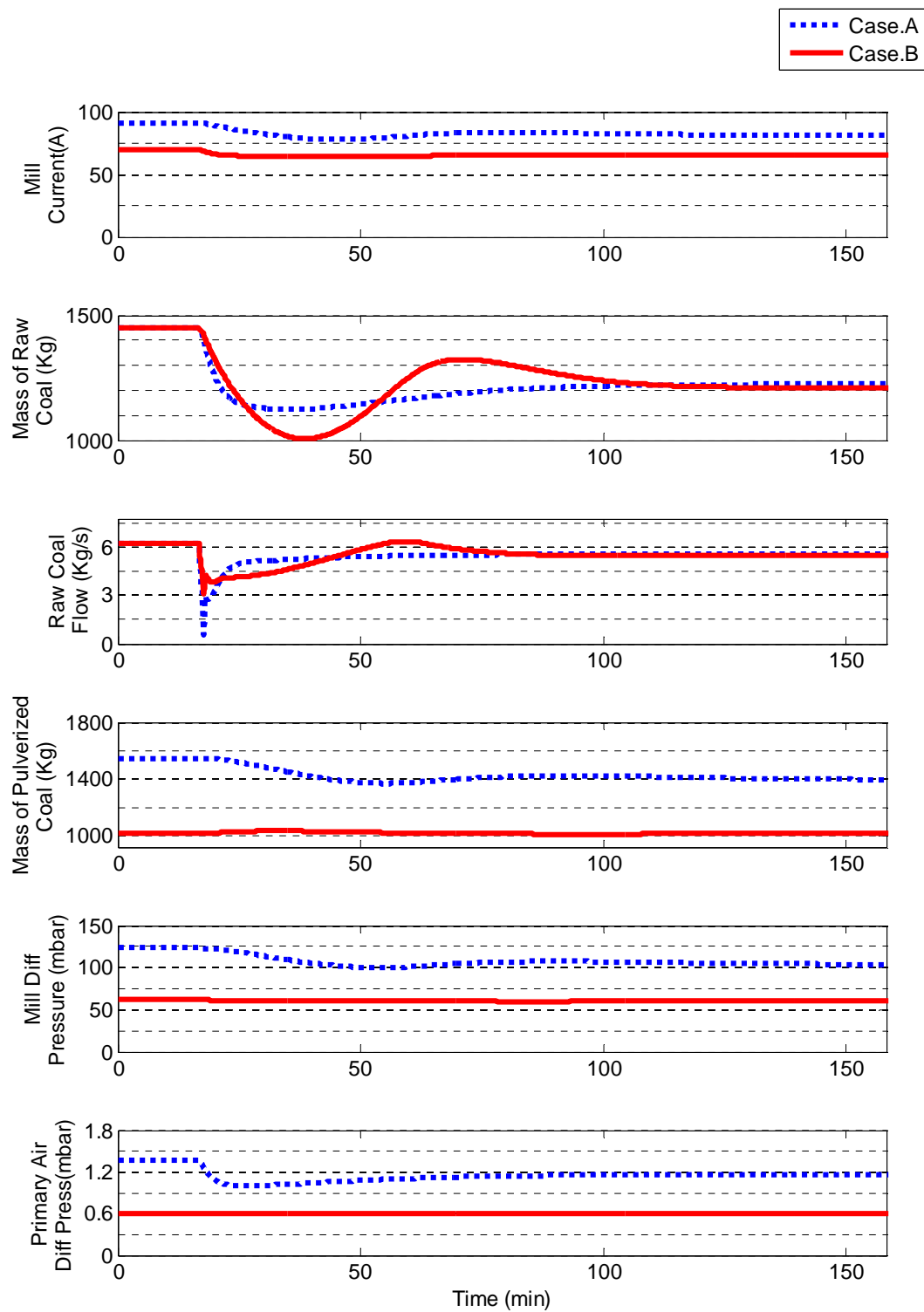


Fig 7.22 Mill responses

In case of 66% partial load rejection, The plant obviously has failed to withstand this rejection of load because the plant output steady is above the load instruction which is indicated by the solid black line in the figure. In practice, this will results in increasing the frequency and disconnecting the plant from the infinite bus. The main reason is that the amount of water or water/steam ratio is high in the water wall due to pressure reduction and there is no sufficient area to store water in once-through boiler. By contrast, drum boilers are better to withstand partial load rejection (Kundur. 1983) which can successfully withstand 60% load rejection (Abdennour. 2000). The once-through mode boilers have to operate above 35%, otherwise, the plant should operate in re-circulation mode which works with the same principles of drum boilers. The plant various responses are reported from Fig 7.22 to 7.24 below.

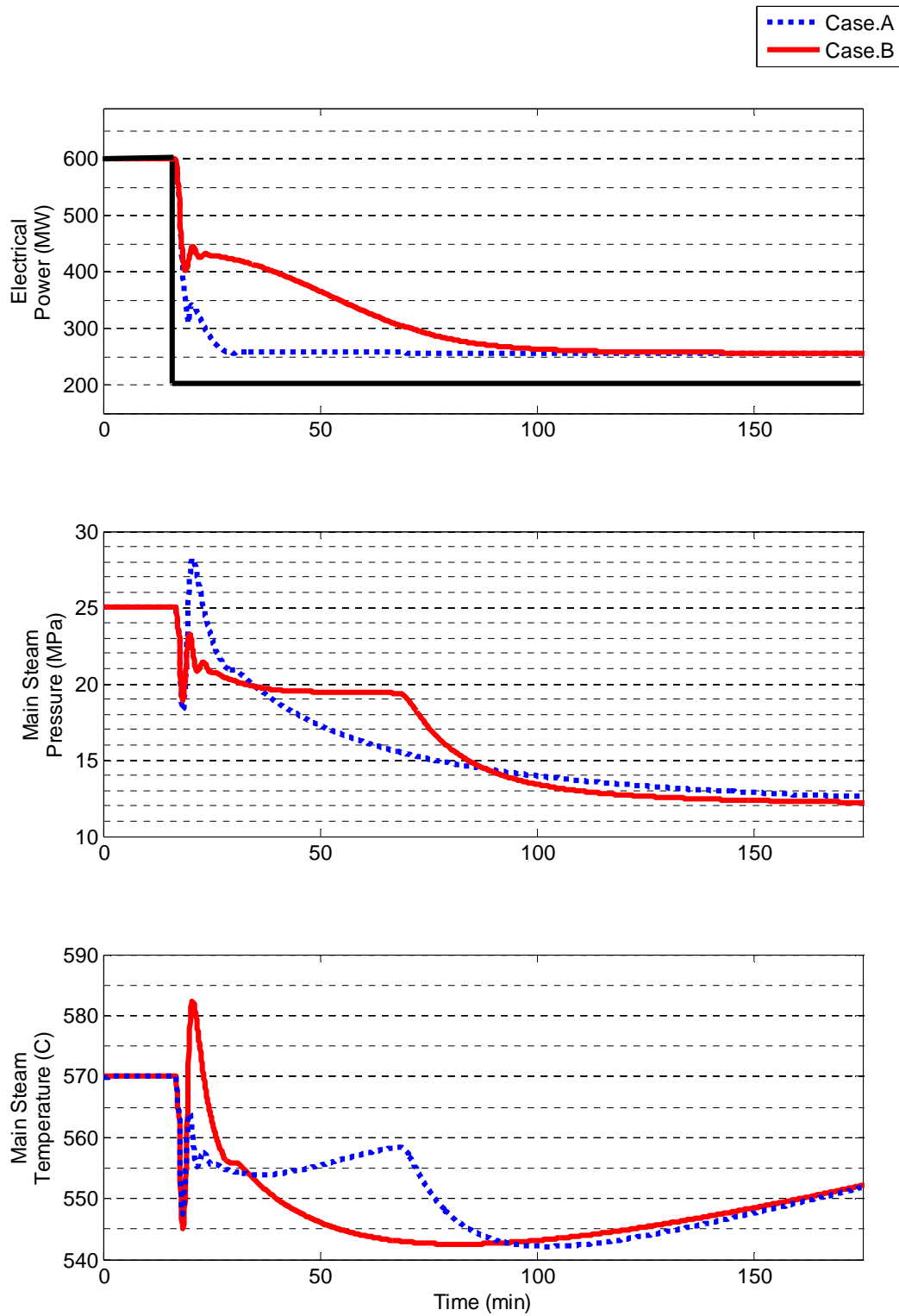


Fig 7.23 SCPP responses to 66% partial load rejection (output variables)

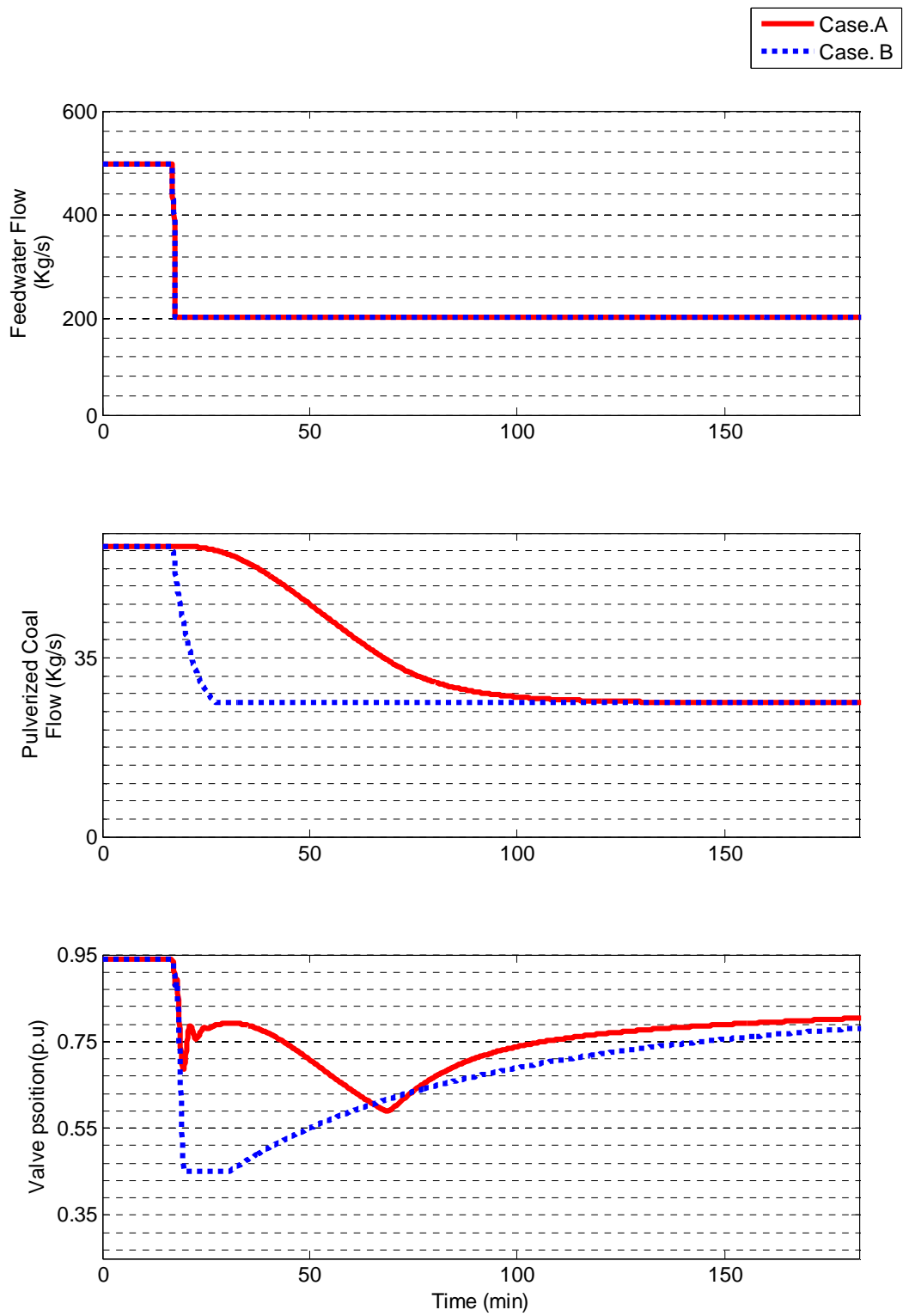


Fig7.24 SCPP responses to 66% partial load rejection (input variables)

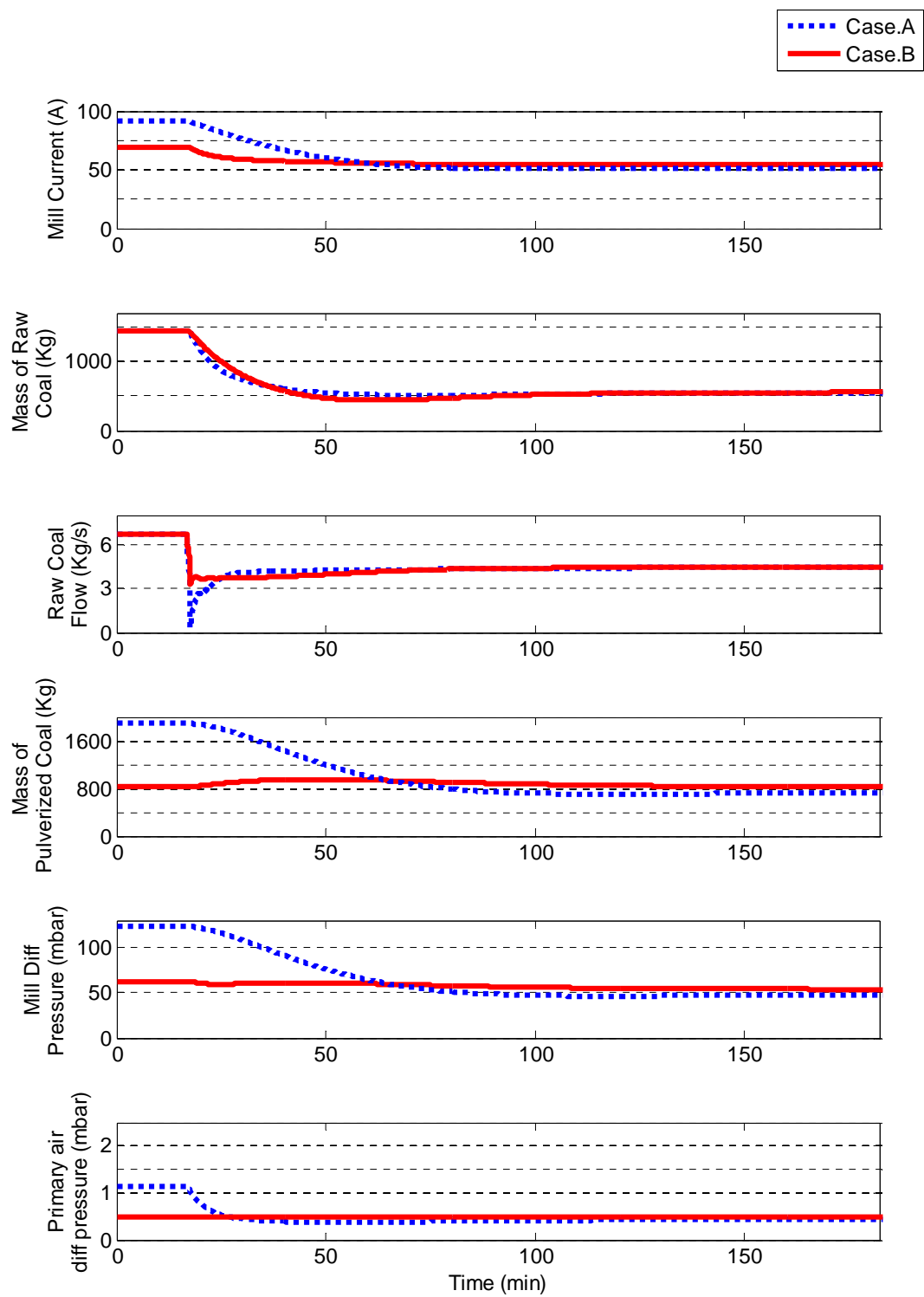


Fig 7.25 Mill responses

7.6 Summary:

Dynamic performance study of SCPP is reported in this chapter. For the sake of this study, the process model of SCPP has been augmented with a simplified predictive control strategy. Through dynamic response simulation study of SCPP as a controlled object, it is found that the primary response (such as the power output) can be improved by introducing a proper control strategy. Also, it is found that the various responses of the plant are feasible within their operating restrictions. It is well known that the temperature and pressure fluctuations are the main contributors to reducing the life time of the boiler equipment. By the proposed MPC strategy, fewer fluctuations and smoother responses are observed in the main steam pressure and temperature.

With linearized model and limited unmeasured disturbance compensation, the MPC is working effectively with small operating range around supercritical conditions. Because the proposed research is interested in plant performance with experience of large load demand changes which may drive the plant into subcritical region, the MPC has been strengthened with two generalized MPCs with different internal augmented models. The switchable MPCs offer an optional scheme control the plant over a wider operating range. Finally, another scheme is studied which is based on using dynamic compensator in parallel with the MPC and tested with partial load rejections. As expected, the plant is able to withstand around 33% partial load rejection without serious problems in its operating conditions or constraints. In comparison to drum boilers, drum type units are more robust in dealing with this issue from the literature survey.

Chapter 8

Conclusions and Suggested Future Research

The dynamic responses of supercritical power plants were studied in this thesis. Through mathematical modeling and simulations, a range of dynamic performance study has been conducted and the simulation results are reported in the thesis. The approach used here for modeling is a hybrid approach between physical principles modeling and system identification with data gathered from the plant operation. A predictive control strategy is proposed in the thesis. The control system configuration is regarded to be special scheme that adjusts the controlled reference values instead of directly applying the control signal. Simulation study on the power plant with the incorporation of predictive control strategy are presented and discussed.

This chapter is dedicated to summarize the work completed and achievement of my PhD research.

8.1 Conclusions

The main conclusions and findings of the thesis is summarized in the section.

- 1) A mathematical model that describes the main features of supercritical power plant has been developed. The model describes the main variables of supercritical power plant from coal grinding up to electrical power output. In comparison with previous research models, in the previous models the fuel source was assumed to be responding instantaneously which is not quite logical assumption, especially, when the grinding

capability of coal has great influence on the overall power plant performance. However, the proposed SCPP model includes the grinding process model which has been simply integrated with the rest of the plant modeled components.

2) A combination of nonlinear system identification and first principle modeling is adopted to establish the model. It is well known that modeling physical systems are either based on black-box identification or based on first principle modeling. The first approach is supposed to be accurate. However, empirical black box models are not trustable to simulate some emergency conditions because they are based entirely on on-site measurement data. On the other hand, physical or first principle models have to be high order models or detailed models in order to attain acceptable simulation results. A hybrid between the two approaches has been just done in this thesis to save time and effort. A simplified model is based initially on physical laws which resulted in nonlinear differential equations. Then the parameters of those differential equations are identified according to on-site measurement data.

3) Genetic Algorithms optimization technique has been used to identify the unknown parameters of the model. It has been noted that the previous parameter identification techniques on SCPP modelling are based on conventional mathematical gradient optimization, not on intelligent techniques. GA is much improved over conventional gradient optimization techniques. GA performs the search on a population of points that are widely distributed on the space of search, not only one point like mathematical gradient optimization. Some optimization problems have global optimal point among many other local optimal points. With appropriate settings of GA operations (i.e.,

termination criterion, number of generation, mutation rate...etc), the GA solution can not be trapped in local optimal point and the global optimal point can be reached. Also, it is worth mentioning that, with GA, the parameters can be optimized simultaneously with the various responses chosen for identification, not just sequential parameter identification which that is used to be done by mathematical gradient optimization techniques. The data set that has been used for identification represents load up variation from 35% to 100% of rated load of the plant.

4) Further study on the model has been conducted to confirm its validity. Three sets of data have been used for additional model investigations: one set of data represents load down data from 100% to 55% of rated load conditions. Another set of data shows small load variations around nominal operating conditions. And the final one used for investigation represents increase in load conditions from 33% to 100% followed by small decrease to around 80%. In all tests, the model responses are in agreement with the real plant responses. Small mismatches have been observed with varying average errors from certain response to another. However, it is also proved that the model can simulate the main variation trends and dynamical features of the real plant responses over a wide operating range with the optimal version of the parameters identified with the 1st set of data. Furthermore, a comparative study between the mathematical model and other simulation tool has been presented. Thermolib is a generic perfect tool for computer representation of thermodynamic systems. It was developed by Eutech in a SIMULINK environment with many functional blocks and fitted with a large thermodynamic data base for some substances' properties. This package has been used to build a complete SC thermodynamic cycle of the SC plant and its output has been compared with the model

output. The models show good agreement towards each other in different operating conditions. Coal mill model that represents the dynamics of real vertical spindle has been coupled to the boiler of the plant. Thereby the model covers longer process from fuel grinding to the electricity output. Set response tests have been performed virtually on the model. Through comparison with real step response tests performed on gas fired supercritical power plant, the responses are generally in agreement with large settling time for the coal fired plant because of the grinding process time delay.

5) A new control strategy is reported. The philosophy for improvement of dynamic responses of a supercritical power generation process through an improved control to the associated fuel preparation performed by the coal milling process. Any control actions taking for the milling process will take a long time to show their influences onto the boiler, turbine and generator responses as the whole process experiences coal transmission, grinding, drying and blowing to the furnace. The control philosophy behind the work presented in the thesis is to develop a control strategy to achieve prediction of the future demand for fuel input and implement control actions at the earliest possible time. The method started from development of generalized predictive control strategy for the nonlinear mathematical model developed for the supercritical coal fired power plant and then moves onto control strategy implementation. Finally, the simulation study has been carried out to demonstrate the effect of the new predictive control. Instead of directly applying the controller signals, the predicted demand values are used as a correction to the reference setup value in power plant local controllers. Controlled reference values scheme is found to be useful to speed-up the response of the coal mills and subsequently the power plant power responses.

6) Thereby it has been proved that the milling conditions play an important role in satisfying the UK grid code demand. Unlike previous attempts which relies either on the condensate stoppage or turbine fast valve acting to speed-up the power response. The MPC fuel signal is used with the mill local control to speed-up the mill response and subsequently the power primary response.

7) Partial load rejection simulation study is presented. This study needs more robust controller to cope with larger load changes. A MIMO compensator has been located in parallel with the MPC. First, the load demand was dropped suddenly by 33% of rated load from 600MW to 400MW and it is observed that the plant outputs follow the load demand with zero steady state error. The pressure dropped to subcritical level which indicates the existence of water level in the water wall. This proves that the SCPP are able to withstand more than 30% rejection of load without and serious problems. Another test was performed; this one is heavier load rejection of 66% of sudden load rejection from rated operating conditions. Because the once through mode is not permissible below 35% of loading, the SCPP failed to withstand this rejection correctly. This was however expected because SCPP cannot normally withstand more than 50% of rejection from survey of utility experience for power plant responses to partial load rejection, and this is due to the boiler pressure sensitivity.

8.2 Recommendations for future research

Apart from the contributions that have been reported in this thesis, there are lots of challenging topics for future research and further development in this subject. The future work should not necessarily be the extension of this research. It might be directed for

developing more accurate models with more advanced approaches and details that are not previously included. Operator training simulators have fewer applications of control schemes than simplified analytical models because control system design normally demands simplified models. However, the control system objective and target affect the shape and states of the designed model which may include components and exclude other components that are not of interest. The following main recommendations are made for future advancement;

- 1) The proposed model is fully dedicated for 600MW SCPP with four major components which are the fuel source or coal mill, the boiler, the turbines, and generator. However, it is suggested to include more detailed boiler and turbine models which include the body of feedwater heater in the boiler input side and more detailed governor model in the turbine part and update the model parameters accordingly.
- 2) It is suggested that the model should be expanded to simulate 800MW or 1000MW Ultra-Supercritical power plants. It is believed that *not* all model parameters must be updated to simulate the behaviour of other plants. Only few parameters on the input portions may be adjusted optimally to attain sufficiently acceptable performance of simulation. Of course the use of evolutionary computation technique is needed for such purpose.
- 3) The compliance with the national grid code is suggested to have much additional attention and research. By extracting other primary means which enhance the

power response of the plant and consequently attain the satisfaction of the UK grid code.

- 4) For the control part, it is suggested the strategy may be extended with more manipulated variables and outputs. Also, the performance of generalized predictive control deteriorates when large setpoint changes occur on the power demand. Neural network or Fuzzy predictive controller may be regarded as advanced solutions to adapt easily with the change and nature of disturbance. These technologies of predictive control are suggested instead of using deterministic nonlinear internal model in prediction algorithm due to the complexity of this algorithm and lack of its application in industry.

References

- Abdenmour, A. 2000. An intelligent supervisory system for drum type boilers during severe disturbances. *International Journal of Electrical Power & Energy Systems*. Vol. 22, issue (5), pp 381-387.
- Adams, J., Clark, D.R., Louis, J.R., & Spanbauer, J.P. 1965. Mathematical modeling of once-through boiler dynamics. *IEEE Transactions on Power Apparatus and Systems*, PAS. Vol.84, issue (2), pp 146-156.
- Andersson, G. 2003, *Dynamics and Control of Electric Power Systems*, Power System Laboratory, ETH Zurich.
- Armor, A.F., Shor, S.W.W., Didomenico, P.N., Bennett, W.E., & Smith, L.P. 1982. Dynamic performance of fossil-fuelled power plants. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-101, issue (10), pp 4136-4146.
- Bemporad, A., Morari, M. Ricker, N. L. 2010. *Model Predictive Control Toolbox User's Guide* The MathWorks.
- Ben-Abdenmour, A., Lee, K.Y., & Edwards, R.M. 1993. Multivariable robust control of a power plant deaerator. *IEEE Transactions on Energy Conversion*. Vol. 8, issue (1), pp 123-129.
- Boeringer, D. W. & Werner, D. H. A comparison of particle swarm optimization and genetic algorithms for a phased array synthesis problem, *In 2003 IEEE International Symposium on Antennas and Propagation: URSI North American Radio Science Meeting, 22-27 June 2003*, pp. 181-184.
- Boyd, S. Vandenberghe, L., 2004. *Convex Optimization* Cambridge University Press.
- Breeze, P. 2006. *Power Generation Technologies* Newnes.
- British Electricity International 1991. *Modern Power Station Practice: Vol.B: Boilers and Ancillary Plant* Pergamon.
- Bulut, B., Katebi, M. R., & Johnson, M. A. Industrial application of model based predictive control as a supervisory system, *In Proceedings of 2000 American Control Conference (ACC 2000), 28-30 June 2000, Danvers, MA, USA: American Autom. Control Council*, pp. 3763-3767.
- Central Electricity Generation Board 1972. *Modern Power Station Practice: Vol. 2: Mechanical Boilers, Fuel, and Ash Handling Plant* Pergamon.
- Chaibakhsh, A., Ghaffari, A., & Moosavian, S.A. 2007. A simulated model for a once-through boiler by parameter adjustment based on genetic algorithms. *Simulation Modelling Practice and Theory*. Vol. 15, issue (9), pp 1029-1051.

- Choi, S.Y., Yoo, K.Y., Lee, J.B., Shin, C.B., & Park, M.J. 2010. Mathematical modeling and control of thermal plant in the district heating system of Korea. *Applied Thermal Engineering*. Vol. 30, issue (14-15), pp 2067-2072.
- Dehghani, M. & Nikraves, S.K.Y. 2008. Nonlinear state space model identification of synchronous generators. *Electric Power Systems Research*. Vol. 78, issue (5), pp 926-940.
- DeMello, F. P., Ewart, D. N., Bloor, W. S., Usry, R. O., Fink, L. H., Leonard, L. V., & Croft, W. H. 1973. MW Response of Fossil Fuelled Steam Units, *In Symposium on Power Plant Response*, Los Angeles, CA, USA: IEEE, pp. 15-23.
- Dimeo, R. & Lee, K.Y. 1995. Boiler-turbine control system design using a genetic algorithm. *IEEE Transactions on Energy Conversion*. Vol. 10, issue (4), pp 752-759.
- Durrant, O.W. 1982. Boiler response to partial load rejections resulting from system upsets. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-101, issue (8), pp 2630-2639.
- EUTech 2004. *Thermolib User's Manual* EUTech Scientific Engineering.
- Fletcher, R. 1987. *Practical Methods of Optimization* John Wiley & Sons.
- Ghaffari, A., Chaibakhsh, A., & Parsa, H. An optimization approach based on genetic algorithm for modeling Benson type boiler, *In 2007 American Control Conference, ACC, July 9, 2007 - July 13, 2007*, New York, NY, United States: Institute of Electrical and Electronics Engineers Inc., pp. 4860-4865.
- Ghaffari, A., Chaibakhsh, A., & Lucas, C. 2007. Soft computing approach for modeling power plant with a once-through boiler. *Engineering Applications of Artificial Intelligence*. Vol. 20, issue (6), pp 809-819.
- Gibbs, B. P., Weber, D. S., & Porter, D. W. Application of nonlinear model-based predictive control to fossil power plants, *In Proceedings of the 30th IEEE Conference on Decision and Control, 11-13 Dec. 1991*, Brighton, England, pp. 1850-1856.
- Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization and Machine Learning* Addison-Wesley Educational Publishers.
- Gregory, C., Jr., Shah, S., & Walker, R. MATRIXX: application to large space structure control design problems, *In Proceedings of the 21st IEEE Conference on Decision & Control, 8-10 Dec. 1982*, California, USA, pp. 912-917.
- Gu, J. J., Zhang, L. Y., & Li, J. Q. Study on mathematical model of coordinated control system for supercritical units, *In 2009 International Conference on Machine Learning and Cybernetics, July 12, 2009 - July 15, 2009*, Baoding, China: IEEE, pp. 2158-2163.
- Haupt, R. L., Haupt, S.E. 2004. *Practical Genetic Algorithms* John Wiley & Sons.
- Hemmaplardh, K., Cate, E.G., Hammond, R.A., & Sackett, S.A. 1985. Applications of dynamic models in dispatcher training simulator and in other system dynamic performance

studies. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-104, issue (6), pp. 1349-1355.

Herreros, A., Baeyens, E., & Peran, J.R. 2002. Design of PID-type controllers using multiobjective genetic algorithms. *ISA Transactions*. Vol. 41, issue (4), pp 457-472.

IEEE Committee 1973. Dynamic models for steam and hydro turbines in power system studies. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-92, issue (6), pp 1904-1915.

IEEE Committee 1977. First benchmark model for computer simulation of sub-synchronous resonance [turbine-generator]. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-96, issue (5), pp 1565-1572.

IEEE Committee 1985. Second benchmark model for computer simulation of subsynchronous resonance. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-104, issue (5), pp 1057-1066.

IEEE Working group 1991. Dynamic models for fossil fueled steam units in power system studies. *IEEE Transactions on Power Systems*. Vol. 6, issue (2), pp 753-761.

IET. 2003. *Thermal Power Plant Simulation and Control* Stevenage, UK.

Inoue, T., Taniguchi, H., & Ikeguchi, Y. 2000. A model of fossil fueled plant with once-through boiler for power system frequency simulation studies. *IEEE Transactions on Power Systems*. Vol. 15, issue (4), pp 1322-1328.

Leyzerovich, A. S. 2007. *Steam Turbines for Modern Fossil-fuel Power Plants* CRC Press.

Kola, V., Bose, A., & Anderson, P.M. 1989. Power plant models for operator training simulators. *IEEE Transactions on Power Systems*. Vol. 4, issue (2), pp 559-565.

Kowalik, J., Osborne, M. R. 1968 *Methods of unconstrained optimization problems* American Elsevier.

Kumon, T., Iwasaki, M., Suzuki, T., Hashiyama, T., Matsui, N., & Okuma, S. Nonlinear system identification using genetic algorithm, *In Proceedings of 2000 IEEE International Conference on Industrial Electronics, Control and Instrumentation*, 22-28 Oct. 2000, pp. 2485-2491.

Kundur, P. 1981. A survey of utility experiences with power plant response during partial load rejection and system disturbances. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-100, issue (5), pp 2471-2475.

Kundur, P. 1994. *Power System Stability and Control* McGraw Hill.

Laubli, F. & Fenton, F.H., Jr. 1971. The flexibility of the supercritical boiler as a partner in power system design and operation. II. Application and field test results. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-90, issue (4), pp 1725-1733.

- Laubli, F. & Fenton, F.H., Jr. 1971. The flexibility of the supercritical boiler as a partner in power system design and operation. I. Theoretical relationships. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-90, issue (4), pp 1719-1724.
- Lee, K. Y., Heo, J. S., Hoffman, J. A., Sung-Ho, K., & Won-Hee, J. Neural network-based modeling for a large-scale power plant, *In 2007 IEEE Power Engineering Society General Meeting, 24-28 June 2007*, p.1- 8.
- Lee, K.Y., Van Sickel, J.H., Hoffman, J.A., Jung, W.H., & Kim, S.H. 2010. Controller design for a large-scale ultrasupercritical once-through boiler power plant. *IEEE Transactions on Energy Conversion*. Vol. 25, issue (4), pp 1063-1070.
- Li, Z., Li, Z., Tan, W., & Liu, J. 2006 Constrained dynamic matrix control for a boiler-turbine unit, *In International Conference on Machine Learning and Cybernetics*, pp. 665-670.
- Littman, B. & Chen, T.S. 1966. Simulation of bull run supercritical generation unit. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-85, issue (7), pp 711-722.
- Liu, C. L., Liu, J. Z., Niu, Y. G., & Zeng, D. L. Genetic algorithm-based multi-variables nonlinear boiler model identification for 300MW power unit, *In 2003 International Conference on Machine Learning and Cybernetics, November 2, 2003 - November 5, 2003*, Xi'an, China: Institute of Electrical and Electronics Engineers Inc., pp. 314-317.
- Ljung, L 1987. *System Identification: Theory for the User*. Prentice Hall.
- Lu, S. & Hogg, B.W. 1997. Predictive co-ordinated control for power-plant steam pressure and power output. *Control Engineering Practice*. Vol. 5, issue (1), pp 79-84.
- Lu, S. 1999. Dynamic modelling and simulation of power plant systems. *Proceedings of the Institution of Mechanical Engineers, Part A (Journal of Power and Energy)*. Vol. 213, (A1), pp 7-22.
- Lu, S. & Hogg, B.W. 2000. Dynamic nonlinear modelling of power plant by physical principles and neural networks. *International Journal of Electrical Power and Energy System*, 22, (1) 67-78.
- Maciejowski, J. M. 2002. *Predictive Control with Constraint* Addison-Wesley Educational Publishers.
- Maffezzoni, C. 1997. Boiler-turbine dynamics in power-plant control. *Control Engineering Practice*. Vol. 5, issue (3), pp 301-312.
- Maffezzoni, C., Ferrarini, L., & Carpanzano, E. 1999. Object-oriented models for advanced automation engineering. *Control Engineering Practice*. Vol. 7, issue (8), pp 957-968.
- Makovicka, J., Havelna, V., Benes, M. Mathematical Modeling of Steam and Flue Gas Flow of a Heat Exchanger in Steam Boiler, *Proceedings of Algorithmy 2002 Conference on Scientific Computing* pp. 171-178.

Miller, B. G. 2010. *Clean Coal Engineering Technology* Elsevier.

Mohamed, O., Wang, J., & Al-Duri, B. Study of a multivariable coordinate control for a supercritical power plant process, *In 2011 17th International Conference on Automation and Computing, 10 Sept. 2011*, Huddersfield, UK: IEEE, pp. 69-74.

Mohamed, O., Wang, J., Guo, S., Al-Duri, B., & Wei, J. Modelling study of supercritical power plant and parameter identification using genetic algorithms, *In World Congress on Engineering 2010, WCE 2010, June 30, 2010 - July 2, 2010*, London, England, pp. 973-978.

Mohamed, O., Wang, J., Guo, S., Wei, J., Al-Duri, B., Lv, J., & Gao, Q. 2011. Mathematical modelling for coal fired supercritical power plants and model parameter identification using genetic algorithms. *Lecture Notes in Electrical Engineering. Electrical Engineering and Applied Computing, Chapter 1, Springer*, pp 1-13.

Mohamed, O., Wang, J., Al-Duri, B., Lv, J., & Gao, Q. Predictive Control of Coal Mills for Improving Supercritical Power Generation Process Dynamic Responses. *IEEE Conference on Decision and Control* Dec 2012. Hawaii, USA, (Accepted and will be presented on Dec 2012c).

Mohamed, O., Wang, J., Al-Duri, B., Lv, J., & Gao, Q. Study of a Multivariable Coordinate Control for a Supercritical Power Plant. *International Journal of Energy Engineering, Scientific and Academic Publishing*. Vol. 2, No. 4, August 2012b.

Mohamed, O., Wang, J., Al-Duri, B Predictive Control Strategy of a Supercritical Power Plant and Study of Influences of Coal Mill Control on its Dynamic Responses. *Proceedings of UKACC 2012, Cardiff*. (Accepted and presented on 5th of Sep 2012a).

Morari, M., Ricker, L.N. 1998. *Model Predictive Control Toolbox for use with MATLAB® User's Guide* Version.1 The MathWorks.

Nalbandian, H. 2012. Performance and risks of advanced pulverized coal plant. *Energia*. Vol. 20, issue (1), pp 2-6.

Nakamura, H. & Akaike, H. 1981. Statistical identification for optimal control of supercritical thermal power plants. *Automatica*. Vol. 17, issue (1), pp 143-155.

Oluwande, G. A. & Eley, C. D. Simulation of a power plant based on the EASY5 package, *In IEE Colloquium on 'Simulation of Power Systems' (Digest No.221)*, 2 Dec. 1992, London, UK: IEE, pp. 2-1.

Oluwande, G.A. 2001. Exploitation of advanced control techniques in power generation. *Computing and Control Engineering Journal*. Vol. 12, issue (2), pp 63-67.

Ong, C. 1998. *Dynamic Simulation of Electric Machinery: Using MATLAB/SIMULINK®*. Prentice Hall.

- Ordys, A. W. & Grimble, M. J. 1999. Predictive Control in Power Generation. *Two-Day Workshop Techniques and Application*, pp. 1-8.
- Peet, W. J. & Leung, T. K. P. Dynamic simulation application in modern power plant control and design, *In Proceedings of the 2nd International Conference on Advances in Power System Control, Operation & Management, December 7-10, Hong Kong*, pp. 121-129.
- Peng, H., Gui, W., Nakano, K., & Shioya, H. Robust MPC based on multivariable RBF-ARX model for nonlinear systems, *In 44th IEEE Conference on Decision and Control, and the European Control Conference, CDC-ECC '05, December 12-15, Seville, Spain*, pp. 3777-3782.
- Peng, H. Multivariable RBF-ARX model-based predictive control for nonlinear systems, *In 7th IFAC Symposium on Nonlinear Control Systems, NOLCOS 2007, August 22, 2007 - August 24, 2007, PART 1 edn, Pretoria, South africa: IFAC Secretariat*, pp. 882-887.
- Po-Feng, T., Ji-Zheng, C., Shi-Shang, J., & Shyan-Shu, S. 2003. Developing a robust model predictive control architecture through regional knowledge analysis of artificial neural networks. *Journal of Process Control*. Vol. 13, issue (5), pp 423-435.
- Poncia, G. & Bittanti, S. 2001. Multivariable model predictive control of a thermal power plant with built-in classical regulation. *International Journal of Control*. Vol. 74, issue (11), pp 1118-1130.
- Prasad, G., Swidenbank, E., & Hogg, B. W. A multivariable predictive control strategy for economical fossil power plant operation, *In Proceedings of UKACC International Conference on Control. Control '96, 2-5 Sept. 1996, London*, pp. 1444-1449.
- Prasad, G., Irwin, G. W., Swidenbank, E., & Hogg, B. W. Plant-wide physical model-based control for a thermal power plant, *In Proceedings of 1999 Conference on Decision and Control, 7-10 Dec. 1999, Arizona, USA*, pp. 4631-4636.
- Prasad, G., Swidenbank, E., & Hogg, B.W. 1999. Neural network model-based multivariable predictive control algorithms with application in thermal power plant control. *Control and Intelligent Systems*. Vol. 27, issue (3), pp 108-131.
- Prasad, G. 2003, "Physical model-based coordinated power plant control," *In Thermal Power Plant Simulation and Control*, Stevenage, UK: IET, pp. 365-393.
- Ramirez, G. R. & Lee, K. Y. Overall control of fossil-fuel power plants, *In Proceedings of 2001 Winter Meeting of the IEEE Power Engineering Society, 28 Jan.-1 Feb. 2001, Piscataway, NJ, USA: IEEE*, pp. 1209-1214.
- Rayaprolu, K. 2009. *Boilers for Power and Process* CRC Press.
- Ricker, N.L. 1990. Model predictive control with state estimation. *Industrial & Engineering Chemistry Research*. Vol. 29, issue (3), pp 374-382.

- Rossiter, J.A., Kouvaritakis, B., & Dunnett, R.M. 1991. Application of generalised predictive control to a boiler-turbine unit for electricity generation. *IEE Proceedings D: Control Theory and Applications*. Vol.138, issue (1), pp 59-67.
- Rovnak, J.A. & Corlis, R. 1991. Dynamic matrix based control of fossil power plants. *IEEE Transactions on Energy Conversion*. Vol. 6, issue (2), pp 320-326.
- Salisbury, J. K. 1950. *Steam Turbines and Their Cycles* John Wiley & Sons.
- Shinohara, W. & Koditschek, D. E. A simplified model based supercritical power plant controller, *In Proceedings of 35th IEEE Conference on Decision and Control, 11-13 Dec. 1996*, Kobe, Japan, pp. 4486-4491.
- Simon, E., Stoica, C., Rodriguez-Ayerbe, P., Dumur, D., & Wertz, V. Robustified optimal control of a coal-fired power plant, *In 2010 American Control Conference - ACC 2010, 30 June-2 July 2010*, Piscataway, NJ, USA: IEEE, pp. 1217-1222.
- Sonntag, R. E., Borgnakke, C., Wylen, J. V. 1998. *Fundamentals of Thermodynamics* John Wiley & Sons.
- Suzuki, Y., Pyong, S.P., & Uchida, Y. 1979. Simulation of a supercritical once-through boiler. *Simulation*. Vol. 33, issue (6), pp 181-193.
- The Math Works 2004. *Genetic Algorithm and Direct Search Toolbox user's guide* The MathWorks.
- Thomas, G.B., Fenny, R.L. 1979. *Calculus and Analytic Geometry* Addison Wesley.
- Trangbaek, K. Constrained control of a once-through boiler with recirculation, *In 17th World Congress, International Federation of Automatic Control, IFAC, July 6, 2008 - July 11, 2008*, 1 PART 1 edn, Seoul, Korea, Republic of: Elsevier.
- Un-Chul Moon & Lee, K.Y. 2010. Step-response model development for dynamic matrix control of a drum-type boiler-turbine system. *IEEE Transactions on Energy Conversion*. Vol. 24, issue (2), pp 423-430.
- Usoro, P. B. & Wormley, D. N. Mathematical modeling of fossil-fuelled steam power plants under normal and emergency operating conditions. I. Methodology, *In Proceedings of the Fifth Power Plant Dynamics, Control and Testing Symposium, 21-23 March 1983*, Knoxville, TN, USA, pp. 6.01-6.22.
- Usoro, P. B. & Wormley, D. N. Mathematical modeling of fossil-fuelled steam power plants under normal and emergency operating conditions. II. Simulation results, *In Proceedings of the Fifth Power Plant Dynamics, Control and Testing Symposium, 21-23 March 1983*, Knoxville, TN, USA, pp. 6.23-6.38.
- Usoro, P.B., Rouhani, R., Mehra, R.K., & Varaiya, P. 1983. Power system modelling for emergency state simulation. *Mathematical Modelling*. Vol. 4, issue (2), pp 143-165.

- Vocke, C. Supercritical boiler control operational experience, *In IET Seminar on Power Generation Control, December 6, 2007*, Institution of Engineering and Technology, pp. 29-35.
- Waddington, J. & Maples, G.C. 1987. The control of large coal and oil-fired generating units. *Power Engineering Journal*. Vol. 1, issue (1), pp 25-34.
- Wang, L. 2010. *Model Predictive Control System Design and Implementation Using MATLAB®* Springer London.
- Wang, J. 2009, *Modeling and Simulation Study of Coal Fired Power Generation with Supercritical Boiler for Grid Code Compliance*, PhD Project Proposal, Power System and Control Research Lab, University of Birmingham.
- Wei-Der, C. 2007. A multi-crossover genetic approach to multivariable PID controllers tuning. *Expert Systems with Applications*. Vol. 33, issue (3), pp 620-626.
- Wei, J. Wang, J. & Wu, Q.H. 2007. Development of a multisegment coal mill model using an evolutionary computation technique. *IEEE Transactions on Energy Conversion*. Vol. 22, issue (3), pp 718-727.
- Weisman, J., Eckart. R. 1985. *Modern Power Plant Engineering* Prentice-Hall.
- Wylen, J. V, Sonntag, R.E. 1994. *Fundamentals of Classical Thermodynamics* John Wiley & Sons Inc.
- Woo, R. & Anderson, G.R. 1969. Dynamic response of a supercritical power plant. *Instrumentation Technology*. Vol. 16, issue (7), pp 41-45.
- Younkins, T.D., deMello, F.P., Dunlop, R.D., Fenton, F.H., Jr., Intrabartola, J.M., Kundur, P., Littman, B., Russell, T.D., Durrant, O.W., Mounts, J.G., Gorzegno, W.P., & Rusche, P.A. 1983. Guidelines for enhancing power plant response to partial load rejections. *IEEE Transactions on Power Apparatus and Systems*. Vol. PAS-102, issue (6), pp 1501-1504.
- Yu, Yao-Nan. 1983. *Electric Power System Dynamics* Academic Press.
- Yue, M., Hu, T., Guo, B., & Guo, X. The research of parameters of genetic algorithm and comparison with particle swarm optimization and shuffled frog-leaping algorithm, *In 2009 2nd International Conference on Power Electronics and Intelligent Transportation System (PEITS 2009), 19-20 Dec. 2009*, pp. 77-80.
- Zachariades, P. & Wang, J. 2009, *On-line Condition and Safety Monitoring for Pulverized Coal Mills Using Model Based Pattern Recognition Technique*, Technical Report, University of Birmingham, Birmingham, UK.
- Zhang, Y.G., Wu, Q.H., Wang, J., Oluwande, G., Matts, D., & Zhou, X.X. 2002. Coal mill modeling by machine learning based on onsite measurements. *IEEE Transactions on Energy Conversion*. Vol. 17, issue (4), pp 549-555.

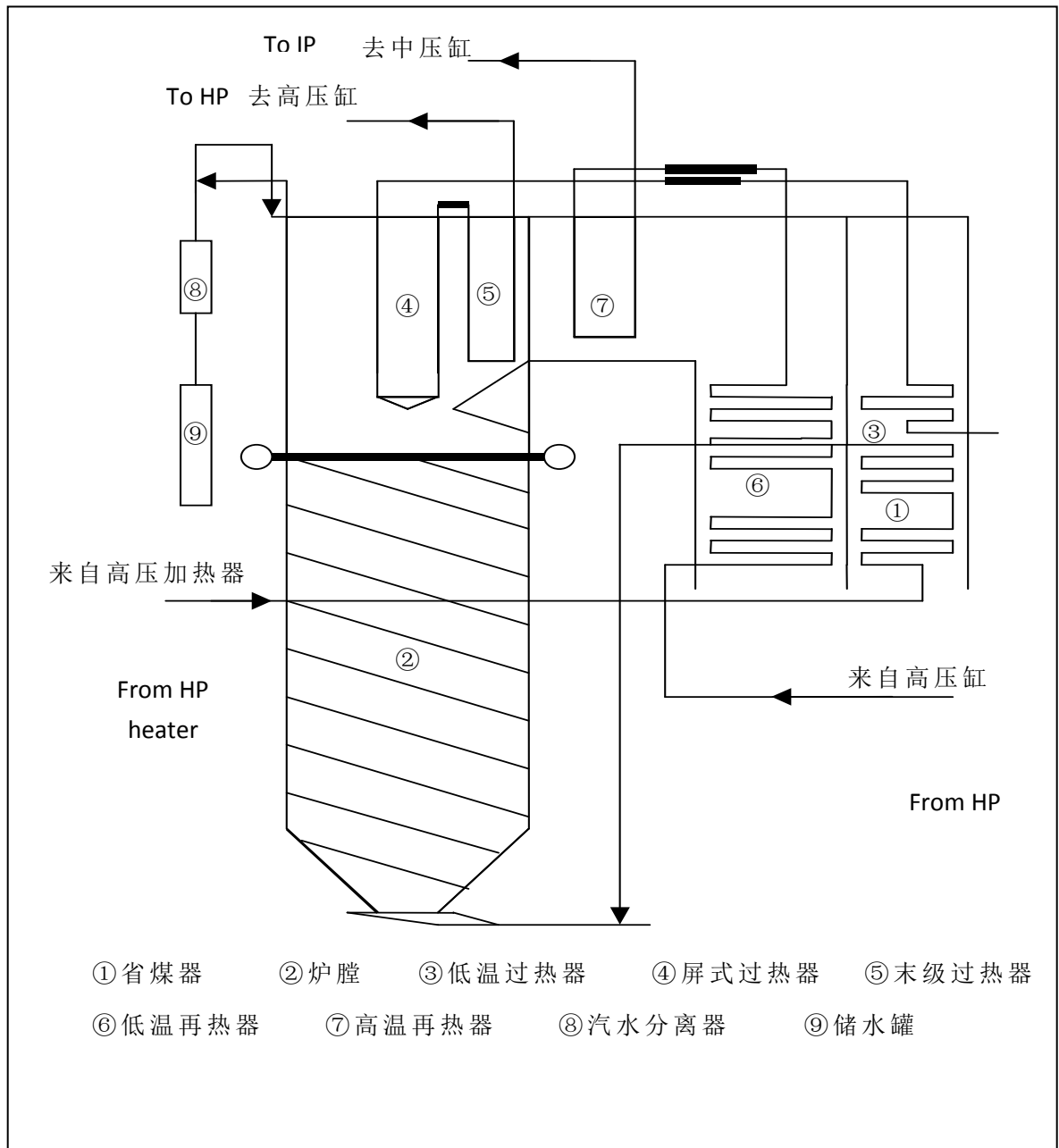
Zhong-Xu, H., Gang, P., Zhong-chang, Q., Chuan-Xin, Z., & Cui-hui, Y. Research on generalized intelligent coordinated control system of supercritical unit, *In 2009 International Conference on Energy and Environment Technology (ICEET 2009)*, 16-18 Oct. 2009, pp. 798-803.

Zhong-Xu, H., Jian, F., Hui, W., Chuan-Xin, Z., & Zhi-qiang, K. Study on simulation mathematical model of supercritical boiler-turbine-generator unit, *In 2008 Joint International Conference on Power System Technology and IEEE Power India Conference (POWERCON)*, 12-15 Oct. 2008, pp1- 5.

Zindler, H. Watler, H. Dynamic Simulation of a 800 MWel Hard Coal One-Through Supercritical Power Plant to Fulfill the Great Britain Grid Code, *In 6th IASME/WSEAS International Conference on Heat Transfer, Thermal Engineering and Environment, Rhodes, Greece, August 20-22, 2008*, pp. 184-192.

Appendix

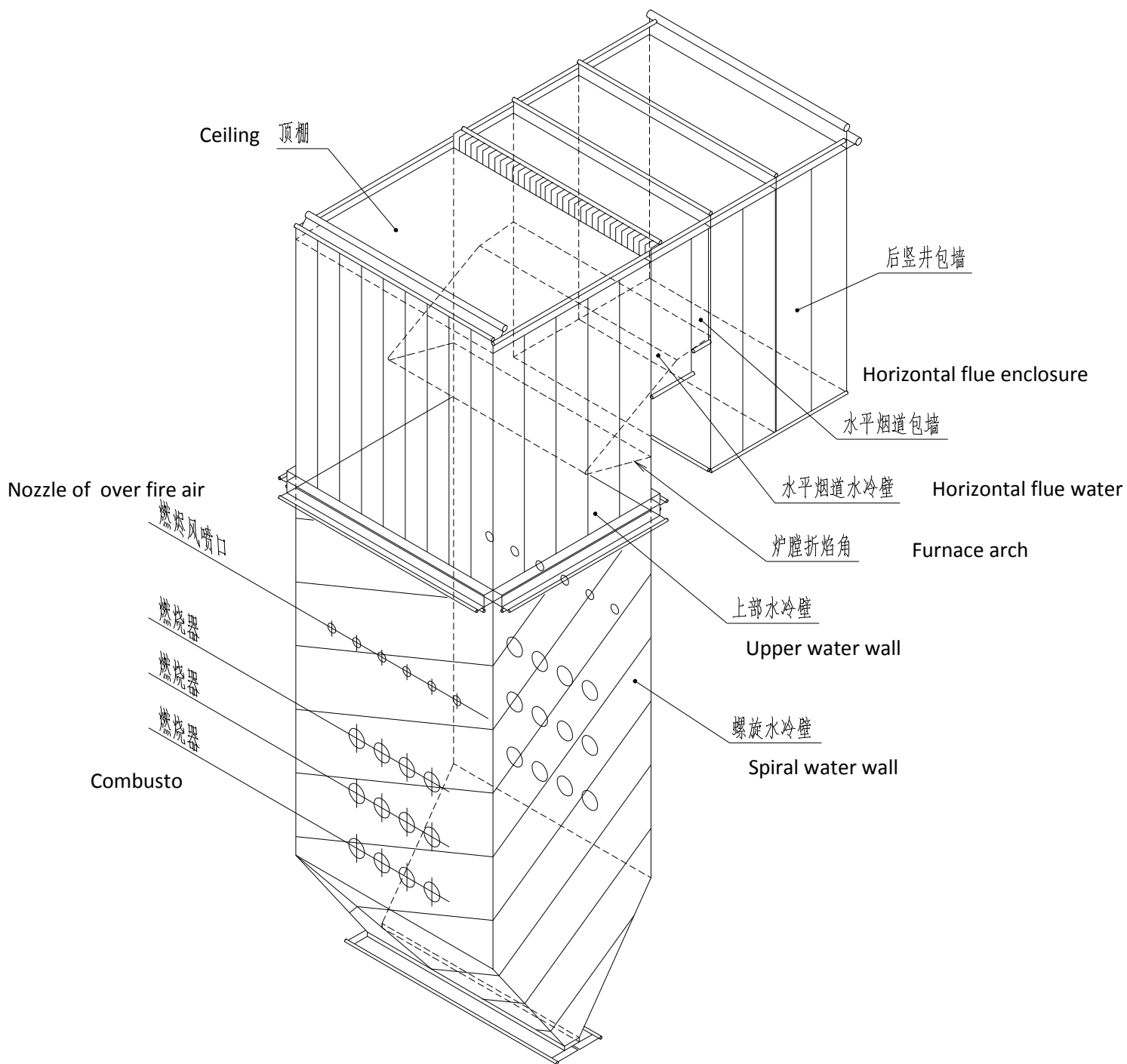
A.1 SC boiler schematic



锅炉水汽流程图

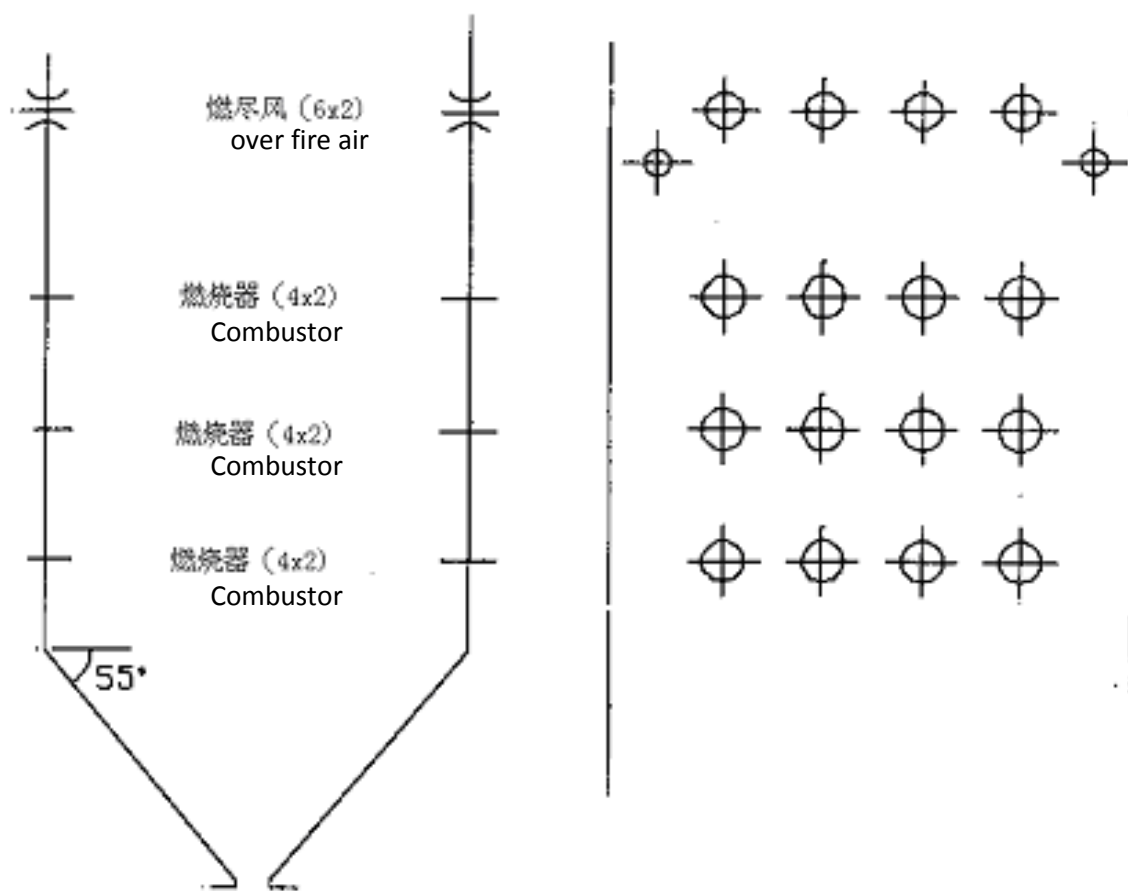
Flow diagram of boiler steam-water progress

- | | | | |
|--|-----------------------------|--------------------------------|-----------------------|
| 1. Economizer | 2. Furnace | 3. Low temperature superheater | 4. Platen superheater |
| 5. Final superheater | 6. Low temperature reheater | 7. High temperature reheater | |
| 8. steam-water separator 9. Water storage tank | | | |



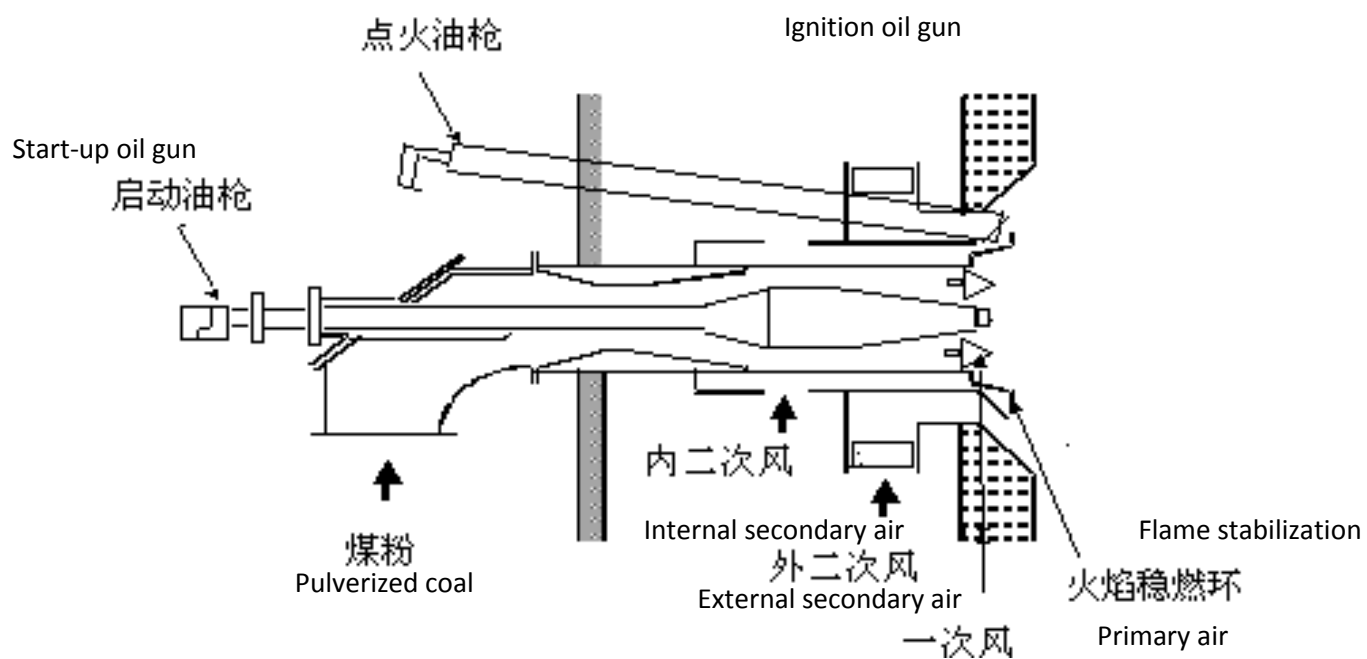
水冷壁总体布置图

Layout of water



燃烧器布置图

Layout of Combustor



燃烧器配风示意图 Air distribution of combustor

A.2 Genetic Algorithm Toolbox and Generalized M-File

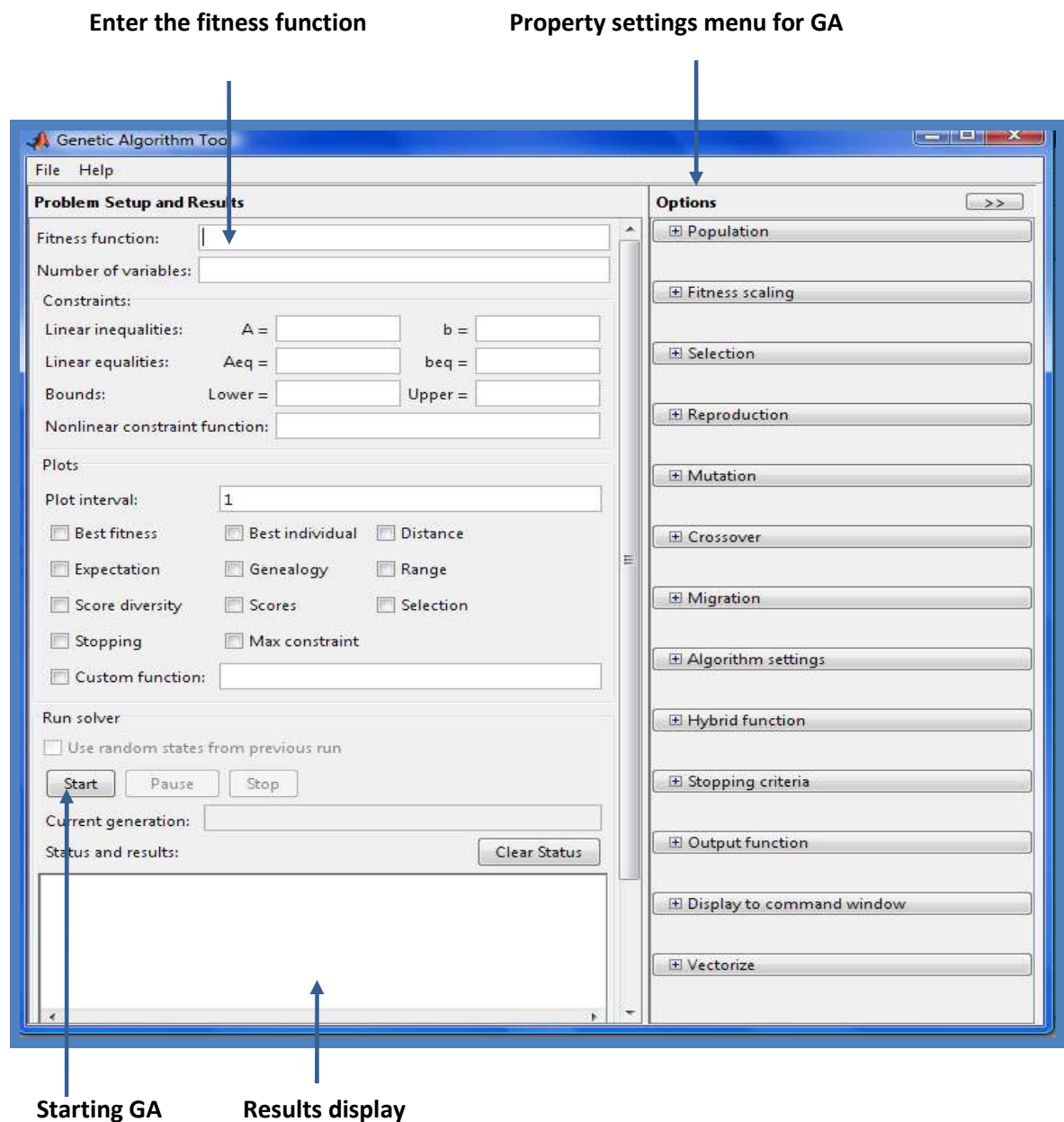


Fig A.1 Genetic algorithm tool

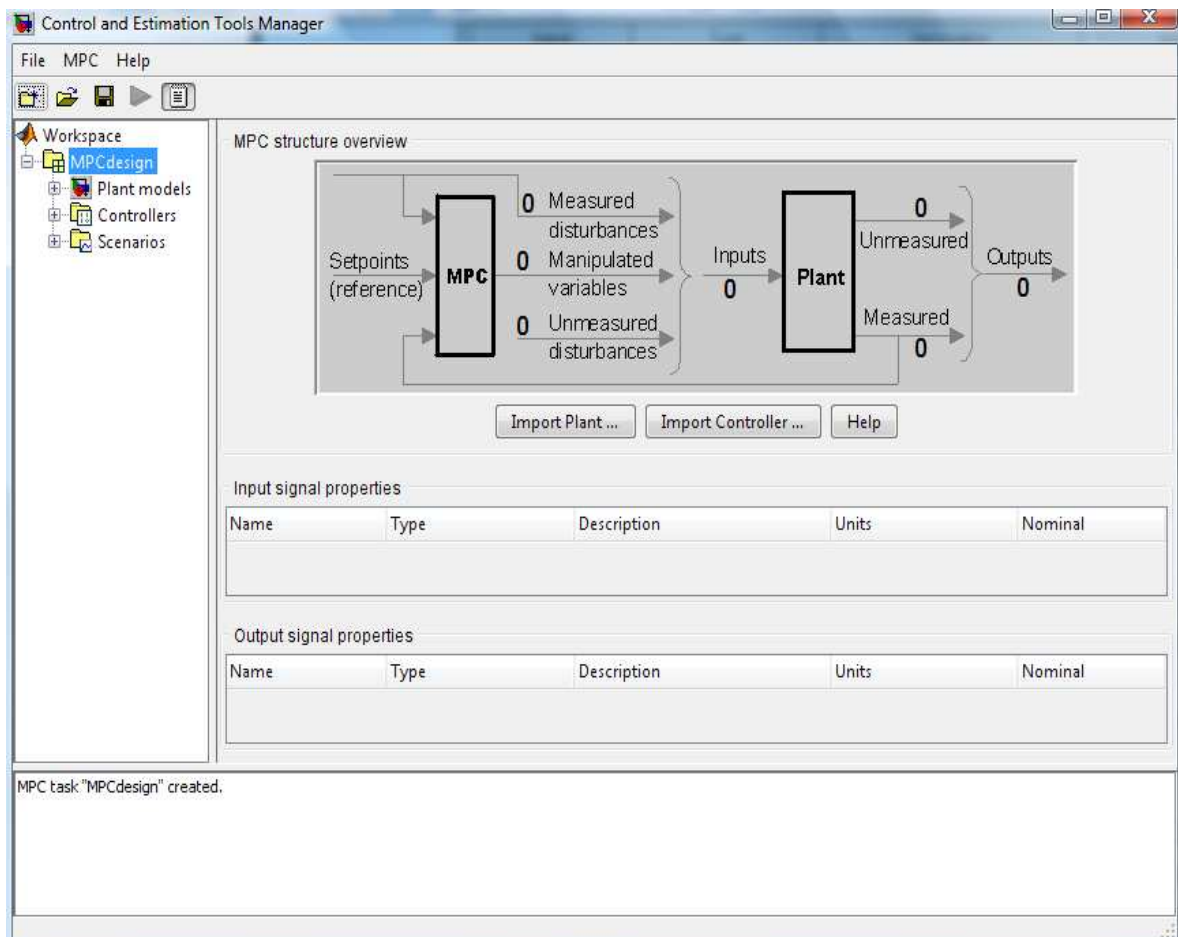
This M-file can be generated from the toolbox to work with and report the parameters instead of the graphical window representation

```
function [X,FVAL,REASON,OUTPUT,POPULATION,SCORES] =  
untitled  
% This is an auto generated M file to do optimization  
with  
% Genetic Algorithm and Direct Search Toolbox.  
  
% Fitness function  
fitnessFunction = [];  
% Number of Variables  
nvars = [];  
% Linear inequality constraints  
Aineq = [];  
Bineq = [];  
% Linear equality constraints  
Aeq = [];  
Beq = [];  
% Bounds  
LB = [];  
UB = [];  
% Nonlinear constraints  
nonlconFunction = [];  
% Start with default options  
options = gaoptimset;  
% Modify some parameters  
options = gaoptimset(options,'Display','off');  
% Run GA  
[X,FVAL,REASON,OUTPUT,POPULATION,SCORES] =  
ga(fitnessFunction,nvars,Aineq,Bineq,Aeq,Beq,LB,UB,nonlconF  
unction,options);
```

The file has been used to identify the unknown parameters of the SCPP model and update the model parameters, throughout the research period, to get the version of parameters as best as possible.

A.3 Model Predictive Control tool and paper machine headbox model

A.3.1 the Model Predictive Controller Tool



FigA.2 Model Predictive control design toolbox

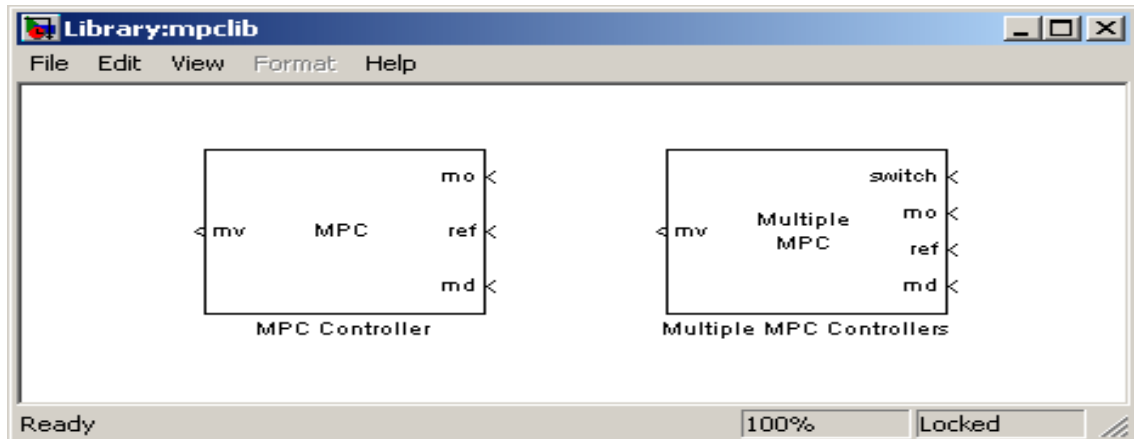


Fig A.3 Model predictive control SIMULINK library.

A.2.2 Paper Machine Headbox Nonlinear Model (mpc_pmmode1.m)

```
function [sys,x0,xstr,TS]=mpc_pmmode1(t,x,u,flag,xp0)

% [sys,x0,xstr,TS]=mpc_pmmode1(t,x,u,flag,xp0)
%
% SIMULINK representation of the paper machine process
described
% by Ying, Rao, and Sun, Chem. Eng. Communications, 1992.
(See
% also, Proceedings of American Control Conference, San
Diego,
% pp 1917, 1990). The model is bilinear. Using
nomenclature in
% the paper, process variables are:
%
% Manipulated variables:    Gp, Gw
% Measured disturbance:    Np
% Unmeasured disturbance:  Nw
% Measured outputs:        H2, N1, N2
% Unmeasured outputs:     H1
% States:                  H1, H2, N1, N2
%
% Accepts standard Simulink inputs for a system model.
% The model expects the input vector (u)
% to contain [Gp, Gw, Np, Nw] (in that order).
% The outputs will be H2, N1, N2 (in that order).
% Use optional parameter xp0 to initialize the state.
% The default initial condition is zero.
```

```

% Copyright 1994-2004 The MathWorks, Inc.
% $Revision: 1.1.4.2 $

% By N. L. Ricker, December, 1991.
% Updated 8/25/96 by N. L. Ricker to work in Simulink 2.

% Initialization

if nargin == 0
    flag=0;
end
if nargin < 5
    xp0=[];
end

if flag == 0

    if nargin == 4
        x0=zeros(4,1);
    elseif isempty(xp0)
        x0=zeros(4,1);
    else
        x0=xp0(:);
        if length(x0) ~= 4
            error('Plant initial condition vector must have 4
elements')
        end
    end
    sys=[4 0 3 4 0 0 1];
    xstr=['H1';'H2';'N1';'N2'];
    TS=[0 0];

% state update if ABS(FLAG) == 1

elseif abs(flag) == 1

    A0=[-1.93 0 0 0; .394 -.426 0 0; 0 0 -.63 0; .82 -.784
.413 -.426];
    B0=[1.274 1.274;0 0;1.34 -.65;0 0];
    U=u(1:2,1);    % Manipulated variables
    W=u(3:4,1);    % Measured and unmeasured disturbance
inputs.

    sys=A0*x+B0*U;
    sys(3)=sys(3)-.327*x(3)*sum(U)+[.203 .406]*W;

% Output update if FLAG == 3.

elseif flag == 3

```

```

        iy=[2,3,4]; % Picks out correct states to use as output
        variables.
        sys=x(iy,1);

% For all other FLAG values, return an empty matrix.

else
    sys=[];
end

```

A.3 MPCs transfer functions

MPC.1

```

% Transfer function of the first MOC controller. This function is used to
% describe the MPC parameters and it can be generated using the command tf
% (MPC object)

Transfer function from input "meas.Y1" to output...

      -0.0002426 z^7 + 0.0005159 z^6 - 0.0003038 z^5 + 3.06e-005 z^4 + 2.956e-019 z^3 - 3.031e-
020 z^2
      - 1.607e-036 z - 3.969e-051

MV1: -----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      -0.0003293 z^7 + 0.0007014 z^6 - 0.000415 z^5 + 4.288e-005 z^4 + 7.725e-021 z^3 + 2.804e-
021 z^2
      - 1.99e-036 z + 3.683e-053

MV2: -----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      0.0004912 z^7 - 0.001369 z^6 + 0.001265 z^5 - 0.0003868 z^4 - 1.316e-019 z^3 + 8.738e-028
z^2
      - 4.941e-046 z

MV3: -----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

Transfer function from input "meas.Y2" to output...

      0.001479 z^7 - 0.003145 z^6 + 0.001853 z^5 - 0.0001866 z^4 + 5.669e-019 z^3 - 8.47e-020
z^2
      + 6.381e-035 z + 1.095e-050

```

```

MV1: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      0.002008 z^7 - 0.004277 z^6 + 0.00253 z^5 - 0.0002615 z^4 - 1.418e-019 z^3 + 2.225e-020
z^2
      + 4.912e-035 z + 5.228e-052

MV2: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      -0.002995 z^7 + 0.008348 z^6 - 0.007711 z^5 + 0.002358 z^4 + 1.836e-018 z^3 + 4.312e-027
z^2
MV3: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

Transfer function from input "meas.Y3" to output...

      -0.006098 z^7 + 0.01297 z^6 - 0.007636 z^5 + 0.0007691 z^4 - 3.345e-018 z^3 + 4.082e
      -019 z^2 + 1.109e-033 z - 6.749e-050

MV1: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      -0.008275 z^7 + 0.01763 z^6 - 0.01043 z^5 + 0.001078 z^4 + 1.707e-018 z^3 - 2.383e-019 z^2
      + 1.05e-033 z + 3.818e-050

MV2: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

      0.01235 z^7 - 0.03441 z^6 + 0.03179 z^5 - 0.009721 z^4 - 1.178e-018 z^3 - 1.118e-026 z^2
      - 2.668e-043 z

MV3: -----
----
      z^7 - 3.278 z^6 + 3.995 z^5 - 2.193 z^4 + 0.5154 z^3 - 0.03888 z^2 + 8.566e-018 z +
1.945e-034

Sampling time: 1

```

MPC.2

```

tf(MPC400)

Transfer function from input "meas.Y1" to output...

-0.01143 z^7 + 0.01143 z^6 + 3.079e-008 z^5 + 9.215e-019 z^4 - 3.074e-032 z^3 + 5.359e-044 z^2
- 2.921e-059 z + 1.173e-075

MV1: -----
z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z
- 1.668e-056

```

$$-0.01542 z^7 + 0.01542 z^6 - 2.284e-008 z^5 - 2.752e-019 z^4 + 4.293e-032 z^3 - 1.104e-043 z^2 + 6.798e-059 z - 4.26e-075$$

MV2: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

$$0.001407 z^7 - 0.001407 z^6 - 9.511e-011 z^5 + 4.196e-020 z^4 - 8.398e-034 z^3 + 3.603e-044 z^2 - 2.276e-060 z - 6.883e-076$$

MV3: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

Transfer function from input "meas.Y2" to output...

$$0.06966 z^7 - 0.06966 z^6 - 1.877e-007 z^5 - 5.699e-018 z^4 + 9.499e-031 z^3 + 7.633e-044 z^2 - 1.975e-057 z - 5.978e-074$$

MV1: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

$$0.094 z^7 - 0.094 z^6 + 1.393e-007 z^5 + 1.737e-018 z^4 - 4.534e-031 z^3 - 2.525e-042 z^2 + 1.389e-057 z + 3.573e-074$$

MV2: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

$$-0.00858 z^7 + 0.00858 z^6 + 5.799e-010 z^5 - 2.556e-019 z^4 - 1.046e-032 z^3 + 3.905e-044 z^2 + 8.064e-059 z + 4.558e-075$$

MV3: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

Transfer function from input "meas.Y3" to output...

$$-0.2871 z^7 + 0.2871 z^6 + 7.737e-007 z^5 + 2.316e-017 z^4 - 2.835e-030 z^3 + 1.91e-041 z^2 + 1.719e-056 z - 1.722e-073$$

MV1: -----

$$z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z - 1.668e-056$$

$$-0.3875 z^7 + 0.3875 z^6 - 5.741e-007 z^5 - 6.918e-018 z^4 + 1.422e-030 z^3 - 9.292e-042 z^2 - 3.68e-057 z - 8.093e-074$$

```

MV2: -----
z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z
      - 1.668e-056

0.03537 z^7 - 0.03537 z^6 - 2.39e-009 z^5 + 1.055e-018 z^4 + 7.512e-032 z^3 - 7.513e-043 z^2
      - 4.964e-059 z - 5.71e-076

MV3: -----
z^7 - 1.049 z^6 + 0.049 z^5 - 3.778e-010 z^4 - 1.538e-017 z^3 + 9.156e-029 z^2 + 1.498e-042 z
      - 1.668e-056

Sampling time: 1

```

MPC.3

```

tf(MPC600)

Transfer function from input "meas.Y1" to output...

0.003715 z^8 - 0.004165 z^7 + 0.0004497 z^6 - 7.809e-014 z^5 - 9.504e-026 z^4 - 4.668e-039 z^3
      - 1.049e-054 z^2 - 6.993e-072 z + 2.223e-087

MV1: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
      + 1.23e-052 z + 1.115e-068

0.005011 z^8 - 0.005617 z^7 + 0.0006066 z^6 + 5.672e-014 z^5 + 5.483e-026 z^4 - 2.139e-039 z^3
      - 2.55e-055 z^2 - 5.985e-072 z + 8.28e-087

MV2: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
      + 1.23e-052 z + 1.115e-068

-0.0004578 z^8 + 0.0005133 z^7 - 5.549e-005 z^6 - 6.228e-018 z^5 - 5.008e-028 z^4
      - 2.617e-041 z^3 + 1.372e-055 z^2 - 4.92e-071 z - 3.179e-087

MV3: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
      + 1.23e-052 z + 1.115e-068

Transfer function from input "meas.Y2" to output...

-0.06102 z^8 + 0.08023 z^7 - 0.01921 z^6 + 3.338e-012 z^5 + 3.828e-024 z^4 - 7.622e-038 z^3
      + 9.272e-054 z^2 + 4.472e-070 z - 5.944e-086

MV1: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2

```

```

+ 1.23e-052 z + 1.115e-068

-0.08231 z^8 + 0.1082 z^7 - 0.02591 z^6 - 2.424e-012 z^5 - 2.389e-024 z^4 + 4.789e
-038 z^3 - 6.095e-054 z^2 - 2.497e-070 z - 1.211e-085
MV2: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
+ 1.23e-052 z + 1.115e-068

0.007523 z^8 - 0.009895 z^7 + 0.002372 z^6 + 1.082e-016 z^5 + 2.14e-026 z^4 - 3.826e-040 z^3
+ 8.817e-056 z^2 + 1.624e-070 z - 3.537e-087
MV3: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
+ 1.23e-052 z + 1.115e-068

Transfer function from input "meas.Y3" to output...

-0.5944 z^8 + 1.087 z^7 - 0.4928 z^6 + 8.564e-011 z^5 + 1.004e-022 z^4 + 9.795e-038 z^3
- 3.004e-053 z^2 + 2.773e-069 z + 5.931e-086
MV1: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
+ 1.23e-052 z + 1.115e-068

-0.802 z^8 + 1.467 z^7 - 0.6649 z^6 - 6.221e-011 z^5 - 6.273e-023 z^4 + 7.922e-039 z^3
+ 1.884e-052 z^2 - 2.851e-068 z + 1.389e-084
MV2: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
+ 1.23e-052 z + 1.115e-068

0.07339 z^8 - 0.1343 z^7 + 0.06087 z^6 + 4.662e-015 z^5 + 5.48e-025 z^4 - 1.985e-041 z^3
- 5.577e-055 z^2 - 5.359e-070 z - 3.93e-086
MV3: -----
z^8 - 2.045 z^7 + 1.093 z^6 - 0.04834 z^5 + 1.746e-014 z^4 + 4.549e-025 z^3 - 2.906e-038 z^2
+ 1.23e-052 z + 1.115e-068

Sampling time: 1

```