Jean Thomas

Model-Based Power Plant Master Control

In this paper a coordinated master control for a solid fuel power plant has been developed and the performance evaluated in terms of tracking capability, stability and robustness. The control strategy has been model-based predictive control (MPC) and it was evaluated on a nonlinear process model of the Vattenfall power plant Idbäcken in Nyköping, Sweden. The developed master MPC with gain scheduling has better performance compared to the existing PID controller which has been thoroughly studied and tuned in a previous project. The robustness of the proposed master MPC controller against common disturbances and parameter variation has been investigated and it shows that the proposed controller is more robust than the existing PID controller.

Key words: Master Predictive Control, Solid fuel power plant, Gain scheduling.

Nadređeno modelsko upravljanje elektranom. U ovome radu razvijeno je koordinirano nadređeno upravljanje za elektrane na kruta goriva te su provjereni pokazatelji kvalitete u smislu praćenja, stabilnosti i robustnosti. Koristi se modelsko prediktivno upravljanje koje je provjereno na nelinearnom modelu procesa Vattenfall elektrane Idbäcken u Nyköping, Švedska. Razvijeni nadređeni MPC s prekapčanjem ima bolje performanse u usporedbi s PID regulatorom koji je bio temeljito proučen i podešen u prijašnjem projektu. Istražena je robustnost predloženog nadređenog MPC-a u odnosu na šum i promjene parametara. Pokazuje se da je predloženi regulator robustniji od postojećeg PID regulatora.

Ključne riječi: nadređeno prediktivno upravljanje, elektrane na kruta goriva, upravljanje s prekapčanjem

1   INTRODUCTION

In a traditional combustion power plant there is usually a master control layer in the control system responsible for coordinating the boiler/turbine low-level controllers. The design and tuning of this master control is crucial for a fast and robust control during load tracking and disturbance rejection. There are a number of objectives to consider when designing such a master control, like plant efficiency (thermal and electrical), wear of plant components and load (output power) tracking performance. A model-based coordinated master control would calculate the optimal set of future input trajectories and, if desired, account for maximal electrical efficiency and minimal component stress.

In recent years, several works have been proposed based on model-predictive control strategies and physical plant models [1-6]. The work by [1] is based on a linear plant model and Generalised Predictive Control (GPC) in a combined-cycle power plant. The proposed control structure is based on a two-level GPC scheme where the solutions for the low-level GPC problems are solved before updating the high-level GPC coordinator. Ordys and Kock [2] present a comparison between GPC and a Dy-

namic performance Predictive Controller (DPC) for a gas turbine power plant simulation. They claim improved performance with the DPC dealing with cross-couplings, especially in constrained cases. Prasad *et al.* [3-4] adopts an approach of non-linear Model-based Predictive Control (MPC) including stochastic variables for disturbance modelling. The extended Kalman filter is then employed to obtain a predictor for the controller. Prasad [5] further discusses the effectiveness of this physical model-based coordinated control strategy by evaluating the control performance under different operating conditions, including large load changes and disturbances. By simulation it is shown that improved performance can be achieved and that operational constraints, e.g. on metal temperature, is handled in a simple way. A drawback with the approach is the large computational effort needed, involving linearization, state estimation and online optimisation during each control sample. Poncia [6] also discusses different approaches for multivariable control based on predictive control theory. He presents a case study based on a state space predictive control technique acting in parallel with the traditional control system correcting its actions and he concludes im-

proved performance, especially when extreme conditions are encountered.

The main goal of this study has been to evaluate the potential of a coordinated master control for a solid fuel power plant in terms of tracking capability, stability and robustness. The control strategy has been model-based predictive control (MPC) and the plant used in the case study has been the Vattenfall power plant Idbäcken in Nyköping, Sweden. A dynamic plant model based on non-linear physical models is used to imitate the true plant in MATLAB/SIMULINK simulations. The existing PID control is used as a reference performance, and it has been thoroughly studied and tuned in previous Vattenfall internal projects.

The rest of the paper is organized as follows. A brief description of the plant model "Idbäcken plant" is given in section 2. Section 3 presents the implementation of the developed model in Simulink including a description of the existing control. The control objectives together with the plant limitations are presented in section 4. Section 5 presents the control design and its simulation results. Finally conclusions and some recommendations for further work are given in section 6.

2 THE SOLID FUEL POWER PLANT

Due to space limitations, in this section we only briefly describe the model of the considered power plant, the complete model of the plant can be found in [7]. The considered solid fuel power plant can be described with the four main blocks as presented in Fig. 1. The four blocks are the furnace, the steam production, the turbine and the condenser. The steam production block consists of the evaporator, the superheater (SH) section and a steam drum.

2.1 Furnace Model

The furnace chamber has three main outputs: the energy (heat) transferred to steam system W, the measured O_2 in flue gas O_2 and the bed temperature T_{bed}. The inputs are: the fuel mass flow m_{in}, the primary air q_p, the secondary air q_s and the recirculated gas q_r. Thus the furnace model inputs and outputs are:

$$u = \begin{bmatrix} m_{in} & q_s & q_p & q_r \end{bmatrix}^T \qquad (1)$$

$$y = \begin{bmatrix} m_{out} & M & O_2 & T_{bed} & W \end{bmatrix}^T \qquad (2)$$

where the first two outputs (combusted fuel flow m_{out} and fuel mass stored in bed M) are only used for model tuning purposes to find and check reasonable dynamics. Oxygen level O_2 and bed temperature T_{bed} are measured and controlled quantities. Heat transferred to steam system W (evaporator, superheaters and economiser) is to be used in those subsystems (a ratio goes to each of the three components). The furnace has non-linear state equations, with ten states.

2.2 Boiler Model – Evaporator and Superheaters

A ratio of the total heat transfer W from the furnace model is transferred to each of the components (evaporator and superheater). The economizer is outside the scope of this model, but also absorbs a small ratio of the total heat transfer. The ratios are assumed to be slowly varying parameters.

The evaporator consists of a drum (dome) at boiling pressure and risers and downcomers. A well-known nonlinear dynamic model for natural circulation drum boilers was presented by [8]. In the superheaters the steam delivered from the evaporator q_s absorb the energy W_{sh} from the combustion gases and the superheated steam is mixed with a spray of attemperator water q_a. The superheaters are the last components before the steam valve to deliver steam to the turbine. The steam flow is drawn from the superheater depending on the pressure difference over the steam valve and the valve opening. The steam flow drawn from the superheater is regarded as an input to the superheater model and is calculated in the valve model.

2.3 Turbine model: Turbine, Steam valve and Condenser

The turbine model block consists of the turbine, the steam valve and the condenser. In Fig. 2 an overview of input and output signal flow is presented. The steam flow through the turbine is driven by the pressure and temperature difference over the turbine (valve and condenser). The electric efficiency also depends on these pressure and temperature states. Since the condenser is at saturated steam state, condenser pressure is known from steam tables as a function of temperature.

The steam valve is assumed isenthalpic (no enthalpy change over valve) and valve characteristics gives steam flow delivered to turbine as a function of steam valve signal, pressure after superheater, turbine inlet pressure after valve and steam density. The enthalpy and density and corresponding derivatives with respect to pressure and temperature are found in steam tables. In the simulation model the enthalpy and density derivatives are approximated to constant values for the valve model.

A steady state heat and mass balance model for the heat and electricity generation in the Idbäcken plant has been developed by Vattenfall Research and Development AB as part of previous company internal work. The model was developed using measurement data from the operation of the plant in order to fit the model to the existing plant characteristics. With the calculated component characteristics as input data, the model was simulated in off-design mode and validated against operation data. The inlet turbine pressure is calculated according to the Stodola equation adopted by Ebsilon, which is a function of the exit pressure, inlet temperature and steam mass flow.
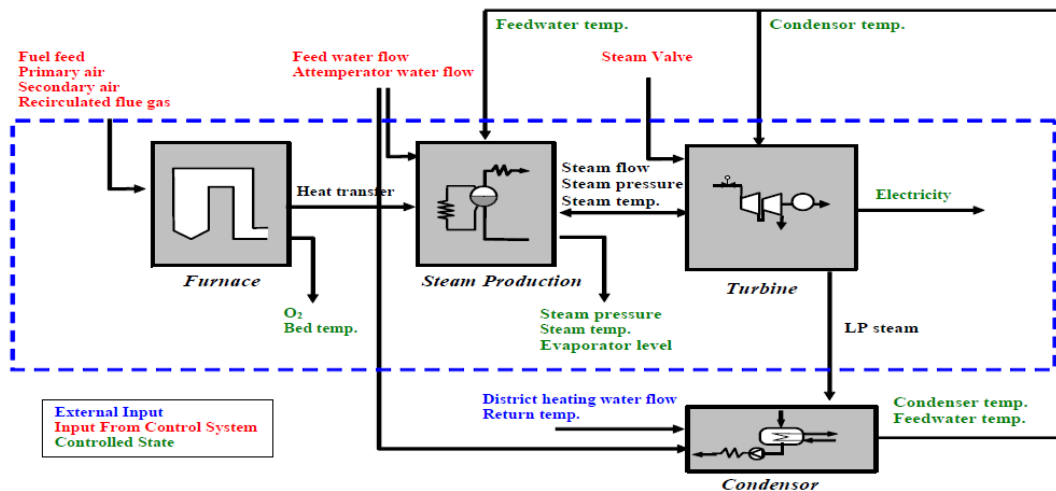
Fig. 1. A schematic image of the plant divided into the four blocks: Furnace, Steam Production, Turbine and Condenser. The part encircled by the dashed rectangle is the part considered in this study

3   MODEL IMPLEMENTATION

The plant model described in section 2 has been implemented in Matlab/Simulink with the addition of sensor dynamics of all measured outputs to avoid algebraic equations in the final closed loop system. The sensor dynamics consist of one first order filter for each output (with a time constant of one second). To compare the performance of a new control strategy a control block was implemented aiming at reproducing the existing control system at Idbäcken. The control was separated into *master* and *slave* control blocks, where the slave controllers would remain in an MPC implementation. The content of the *master* control block is seen in Fig. 3 where the inputs to the control blocks are: Setpoint Electric Load, Setpoint SH Pressure, Setpoint SH Temperature, Setpoint O_2, Calculated Load, Measured SH Pressure, Measured SH Temperature, O_2.

And the outputs to the control blocks are: Setpoint Electric Load adjusted, Setpoint fuel, Setpoint total air, Attemperator water flow.

The description of the respective slave controllers are summarised as following:

- *Electric load slave controller*: PI controller with inputs: Setpoint electric load and measured electric load, and output: Steam valve signal.

- *Drum level slave controller:* PI control and feed forward from steam flow with inputs: Setpoint drum level, Measured level, Measured steam flow and Measured attemperator flow, and outputs: Feedwater flow to evaporator.

- *Fuel load slave controller:* Transfer function from setpoint (fuel feeder speed) with inputs: Fuel flow setpoint, and outputs: Fuel flow.

- *Air control slave controller:* Set of PI controllers and a linearised transfer function for fans and dampers with inputs: Setpoint total air, Setpoint total primary gas, Setpoint bed temperature, Measured total air, Measured primary gas and measured bed temperature, and outputs: Primary air, Secondary air and Recirculated gas.

4   LIMITS AND CONTROL OBJECTIVES

The plant is operated to follow a setpoint electricity load as efficiently as possible within specified operating limits. The efficiency is a function of several of the measured output states. In addition, stable operation and smooth transitions are desired to minimize the component wear and tear due to mechanical stress and temperature stress.

The turbine is classed to operate at steam pressures up to 13.8 MPa and temperatures up to 550 °C for short periods, but the operating temperature of 540 °C is the maximum setpoint temperature allowed. The superheaters are also designed to tolerate a maximum temperature of 540 °C. If the steam temperature is below or close to condensing temperature no steam is delivered to the turbine (start-up) since it would damage the turbine. In practice steam temperatures below 500 °C are not desired. Temperature stress is a major factor contributing to component failure.
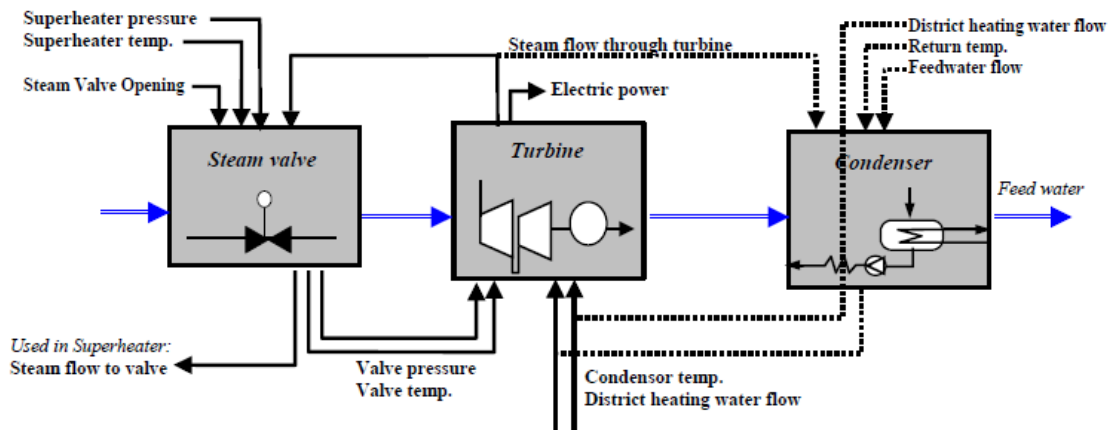
Fig. 2. Turbine and valve model inputs and outputs. The condenser is not included in the simulated model and is included in the figure only for reference. Direction of physical steam flow is from left to right with double-lined arrows.

The electric efficiency is increased with a more open steam valve (reduced pressures) and increased steam temperatures. To push the valve signals past 70% is not recommended at this plant since it does not have any significant impact on steam flow. To have a control margin the pressure setpoint selected should correspond to valve signals below 60%. The allowed pressure range is (10.5-13.5 MPa). For optimal efficiency considering the constraints, the pressure setpoint is implemented as a function of electric load as in Figure 4.

The normal operating range (90% of operating hours of autumn 2009) is within 15-29 MW electric power, corresponding to 50-85 MW total power. Most of the time the plant is run close to maximum power (27-29 MW). The main operational plant limitations for the Idbäcken BFB are given in Table 1 and the control input limitations are implemented with a maximum rate of change as well as upper and lower bounds.

5 MASTER CONTROL BY MPC

The main goal of this section is to evaluate the potential of a coordinated master control for the considered power plant. The control strategy chosen is MPC. Our goal is to develop a master MPC controller that can achieve the following objectives: (i) Stable and fast electric power load tracking, (ii) Increase plant efficiency, (iii) Increase components lifetime, (iv) Comply with safety and environmental constraints.

5.1 MPC – Model Predictive Control

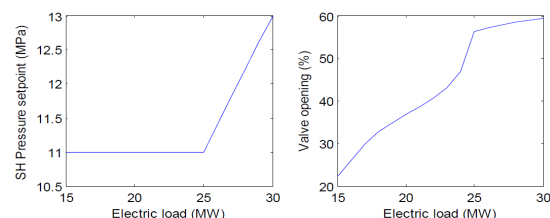Predictive control was first developed at the end of 1970s [9]. In the 1980s, many methods based on the same

Table 1. The main operational limits for the Idbäcken plant.

	Trip at low limit	Alarm low limit	Alarm high limit	Trip at high limit
Steam pressure		10.5	13.8 MPa	14.6 MPa
Steam temperature			550 °C	560 °C
O_2	0.5%	1 %	3.5 %	
Fluidization air flow (primary air+ recirculated gas)		45 Nm³/s	60 Nm³/s	
Bed temperature		700 °C	850 °C	
Dome level	-200 mm	-100 mm	-50 mm	200 mm
Condenser output temperature		Max (temp, 72 °C)		

Fig. 4. Selected design pressure setpoint with resulting valve opening as a function of electricity setpoint.
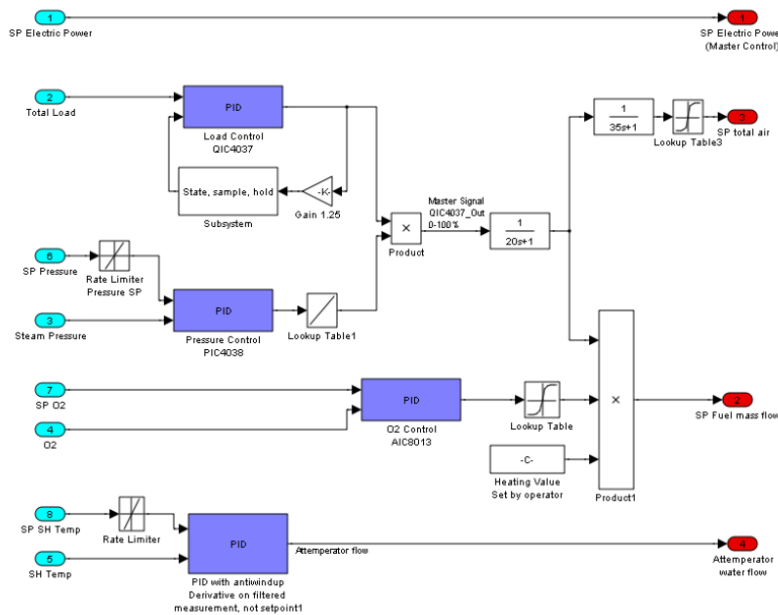
Fig. 3. The existing master control.

concepts were developed. This family of control algorithms is now grouped under the name Model Predictive Control [10-11]. The main idea of model predictive control is to use a model of the plant to predict future outputs of the system. Based on this prediction, at each sampling period, a sequence of future control values is computed through an on-line optimization process, which maximizes tracking performance while satisfying constraints. Only the first value of this optimal sequence is applied to the plant, the whole procedure is repeated again at the next sampling period according to the 'receding' horizon strategy [10-11].

MPC is a suitable control technique for power plants for the following reasons:

- The inclusion of constraints such as limits on the operability of actuators and admissible ranges on the thermodynamic variables imposed to guarantee safe operation,

- The possibility of dealing with the compensation of measurable disturbances,

- The fact that MPC has a tradition of success in the field of thermo-chemical processes.

5.2 Master Model Predictive Control for solid fuel power plant (Idbäcken)

The Master MPC should calculate the optimal set-points for the slave PI controllers, and also calculate di-

rectly the optimal control signals for some additional manipulated variables. Then, using these optimal set-points, the PI controllers give their control action.

The optimisation variables proposed here are:

$$u(k) = \begin{bmatrix} u_1(k) \equiv \text{set} - \text{point of Electrical Power} \\ u_2(k) \equiv \text{set} - \text{point of Fuel Mass Flow} \\ u_3(k) \equiv \text{set} - \text{point of Total Air} \\ u_4(k) \equiv \text{Attemperator Water Flow} \end{bmatrix}$$
(3)

The Master MPC controls the following output variables:

$$y(k) = \begin{bmatrix} y_1(k) \equiv \text{SH Pressure} \\ y_2(k) \equiv \text{O}_2 \\ y_3(k) \equiv \text{SH Tempreature} \\ y_4(k) \equiv \text{The produced Electrical Power} \end{bmatrix}$$
(4)

The Master MPC controller is applied in a hierarchical structure to the slave controller and the power plant model is developed and simulated under the MATLAB/Simulink environment.

5.2.1 Linear model

Linear state space models representing the power plant, the PID slave controllers and the sensors dynamics are calculated by linearising the system around certain operating

points as well be shown later. The linearised models are presented by a discrete state space model:

$$x(k + 1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k) \tag{5}$$

where $A \in R^{45*45}$, $B \in R^{45*4}$, $C \in R^{4*45}$. The system has 4 inputs, 4 outputs, and 45 states; 22 states representing the power plant model (involving the furnace, the evaporator, the superheater (SH), the valve and the turbine), 8 states presenting the sensors dynamics and 15 states in the four slave PID.

5.2.2 Cost function configuration

The proposed quadratic cost function includes the following terms:

- *Output error:* A term penalizing the output errors is essential to force the system outputs to follow their reference trajectory. Throughout this report, we assume that we only know the current value of the reference values (no preview allowed), hence $w(k + j) = w(k)$.

- *Integrated output error:* To reduce the steady state errors an integral action is introduced. To include the integral action, an additional state $x_{int}(k)$ representing integration of the control error is defined:

$$x_{int}(k+1) = x_{int}(k) + k_{int} * T_s * (y(k) - w(k)) \tag{6}$$

where y is the measured output, w is the reference for y, T_s is the sampling time and k_{int} is the integrator gain. A penalty term including the integrator state is added to the cost function to reduce the steady state error.

- Soft constraints: To increase the robustness of our proposed controller, we introduce soft constraints, which allow, at a prise, temporary the violation of some constraints according to the limitations given in Table 1. Due to model errors in our model, our predictions are not perfect. Even though we solve the constrained problem at a certain time-instant, model errors might move the actual output (and its future predictions) outside the original constraints thus rendering the optimization problem infeasible. Hence, adding these semi-soft constraints allows us to recover from small model mismatches, thus improving practical robustness. A term penalizing the violation of semi-soft constraints is added to the cost function.

- Control variation: A term penalizing control signal variation$\Delta u(k+j)$is added to reduce the control variation and avoid unnecessary and rapid changes.

Combining the introduced terms leads to the following cost function:

$$\min_{u_k^{k+N_u-1}} J = \sum_{j=1}^{N} \{ (\hat{y}(k+j \,|k) - w(k+j))^T$$
$$\cdot Q \, (\hat{y}(k+j \,|k) - w(k+j)) \}$$
$$+ \sum_{j=1}^{N} \{ \hat{x}_{int}(k+j)^T P_{int} \hat{x}_{int}(k+j) \tag{7}$$
$$+ \varepsilon(k+j)^T Q_{con} \varepsilon(k+j) \}$$
$$+ \sum_{j=1}^{N_u} \{ \Delta u(k+j-1)^T Q_{inc} \Delta u(k+j-1) \}$$

where $\hat{y}$, w and Δu represents the predicted output, the reference trajectory and the control variation over the future horizon, respectively. The variable N is the prediction horizon on the output, and N_u is the control horizon. Separating the output and control horizon permits us to decrease the number of calculated future control signals, by making some kind of assumption on the remaining input signals, for instance $u(k + j) = u(k + N_u)$ for $N \geq j > N_u$. The vector ε includes the soft constraint variables. The variables Q, P_{int}, Q_{con} and Q_{inc} are weight matrices and constitute the main handle to tune the response of the master MPC controller.

5.2.3 Constraints configuration

Several constraints and limits over output and input signals are considered to guarantee safe operation, respecting the environment constraints and to take the actuators limits in consideration. Also, as mentioned before, semi-soft constraints are defined over the range of alarm limits, where violation of this limits can be accepted for a short time. Hard constraints are instead added for the range of trip limits, where no violation of these constraints is accepted.

Taking into account the alarm limits and the trip limits, the following constraints over output variables and input limits are considered.

- SH pressure: $y_1 \leq 13.8 + \varepsilon_1$, with $0 \leq \varepsilon_1 \leq 0.8$

- O2: $y_2 \leq 3.5 + \varepsilon_2$, with $0 \leq \varepsilon_2 \leq 2$

- O2: $y_2 \geq 1 - \varepsilon_3$, with $0 \leq \varepsilon_3 \leq 0.7$

- SH Temperature: $y_3 \leq 550 + \varepsilon_4$, with $0 \leq \varepsilon_4 \leq 10$

- Set-Point (SP) for Electrical Power: $0 \leq u_1 \leq 30$

- Attemperator Water Flow: $0 \leq u_4 \leq 4$

Constraints over the control signal variations are considered to avoid hard changes, which are not preferable, and to guarantee practically acceptable signal variations:

- Set-point for Electrical Power: $|\Delta u_1| \leq 0.36/step$

- Set-point for Fuel Mass Flow: $|\Delta u_2| \leq 0.51/step$

- Set-point for Total Air Flow: $|\Delta u_3| \leq 1.5/step$

- Attemperator Water Flow: $|\Delta u_4| \leq 0.105/step$

5.2.4   Control Configuration

After successive iterations with some knowledge and experiences on power plants and MPC controller, the parameters of the Master MPC controller that give a good response and good robustness (as will be shown later) are as follows: Prediction horizon *N = 30,* Control horizon *Nu = 12, Ts = 3 s,* k_{int} = 0.075, and weight matrices:
$Q = diag(40, 20, 9, 32), \quad P_{int} = 0.01*diag(4, 20, 3, 4),$
$Q_{con} = 100*I_{4*4}, \quad Q_{inc} = 0.125*diag(40, 40, 0.01, 2)$

For the development of the optimization model and the simulation of the MPC controller, the MATLAB toolbox YALMIP [12] was used. YALMIP is a general toolbox for rapid prototyping and testing of optimization based algorithms. Three controllers, using the *optimizer* function in YALMIP, have been built, one for high-load, one for medium-load, and a third one for low load, as will be shown in next section. Based on the current reference load value, the working range is determined and the related controller is used, i.e. the associated optimization problem is solved. In the simulations performed here, the quadratic programming solver BPMPD [13] was used.

5.3   Master MPC with gain scheduling

The range of operation for Idbäcken power plan is from 15 to 30 MW electric output power. For a good plant response over the whole non-linear operating region the required number of linearised models (regions of different operating points) used by the controller is examined. It is found that a three region linearised model gives an acceptable performance and this scheme is chosen in the following simulation cases. The three-region operating points are given in Table 2.

Remark 1 The difference in the plant response with one, two and three linearized models is not that large and the response is comparable in the three cases. But only one controller will be active on-line, based on the operating range, thus using three linearized models will improve the

Table 2. Gain Schedule scheme for the MPC controller

Reg.	Load Level	The covering range	Linearized around an operating point characterized by $SH\_T = 540, O_2 = 2$ and:
1	High Load	$24 \leq E_{ref}$	$E = 27$, $SH\_P = 11.8$, $Load = 80\%$
2	Medium Load	$20 \leq E_{ref} < 24$	$E = 22$, $SH\_P = 11.0$, $Load = 66.2\%$
3	Low Load	$15 \leq E_{ref} < 20$	$E = 17.5$, $SH\_P = 11.0$, $Load = 54\%$

plant performance without increasing the controller complexity keeping in mind (as will be stated later) that the proposed controller does not require excessive computing and is capable of being implemented in real-time.

5.4   Comparison between the Master MPC controller and the existing PID Controller

5.4.1   Step response simulations

In the following we will call the Master MPC controller including integral action and the gain schedule technique, the MPC controller (the proposed controller) to simplify the notation. Figure 5 shows a comparison between the MPC controller response and the existing PID controller response for a load step from 27:29 MW at time = 200 s. The MPC controller has a faster response compared to the existing PID controller response. Moreover, the existing PID controller has high deviation from set-points especially on SH Temperature and SH Pressure and a large variation on the SH temperature, which is not good for the component lifetime, while the MPC tracks the set-points well as shown in Figure 5.

5.4.2   Simulation of on-site test signals

The on-site tests performed at Idbäcken plant were used to identify parameter values of the simulation model and the existing control system. Steps were carried out in set-point of Electric load, Steam Pressure, Steam temperature, O_2 and Drum Level. Here we compare simulated existing control performance to the Master MPC controller performance and show the simulated response to the various combinations of set-point changes of the on-site tests.

The plant performance for both of Master MPC and existing PID controller was comparable for Electrical load and Steam pressure with a slightly faster response for the Master MPC controller. For Steam temperature and O_2, however, the existing PID controller response was slow and has a relatively big deviation from the set-points while
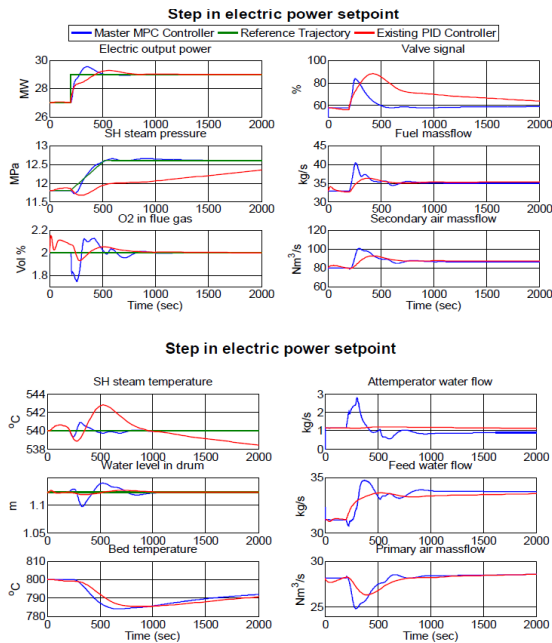
Fig. 5. *Plant response with the Master MPC controller (blue), and the existing PID controller (red) for load step from 27:29 MW at time = 200s.*
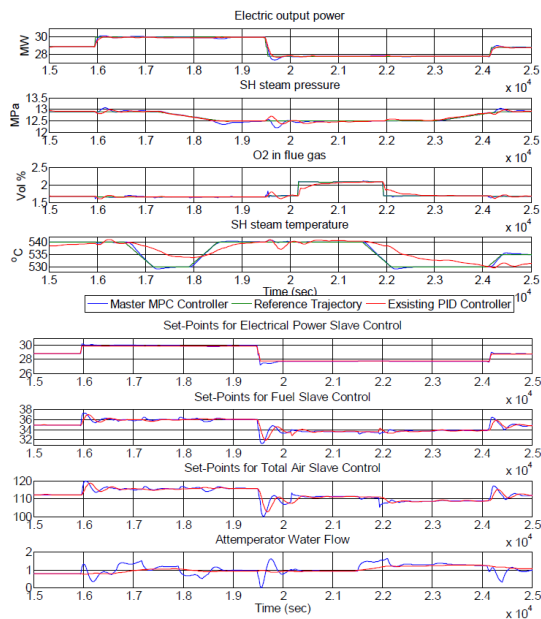

Fig. 6. *Plant output and Input variables for the on-site test performed at Idbäcken plant. Steps were carried out in set-point of Electric load, Steam Pressure, Steam temperature, O2 and Drum Level. Showing the performance with Master MPC controller (blue), and also with the Existing PID controller (red).*
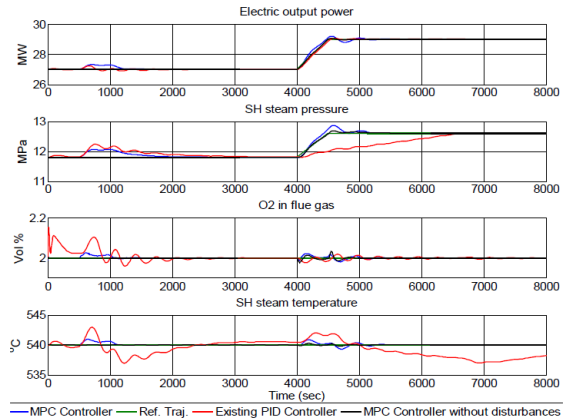

Fig. 7. *The Plant output performance for the case of increasing the value of hm by 100% for both the MPC controller (blue), and the existing PID controller (red). The variation in hm is a ramp starting at 500s and ending at 1000s.*

the Master MPC controller track the set-points of the steam temperature and O_2 well, with almost no deviation as shown in Figure 6. It can be concluded, from these results and other results that omitted here for space limitations, that the MPC controller achieves better overall performance and load tracking.

5.5 Robustness of the proposed Master MPC controller

In this section we examine the robustness of the proposed Master MPC controller against disturbances and parameter variation. The most common disturbances are the fuel mass flow and the heat distribution (heat ratio) between evaporator and superheater. Both these disturbances are therefore considered in the following. Also for the case of parameter variation, we consider the case of variation of produced energy per ton of fuel (hm).

5.5.1 Parameter Variation: Produced Energy per Ton Fuel

The proposed MPC controller is robust against a variation in h_m parameter up to more than a 100% increase and 55% decrease from its nominal value. The response for the case of increasing h_m by 100% is shown in Figure 7 for both the MPC Controller and the existing PID controller. As shown in Figure , the response of the Master MPC controller is faster than with the existing PID controller and it has less variations and deviations from set-points especially for SH temperature and SH pressure.
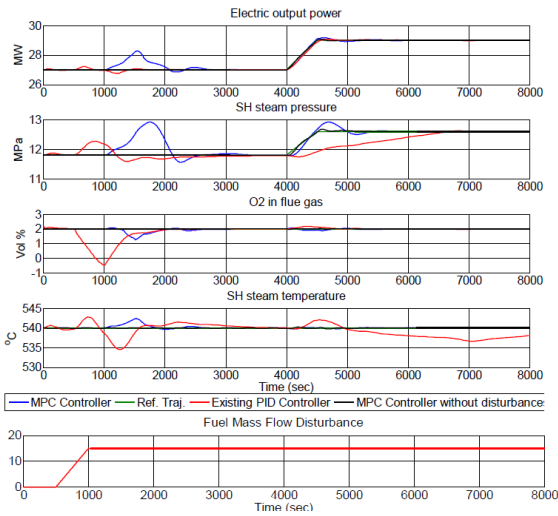
Fig. 8. The Plant output performance for the case of Fuel mass flow disturbance of value 15 kg/s, for both the MPC controller (blue), and the existing PID controller (red). The Fuel mass flow disturbance is shown in the lowest plot.
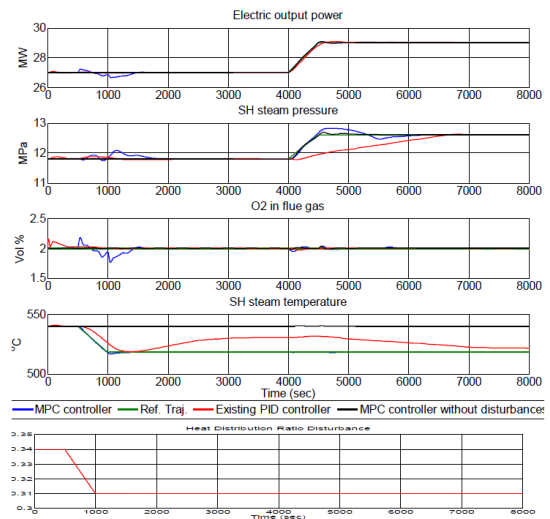

Fig. 9. The Plant output performance for the case of heat distribution ratio changed from 0.34 to 0.31, with the MPC controller (blue), and also with the existing PID controller (red). The heat distribution ratio disturbance for the superheater is shown in the bottom plot.

5.5.2 Fuel Mass Flow Disturbance

Fuel mass flow disturbance is the most common disturbance that may occur during operation. The proposed MPC controller is robust up to 17 kg/s disturbance of fuel mass flow at high load, which corresponds to about 50% increase in the fuel mass flow. At low load the proposed controller could support larger disturbance.

Figure 8. shows the system response for the case of a disturbance of 15kg/s over the fuel mass flow for both the MPC controller and the existing PID controller. The response of the existing PID controller looks better in this case, but actually it violates the constraints over O_2 having negative value, which is not possible in practice. In other words, the controller drives the signals outside the domain in which the model is valid.

5.5.3 Heat Distribution Ratio Disturbance

The nominal heat distribution ratio from the furnace to the evaporator and superheater is 64% and 34% respectively. In this section we consider a case where this ratio is changed due to some disturbances and become 67% and 31% for evaporator and superheater respectively. Neither the master MPC controller nor the existing PID controller was able to track the load reference with SH temperature set-point equal 540 °C, a lower set-point temperature has to be chosen. Figure 9 shows the system response for the case of heat ratio changes from 0.64:0.34 to 0.67:0.31 and the SH temperature set-point is decreased to 518 Co.

Based on a sensor that can detect the change of the heat distribution ratio a change on the SH temperature to 518 °C can be done. The response for the case of the existing PID controller is shown also in Fig.9 (red). Again, as shown in Fig. 9, the MPC controller has a faster load tracking response than the existing PID controller.

5.5.4 Multiple disturbances

In this section we consider a more complex case; we consider the existence of previous disturbances and parameter variation simultaneously as following: fuel mass flow disturbance (10 kg/s), heat distribution ratio disturbances and increased value of the parameter *hm* (60%). Figure 10 shows the system response for both of the MPC controller (blue) and the existing PID controller (red). Disturbance signals are shown on bottom plots of Figure 10.

The MPC controller tracks the load change very well even with the existence of the three disturbances, the existing PID controller was also able to track the load variation but much slower compared to the MPC controller, and with higher deviations from set-points of O_2, Steam pressure and steam temperature (Figure 10).

6 CONCLUSION AND SUGGESTIONS FOR CONTINUED RESEARCH

The main goal of this study has been to evaluate the potential of a coordinated master control for a solid fuel
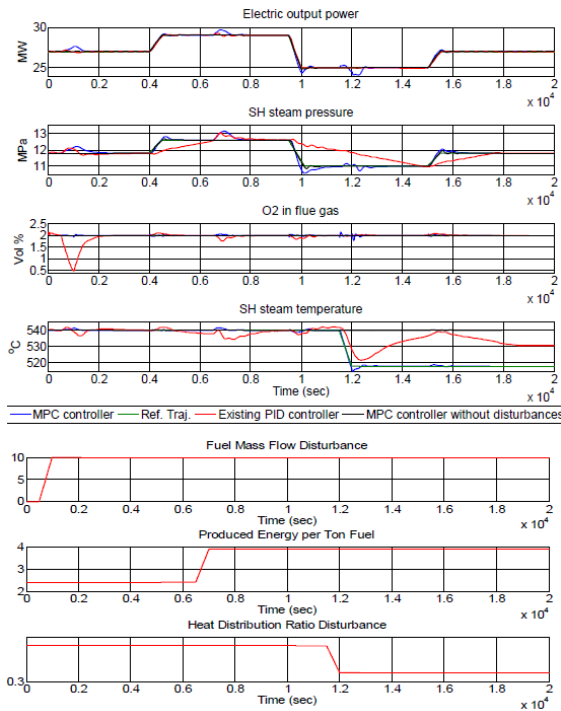
Fig. 10. Output variables for the case of the existence of Fuel flow disturbance, hm parameter variation and heat distribution ratio disturbances, with the MPC controller (blue), and with the existing PID controller (red).

power plant in terms of tracking capability, stability and robustness. The control strategy has been model-based predictive control (MPC) and the plant used in the case study has been the Vattenfall power plant Idbäcken in City Nyköping, country-region Sweden. For this purpose, a realistic model has been developed based on first-principles and experimental data from the Idbäcken CHP plant. The existing PID control is used as a reference performance, and it has been thoroughly studied and tuned in a previous Vattenfall internal projects. Using a model as a representative for the actual process, an MPC control strategy was developed using linearization and gain-scheduling. The MPC tuning in this study has been focused on tracking performance. From the study, the following has been concluded.

- The proposed Master MPC control design is able to consider all relevant plant limitations and constraints in a direct way.

- The proposed Master MPC controller (including the integral action and gain schedule technique) shows excellent set-point tracking performance even though the plant has strong interactions and non-linearity, and the controls and their rate of change are bounded.

- The proposed Master MPC controller is robust, that is, it is not sensitive to disturbances and parameter variations. Even though the current study only considered a very small number of the possible disturbances and modelling errors, the considered cases are good indications of robustness.

- The Master MPC controller does not require excessive computational requirements as one might think, and is definitely possible to implement in a control operation environment. On a standard desktop simulation computer, computation of a control input takes around 40 ms, which is 75 times faster than the sampling time of 3 seconds.

The presented study has taken one step further towards an implementation of an MPC strategy for a coordinated master control in a power plant. Future work includes designing a state observer, since the controller requires the complete state of the system, and On-line testing to show the potential in practice.

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Jean Thomas received his Bachelor degree in electrical engineering from Minia University, Egypt in 1991, the MSc in Process Control from Eindhoven Technical University, Netherlands in 1997, and the PhD degree in Automatic Control from Supélec, France in 2004. During 2009 and 2010, He has been a postdoctoral researcher in Control Department, Linkoping University, Sweden. Currently, he is an associate professor at Process Control Department at FIE Beni-Suef University, Egypt. His research interests include model predictive control, hybrid systems and robust control.

AUTHOR'S ADDRESS
Jean Thomas, Ph.D
Process Control Department,
FIE Beni-Suef University, Egypt
email: dr.j.thomas@ieee.org.