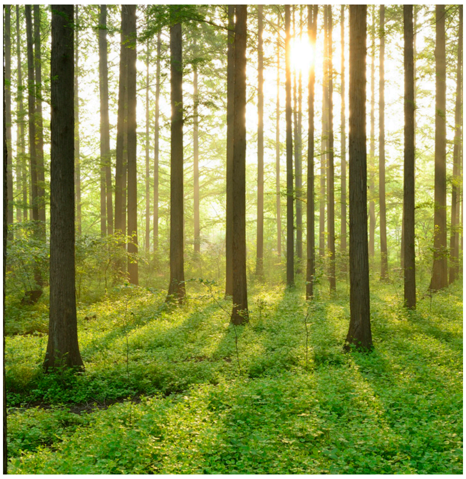
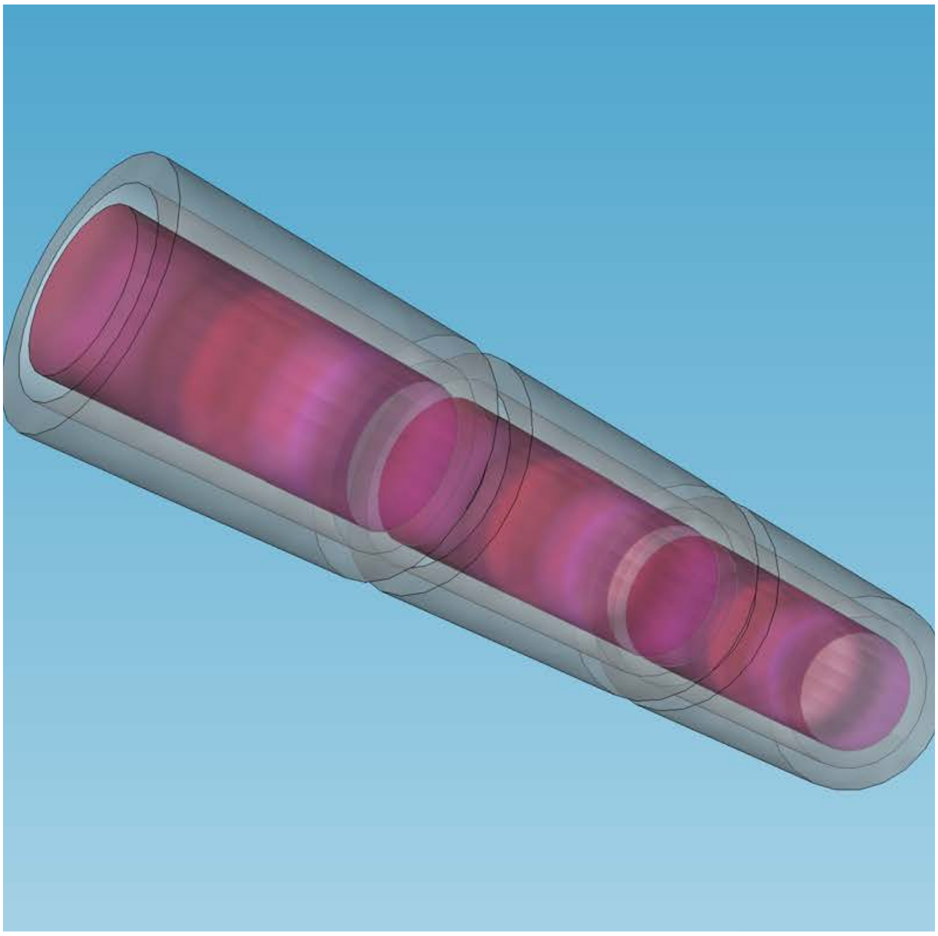
IMPROVED SUPERHEATER CONTROL WITH FEEDFORWARD FROM PHYSICS-BASED PROCESS MODELS

REPORT 2015:220



FUEL-BASED ELECTRICITY
AND HEAT PRODUCTION



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Improved superheater control with feedforward from physics-based process models

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Förord

Denna rapport är slutrapportering av projekt P 39216 Förbättrad överhettarreglering med framkoppling från fysikaliska processmodeller (Energimyndighetens projektnummer P 39216) som faller under teknikområde processtyrning inom SEBRA, samverkansprogrammet för bränslebaserad el- och värmeproduktion.

Projektet har följts av en referensgrupp bestående av:
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SEBRA, samverkansprogrammet för bränslebaserad el- och värmeproduktion, är efterföljaren till Värmeforsks Basprogram och startade som ett samarbetsprogram mellan Värmeforsk och Energimyndigheten 2013. All forskningsverksamhet som bedrevs inom Värmeforsk ingår sedan den 1 januari 2015 i Energiforsk. Därför ges denna rapport ut som en Energiforskrapport.

Programmets övergripande mål är att bidra till långsiktig utveckling av effektiva miljövänliga energisystemlösningar. Syftet är att medverka till framtagning av flexibla bränslebaserade anläggningar som kan anpassas till framtida behov och krav. Programmet är indelat i fyra teknikområden: anläggnings- och förbränningsteknik, processtyrning, material- och kemiteknik samt systemteknik.

Stockholm januari 2016

Helena Sellerholm
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Sammanfattning

Framkoppling är en av de mest fundamentala reglerstrukturerna inom reglertekniken. Alla som har läst en grundkurs i reglerteknik på universitetsnivå bör ha stött på begreppet framkoppling. Framkoppling används främst för att hantera störningar i processen och traditionellt så består den i enklaste fallet av en ren förstärkning eller dynamiskt linjära modeller, alternativt statiskt olinjära modeller.

Nyheten i detta projekt är att använda dynamiska olinjära fysikaliska flervariabla modeller till framkoppling. Utmaningen med olinjära fysikaliska modeller är den matematiska inverteringen som krävs för att kunna använda dem i framkopplingen. Modelleringsspråket Modelicas automatiska metoder för att beräkna och simulera modellinverser har nyligen öppnat för nya applikationer tack vara det icke-kausala modelleringsspråket och de symboliska metoderna för ekvationsmanipulering. Detta används för att ta fram en inverterad processmodell i form av en Modelica-modell. Denna inverterade processmodell utgör sedan grunden för den robusta och approximativa invers som implementeras i ett industriellt styrsystem (i detta fall ABB Freelance).

Projektets huvudmål har varit att utvärdera och undersöka potentialen hos modellbaserad framkoppling utifrån dynamiska fysikaliska modeller av termodynamiska system och implementera det i en processanläggning. Framkopplingen har implementerats och testats på en överhettarreglering till en gaseldad ångpanna (Heleneholmsverket i Malmö), där den läggs till befintliga de PID-regulatorerna i styrsystemet.

Modellering i Modelica kräver relativt mycket förkunskap och förståelse om fysikalisk modellering av termodynamiska processer. Utbildning motsvarande civilingenjör eller högre är att föredra. För att göra nödvändiga avgränsningar och förenklingar av modellen krävs gedigen kunskap i integrationen mellan process och reglering. Metoden för modellering och modellinvertering som beskrivs i denna rapport är dock tämligen rättfram och generell, och kräver endast anpassning utifrån den process där den ska tillämpas. Detta gör att det är enkelt att överföra resultaten till vilken process som helst.

Den befintliga regleringen av överhettarna på Heleneholmsverket är väl genomarbetad och noggrant injusterad. Den hade redan före detta projekt en relativt avancerad framkoppling som det har lagts flertalet ingenjörstimmar på att trimma in. Det är därför en utmanande jämförelse för den nya framkopplingen som utvärderas i detta projekt. Trots detta så visar tester på pannan tydliga förbättringar i både störningshantering och börvärdesföljning med den nya framkopplingen. Det visar att metodiken som beskrivs rapporten är korrekt och relevant.

Den stabilare regleringen möjliggjorde en börvärdesökning på tio grader. Genom en anläggningsmodell beräknades eleffektökningen till 601 kW vid konstant fjärrvärmeeffekt. Denna eleffektsökning kräver endast 635 kW extra panneffekt. Med en pannverkningsgrad på 90 % ger det en extra bränsleeffekt på 706 kW. Ökningen ger alltså en elverkningsgrad på 85 %. Det är detta resultat som gör en temperaturhöjning efter överhettarna så intressant. För den aktuella anläggningen är ökningen värd ca 120 000 kr per år. För en anläggning med billigare bränsle är vinsten mycket större.

Även om testerna är utförda på en gaseldad panna så kan resultatet direkt anpassas till bio- och avfallseldade. Den fysikaliska modellen kommer troligen att se något annorlunda ut, detta beskrivs mer utförligt i slutet av denna rapport.

Summary

Feedforward is one of the most fundamental structures in control engineering. Anyone who has taken a basic course in control engineering at university level should have encountered the concept of feedforward. Feedforward is used mainly to deal with process disturbances and traditionally it is in the simplest case a pure gain, or alternatively dynamic linear models or static nonlinear models.

The novelty of this project is to use dynamic nonlinear physics-based multivariable models used for feedforward. The challenge of nonlinear physics-based models is the mathematical inversion required in order to use them as feedforward. The automatic methods in the modeling language Modelica to calculate and simulate inverted models has recently opened for new applications thanks to the non-causal modeling language and symbolic methods of equation manipulation. This is used in this report to produce an inverse process model in the form of a Modelica-model. This inverted process model then forms the basis for the robust and approximate inverse implemented in an industrial control system (in this case ABB Freelance).

The main objective of the project is to evaluate and explore the potential of model-based feedforward based on nonlinear dynamic physics-based modeling of a thermodynamic system and to implement it in a real process plant. The feedforward has been implemented and tested on one superheater temperature control loop in a gas-fired boiler (Heleneholmsverket in Malmö), where it is added to the existing PID controllers in the control system.

Modeling in Modelica requires quite a lot of knowledge and understanding about physics-based modeling of thermodynamic processes. Education corresponding to Master of Science or higher is preferred. To be able to define and condition the model and make necessary simplification intricate knowledge of the integration between process and controller are required. The method for modeling and model inversion described in this report is fairly straightforward and general, and it only requires adjustments based on the actual process application. This makes it easy to transfer the results to any process.

The existing temperature control of the superheaters at Heleneholmsverket is well prepared and carefully adjusted. It had even before this project a relatively advanced feedforward with several of engineering hours on fine-tuning. It is therefore a challenging comparison for the new feedforward that is evaluated in this project. Despite this, according to tests on the superheater shows improvements in both handling and noise and set-point following with the new feedforward. This proves that the methodology outlined in the report is correct and relevant.

The increase in controller stability enabled a set-point increase of ten degrees Celsius. A plant model calculates the increase in electric power to 601 kW at a constant district heating power. This increase in electrical power output only requires 635 kW additional boiler output. With a boiler efficiency of 90%, the extra fuel power required is only 706 kW. The increase thus provides an electrical efficiency of 85 %. This high efficiency is the reason that makes the temperature rise so interesting. For the current facility the increase is worth approximately 12 000 euro per year. In a power plant with a greater difference between electrical price and fuel price together with the longer yearly operation time the benefits will be even greater. Although the tests are

conducted on a gas-fired boiler the results can directly be adapted to biomass and waste fired boilers. The physics-based model will then probably be a bit different compared to a gas-fired boiler, this is described in more detail in the end of this report.

Table of Contents

1 Introduction

1.1 BACKGROUND

1.1.1 PID Control Structures

The PID-controller is by far the most used controller in industry, see e.g. (Hägglund & Åström, 2006), (Bialkowski, 1993). The fundamental function of the PID is to use feedback to control the measured values to its desired set-points. The feedback algorithm uses only the measured values to calculate how to manipulate the actuator (e.g. the motor speed or valve opening) in order to meet the set-points.

The natural way to handle process disturbances is to add feedforward to the controller. By measuring the disturbances and take the appropriate action the controller can handle them before they disturb the controlled values.

Feedback has the disadvantage that it can create instability while feedforward is sensitive to modelling errors. By combining the two structures the advantages can be utilized while the disadvantages can be minimized, therefore feedback and feedforward are complementary (Hägglund & Åström, 2006).

1.1.2 Modeling and Simulation of Process Systems

Physics-based modeling combined with computer simulation has a history that started around 1960 when analog computers where available. It has since then been a fast-growing field, hand-in-hand with the development of computer power and software, where today Matlab and Simulink are dominant products (Åström & Kumar, 2014).

Modelica is an object-oriented multi-domain modeling language of complex systems. The design effort was initiated in September 1996 by Hilding Elmqvist and the first specification was released in 1997 (Elmqvist, Mattsson, & Otter, 1998).

Modelica itself is only a language. Several simulation environments, based on Modelica, are available, such as Dymola, Amesim, MapleSim, and Wolfram SystemModeler.

1.2 PROPOSED APPROACH AND NOVELTY

This project links together nonlinear dynamical physics-based multivariable process models with the traditional PID controller. By measuring several process values and use them in a nonlinear physics-based model of the process, an actuator output can be calculated that ideally will drive the process to the desired set-point. Unmeasured disturbances and modeling errors will always give a discrepancy between set-points and process values. This calculated actuator output is therefore connected to the feedforward input signal of the PID, and the feedback will take care of unmeasured disturbances and modeling errors.

The process model needs to be inverted to be used in feedforward. This will be shown in later theory chapters, but can easily be understood by a simple example where two media with different flows and temperatures are mixed, see Figure 1. Assume that the outlet temperature T_{out} is controlled by adjusting the inlet temperature T_{1in}, e.g. by steam heating in a heat exchanger (not shown in the figure). T_{2in}, q_{2in}, and q_{1in} are flows given by the design of other process parts and are not possible to manipulate here in this process section. Without going into the exact modeling of this system we assume that we have a dynamic physics-based model, G, of the process with a number of inputs and an output, as noted in Figure 1b.

If we want to compute how to adjust the input variable T_{1in} in order to drive temperature T_{out} to its set-point the model G obviously needs to be inverted, since we need to calculate an input based on, among others, the trajectory of an output.

Note that the inverse function might not be possible to write as an explicit expression and might not be causal (where the inverse of a time delay is an example), and different assumptions can be made to address this. Later chapters will go deeper into this.

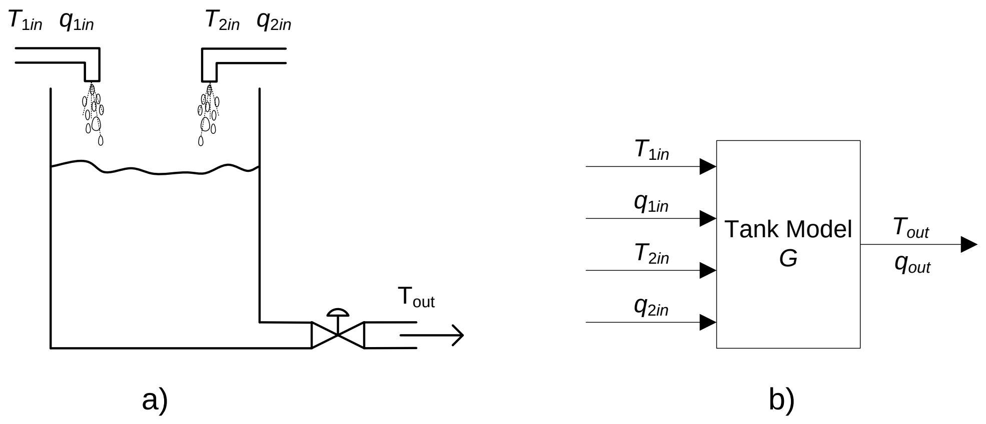

Figure 1. a) Mixing of two media in a tank with flows q_{1in} and q_{2in}, and temperatures T_{1in} and T_{2in}. b) The outlet temperature T_{out} is a dynamic function of the driving inputs. Note that the process contains dynamics and not just a static relationship, and because of the valve characteristic it is likely to be nonlinear as well.

Feedforward is clearly not a new concept but the novelty is to use nonlinear dynamic physics-based models in combination with feedforward. The advantage with nonlinear models, compared to linear, is that they cover a greater number of operating points of the process. Linear models mainly describe a small range round one operating point. The challenge with nonlinear models is the mathematical inversion. Both numerical and analytical methods for inversion of nonlinear models have been developed and have mainly been applied on mechanical systems, (Murray-Smith, 2011). Inversion can give problems with singularities, multiple solutions and instabilities, see (Reiner, 2014) for solutions for this. Approximations need to be adapted to be used in feedforward to give solutions that are robust and possible to implement in an industrial control system.

The dynamics of the process model must not necessarily come from theoretical physics-based modeling. A static nonlinear physics-based model that describes the process gain for different process variables can also be used. Since processes normally are designed using static process models, the empirical data using these kind of models are vast. To adapt the static nonlinear model to the dynamic reality of the process, linear filters are applied to the input signals as well as the output signal to be empirically tuned to fit the dynamical behavior of the plant.

The novelty of this project is to test the theory of mathematical inversion of dynamic nonlinear physics-based models in a real controller environment. The case study is a super heater in a thermal combined heat and power plant. This is a process that can yield the revenue needed for this type of complex project.

The automatic methods in Modelica for model inversion and simulations have recently opened up for new applications because of the non-causal language and the symbolic methods for manipulation of equations, see (Looye, Thümmel, Kurze, Otter, & Bals, 2005), (Gräber, 2014), and (Varchmin, 2014). These methods are used in this project to give a robust feedforward that will be implemented into an industrial application.

The dynamic model inversion technique is tested on a superheater in a boiler at Heleneholmsverket (Heleneholm power plant) in Malmö, Sweden. In a superheater, steam temperature is raised above the corresponding saturation pressure in the boiler drum. Higher steam temperature before the turbine means more produced electricity per kg of steam. A rule of thumb says that a 10°C higher temperature on fresh steam will give 0.25% increase in efficiency at a 400 MW_e plant. Material properties in the steam system set the limit how high the temperature can be but also how quickly the temperature can be changed. The steam temperature is controlled by injection of feed water. By having a better control with less variation in temperature, the temperature set-point can be closer to the material boundary and thus get more power output. This is especially interesting during transients and disturbances.

Nonlinear physics-based models for the process around the superheaters will be used as a feedforward to the PIDs that control the steam temperature. If any set-point or measured process variable that affect the steam temperature is changed, the injection valve is adjusted in precisely the right time to counteract the disturbances so that the steam temperature follows the set-point.

Since the PID primarily does not have to handle set-point changes (set-points are seldom changed) its tuning can be based solely on modeling errors and noise. As the feedforward relieves the controller from the effect of all measurable disturbances and set-point following, it can be detuned and be more robust.

1.3 PROJECT GOAL

The main goal is to evaluate the potential and implement model based feedforward from dynamic physics-based models of thermodynamic systems. The feedforward will be implemented on a steam superheater control loop where it is added to the existing PID:s. The existing superheating control uses six PID:s with physics-based nonlinear models with empirically tuned dynamics as described above. The part to be studied in this project is the model of the last superheater. In the existing feedforward it is modeled by a static mass and energy balance. During the tests this part is exchanged with its inverted dynamical counterpart, the rest of the existing feedforward scheme remains unchanged.

The result is evaluated, in first place, by measuring the disturbance rejection with the new feedforward. This will be done both in normal operation but also with forced tests and set-point changes. The economic gain of an increased steam temperature set-point will be estimated.

In second place, the result is evaluated by judging the working methods used in the project. This will give an answer to what a plant owner should expect and what level of knowledge that is required to perform the modeling work based on Modelica and to use tools like Dymola. Examples of typical pitfalls and challenges will be given.

1.4 SHORT DESCRIPTION OF HELENEHOLMSVERKET

The experimental data used in this report have been collected at Heleneholmsverket (HVK), an *E.ON owned and operated* combined heat and power plant in Malmö. The plant is equipped with three boilers (named as P10, P11 and P12) with approximately 150 MW thermal power each and a single smaller boiler of approximately 80 MW thermal power that feeds superheated steam to two steam turbines, G11 and G12 with a capacity of 45MW and 95MW electricity respectively. Each turbine has four steam extraction points for feed water pre-heating as well as for pressure control in the three feed water tanks.

1.4.1 General Description of the Steam System

The feed water is directed into the economizer, where it is preheated by means of the hot flue gases. The boilers are of the type natural circulating drum boiler. This means that the steam is generated by heat transfer to the riser tubes and then separated from the water in the boiler drum. The water, heavier than the steam/water mix in the riser, sinks down to the collection boxes in the bottom of the boiler trough the downpipes. The drum is level-controlled via the feed water flow and this is the main supply of water to the boiler. Steam from the boiler drum (saturated steam) goes to the first superheater (SH1) to ensure that the steam is superheated before the first injection of feed water, which takes place after SH1. The water injection is used to control the steam temperature after the superheater.

The superheaters at HVK consists of a high, a medium and a low temperature section: where the high temperature section is connected in parallel flow and the other two in counter. The different super heaters are interconnected with externally mounted collector boxes in combination with feed water injectors for steam temperature control. The set-points are inherited through the controller structure so the operator´s only concern is the output steam temperature.

The cooling of the steam in the various steps is done with feed water injection, which is taken out after feed water main valve after the feed water-box to the nozzles, which are placed before SH2a, SH2b and SH3. After SH3 the superheated steam has a temperature of 510°C at 110 bar. All SH parts are drainable. The design normal operating temperature is 530°C. This difference in set-point and design temperature can be decreased by having better control, which is what this project aims for.

The boilers are also equipped with a blow-off valve (steam evacuation valve) used to regulate the steam temperature during start-up and turbine malfunction.

The boiler drum that is transverse, is fully welded and fitted with manholes (round) in both sides. It is furnished with the necessary separation devices and fluid separation for outgoing steam. A level-indication gauge is placed at each end of the drum, one of the gauges are monitored from the control room with a camera.

Figure 2 shows the operator display of the superheaters of a boiler at Heleneholmsverket.

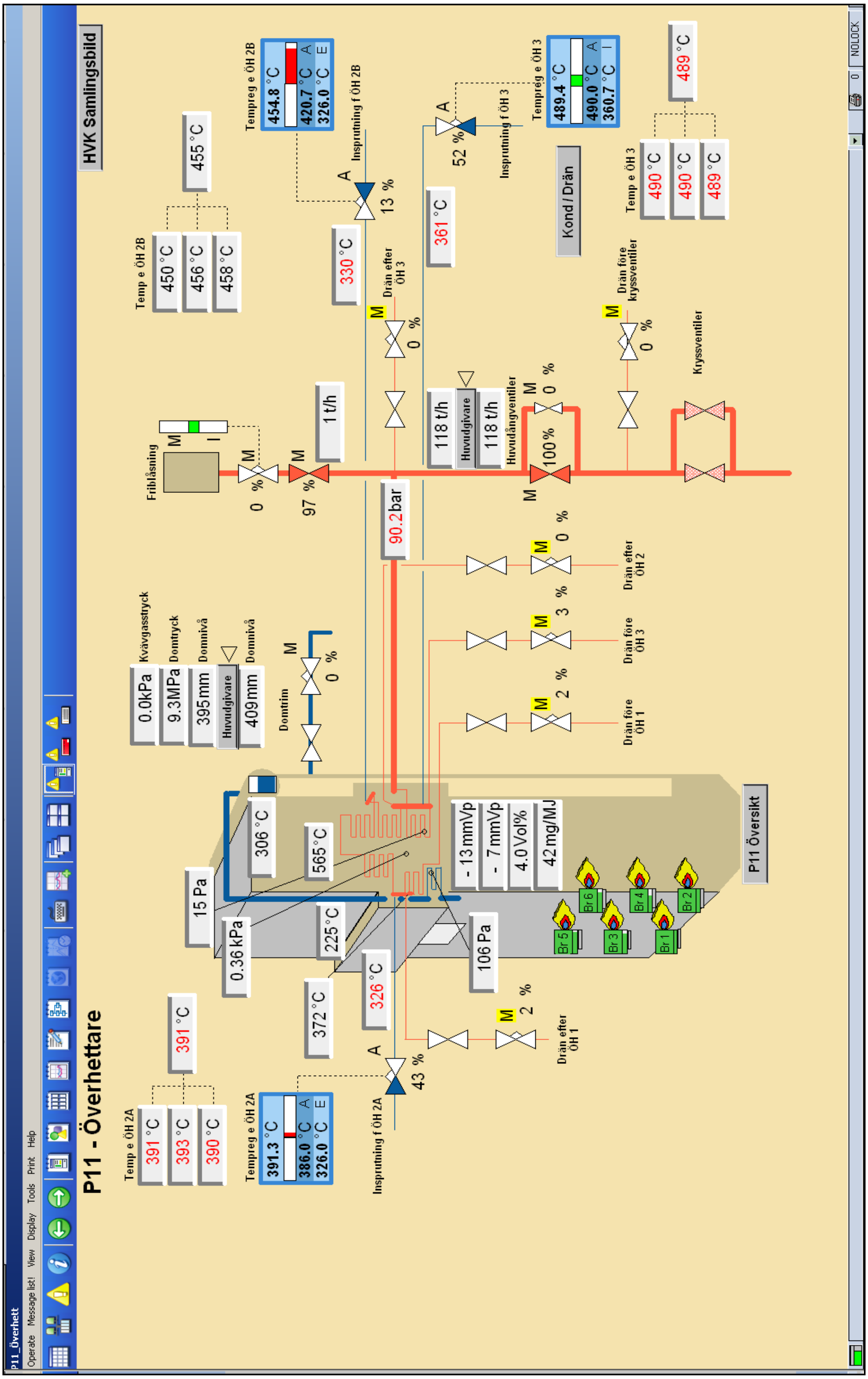

Figure 2. Operator display of the superheaters in a boiler at Heleneholmsverket.

2 Feedforward Control

The most common control scheme is the feedback scheme with the following basic steps:

1. Measure outputs of the system to be controlled
2. Compute the control signals based on the difference between reference values and measured outputs (control error), and then
3. Apply the control signals to the inputs of the system.

This gives at least two implications when considering reference changes and disturbances acting on the system:

1. The feedback controller needs to handle set-point changes by comparing system outputs and reference values. If the feedback controller is tuned towards disturbance attenuation, reference following may be poor (sluggish, oscillatory)
2. The disturbances acting on the system must effect the system outputs before any control action can be computed and taken. Depending on the system dynamics, both time constants and delays, the severity of the output deviations will differ.

The control structure to remedy these deficiencies is feedforward, which is a conceptually simple and powerful control strategy. It can be applied to both reference values as well as disturbances if they can be measured. That is, if we can place a sensor to find information about the disturbances before they effect the system outputs, we should be able to perform better.

2.1 LINEAR SYSTEMS

Consider the linear system in Figure 3, where we have the reference values R, measured outputs Y and disturbances D acting on the system G, feedback controller C, and disturbance transfer function G_d. The reference values R effect the output Y by

$$Y = (I + GC)^{-1}G(C + G_{ff,ref})R.$$

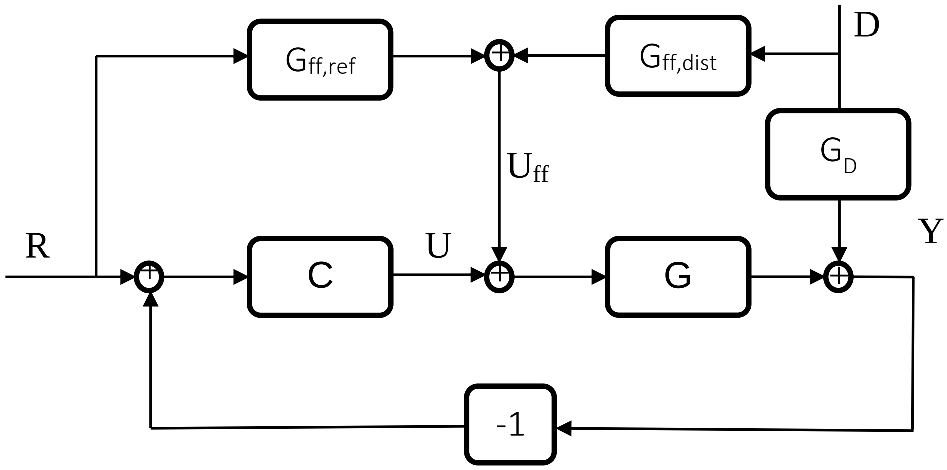

Figure 3: Control structure with feedforward from reference value and measured disturbance.

The ideal transfer function matrix from references to outputs is I, i.e., Y and R are equal, which can be achieved if the feedforward from the references R is designed as

$$G_{ff,ref} = G^{-1}.$$

If we instead consider measurable disturbances D acting on the system, also seen in Figure 3, they will influence the outputs as

$Y = (I + GC)^{-1}(G_D + GG_{ff,dist})D.$

This means that we can remove the effect of the disturbances D if designing the disturbance feedforward as

$$G_{ff,dist} = -G^{-1}G_D.$$

From the expressions of how the reference and disturbance influences the output we can see that

1. Feedback tries to remove the effects by having a high loop gain, i.e., $||GC||$.

2. Feedforward tries to remove the effects by matching two transfer function matrices so that their sum is 0.

A consequence of this is that feedforward is much more sensitive to modelling errors than feedback. However, feedback has the risk of yielding instability which feedforward cannot do. Feedback and feedforward are thus complementary and useful to combine (Hägglund & Åström, 2006).

2.1.1 Model Inversions

As seen in the previous section, perfect feedforward from references and disturbances requires model inversion. If this is possible, the feedforward is straight forward to implement. Although inversions can theoretically often be computed, they are problematic in the implementation phase of a control system. Below we will give some examples of such problems for linear systems.

Three fundamental problems with model inversion are time delays, pole excess and unstable zeros of the disturbance/system model. They are fundamental problems for both SISO and MIMO system, and are shown below for SISO systems.

The first two problems can be exemplified by one of the simplest process models used, the first order system with time constant T, static gain Kp and time delay L,

$$G = \frac{K_p}{sT+1} e^{-sL}.$$

which has the theoretical inverse

$$G^{-1} = \frac{sT+1}{K_p} e^{sL}.$$

This model cannot be used in a feedforward controller because

1. It contains a pure derivative, which is a direct consequence of that G has a pole excess ≥ 1. This is not suitable to implement as taking the derivative of a measurement signal with noise will yield too rapidly varying control signal.
2. It contains a prediction, i.e., the system is non-causal, and can thus not be realized.

The second example is a system which has a step response that in the beginning moves in the opposite direction compared to the step, i.e., a non-minimum phase system that has unstable zeros. An example is the system

$$G = \frac{s-1}{s+1},$$

which has the theoretical inverse

$$G^{-1} = \frac{s+1}{s-1}.$$

This system is unstable (pole in +1) and can thus not be used as feedforward.

When the feedforward controller can be calculated without the problems above, there is the risk that it will compute control signals that cannot be realized by the actuators of the system. This could be for instance too large/small control signals and control signal rates. This need to be handled with special care to avoid actuator damage.

2.1.2 Model Uncertainties

Another difficulty in feedforward is the presence of model uncertainty, and the below follows the outline in (Skogestad & Postlethwaite, 2005). With feedforward from both reference and disturbance, the feedforward is

$$U_{ff} = G_{ff,ref} R + G_{ff,dist} D$$

The control error E = R-Y then becomes

$$E = (I - G G_{ff,ref}) R - (G_D + G G_{ff,dist}) D = S_R R - S_D G_D D$$

where S_R and S_D are the feedforward sensitivity functions that should be less than 1 in magnitude (singular value) if the feedforward is effective. Applying the ideal feedforward controllers, we have $S_R = S_D = 0$. However, analyzing with uncertainties in the system and disturbance model, the sensitivity of the feedforward is shown. If the real system and disturbance have the transfer functions G'_D and G' instead, we have the following error if using the expressions for the ideal feedforwards

$$E = (I - G'G^{-1})R - (G'_D + G'G^{-1}G_D)D.$$

For the three different uncertainties in G:

$G' = (I + E_o)G$ output uncertainty

$G' = G(I + E_I)G$ input uncertainty

$G' = G + E_A$ additive uncertainty

we get the following errors

$E = -E_o R + E_o G_D D$ output uncertainty

$E = -GE_I G^{-1}R + GE_I G^{-1}G_D D$ input uncertainty

$E = -E_A G^{-1}R + E_A G^{-1}G_D D$ additive uncertainty

The same calculations, when considering the following three uncertainties in G_D,

$G'_D = (I + E_o^D)G_D$ output uncertainty

$G'_D = G(I + E_I^D)G_D$ input uncertainty

$G'_D = G_D + E_A^D$ additive uncertainty

give the following errors

$E = E_o^D G_D D$ output uncertainty

$E = -G_D E_I^D D$ input uncertainty

$E = -E_A^D D$ additive uncertainty

Two notes that can be taken are

1. An uncertainty in the system effects both feedforward from the references as well as feedforward from the disturbance, while an uncertainty in the disturbance only effects the feedforward from disturbance.

2. As the system and disturbance models are MIMO, the direction of the error will matter. For instance, the uncertainty matrices, e.g., E_I, can have off-diagonal elements.

In the above calculation, errors have been computed when having only system or only disturbance model uncertainties. They may very well be jointly analyzed.

2.2 NONLINEAR SYSTEMS

For nonlinear systems, the analysis presented above does not hold in general. A typical approach in order to circumvent this is to linearize the system around an operating point and base the design of the control structure on the linearized system instead. The results presented for linear systems are then guaranteed to hold for the nonlinear system as well, but only as long as the system is close to the linearization point. There are however also additional problems that can occur in the nonlinear case, such as functions not having a uniquely defined inverse.

For highly nonlinear systems, the linearization can be extended by using gain scheduling, which means that different linearizations are used for different operating points. For more advanced users, non-linear feedforward can be developed and give a much better response than methods based on linearization. This method is used in this project, with feedforward based on a physics-based model of the system. The control structure with nonlinear plant and feedforward is presented in Figure 4, where G_{ff} now represents the nonlinear feedforward.

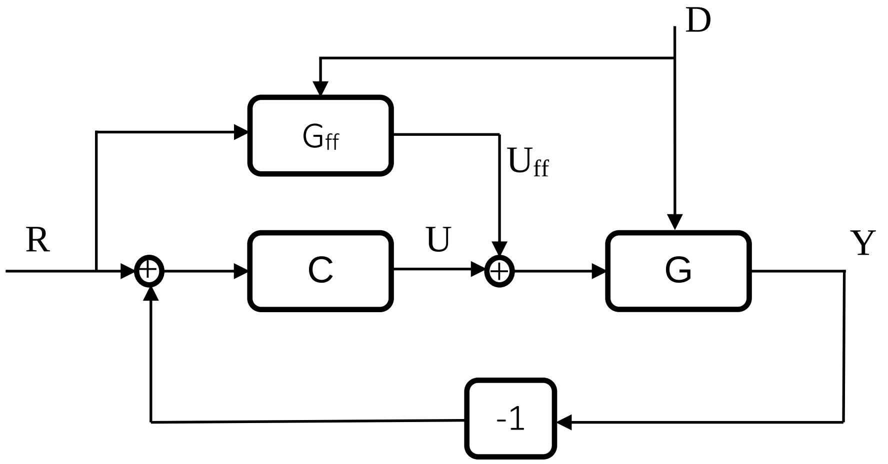

Figure 4. Control structure with nonlinear plant model and feedforward.

2.3 IMPLEMENTATIONAL METHODS

A perfect feedforward would result in no control action from the feedback. This is however difficult to have in implementations, but a feedforward that helps the feedback such that reference following or disturbance attenuation is faster is still useful. It is then important to tune the feedback and feedforward together, to obtain the best control action.

Some of the available choices at implementation is to use:

1. A static, possibly non-linear feedforward, based on inverse or pseudo-inverse of the steady-state gain, focusing on setting the correct steady-state value of the control signal given the disturbance or reference value. Taking uncertainties into account, one often backs off a bit and use the feedforward to give the control signal a push in the correct direction without trying to remove full error. Using static relationships is also a typical method for handling pure time delays.

2. When the model to be inverted has a pole excess ≥ 1, one can try adding poles to the feedforward to get it strictly proper. However, it is important that not to add too much attenuation at high frequencies as it is here the main gains of the feedforward is given. Additionally, one can also reduce the noise sensitivity with additional poles.

3. Low order filter with correct steady-state gain that has similar time constant compared to the perfect feedforward. Most typically, it is designed to match well to the desired feedforward at a certain frequency, see e.g. (Hägglund & Åström, 2006).

4. For highly non-linear systems, gain scheduling or non-linear inversion, as explained in Section 2.2, can be used.

The current implementation of the feedforward in superheater control in Heleneholmsverket is based on a combination of the first and the third method presented above. This is achieved by combining static mass- and energy balances based on nonlinear steam properties and nonlinear pressure/flow calculations with linear filtering.

As mentioned in Section 2.1.1, it can be that the feedforward calculates a control signal that cannot be applied by the actuators. In this case there is a need for control signal saturation and thus also an anti-windup strategy that is applied to the sum of feedback and feedforward control signals, as recommended in (Hägglund & Åström, 2006).

3 Methodology

In this chapter the steps that should be taken in order to implement a dynamic inverse model to be used in feedforward control are described. The basis of this method is the understanding of the physics of the process and the ability to describe it mathematically.

3.1 MODEL BOUNDARIES

The first step of the inversion task is to define the boundaries of the inverse model. It is then determined which disturbances and control signals that should be used as inputs to the inverse, and which signal the feedforward should calculate and provide as output. It is desirable to limit the size of the inverted model to avoid having a too difficult inverse problem to solve later.

3.2 MODELING OF PROCESS

The process dynamics that should be inverted is first modeled without any inversion. Using suitable assumptions of the physics governing the process and parameter values based on data from the process a physics-based model of the process is created. This model will have the form of a dynamic algebraic equation (DAE), which is a system of differential and algebraic equations. By simulating the model with measured signals from operations of the real plant as input, the model is validated. If significant differences between the model and real process are observed, the parameter values or modeling assumptions might be altered to obtain a better fit between measurements and simulation results. As it will typically be hard to determine which modeling assumptions that are ideal for inverse implementation at this stage of the process, a viable strategy is to continue modeling on several models using different assumptions into the next steps.

3.3 ANALYSIS OF PROCESS MODEL

The process model is analyzed in order to determine how suitable it is for inversion. There are several factors that need to be considered, presented below.

3.3.1 Speed of Dynamics

The dynamic feedforward model will be implemented in a sampled system with a fixed sampling rate. The sampling time must be considered when the inverse model is created, as the sampling rate gives a boundary for how fast dynamics that can be modeled. Linearizing the process model at typical working conditions is a standard method to analyze the dynamics of a system. The linearized model can be used to determine whether the modeling assumptions regarding the dynamics of the model are suitable given the sampling rate of the control system where it should be implemented.

Another matter regarding the speed of the process dynamics is related to the actuators. An inherent problem with normal feedback control is that the controller should not handle dynamics faster than the actuators effect the process up to the feedback signal. Trying to counteract these fast dynamics will only lead to unnecessary fluttering and wear of the actuator and process. When applied to feedforward the reasoning becomes that the feedforward should not include dynamics faster than the actuators can affect the process up to the disturbance injection. This implies that the feedforward can handle dynamics faster than the feedback since the dynamics of the process part from the disturbance injection to the feedback measurement are not included in the feedforward “loop”.

For both these issues, if the dynamics are too fast, assuming static relationships instead is the standard method to avoid these problem. This should also be considered when designing filtering of process measurements, frequencies higher than handled by the actuator and process part up to the actual disturbance injection should be filtered so they are not introduced into the feedforward calculation. The filters could be different for different disturbances.

During the later inversion index reduction might occur, which would lead to an inverted system with fewer states. This would affect the dynamics of the inverse, which means that the dynamic analysis at this stage will not give a complete picture of the inverse dynamics.

3.3.2 Stability

It is necessary that the inverse model is stable. Looking at the zeroes of a linearized model at working conditions is one method to detect whether the inverse might be unstable. If stability problems with the inverse model arises, the modeling assumptions of the model have to be reconsidered. Understanding of the physics of the system will simplify for this task, as it is very helpful to understand why the instability occurs, when the model is redesigned to avoid this. It could also be beneficial to investigate the dynamics of simplified models to get a better understanding of the issue.

3.3.3 Non-Invertible Phenomena

Some phenomena cannot be inverted. This includes pure time delays, saturations and hysteresis. These must be removed or replaced with invertible approximations in order to enable inversion of the system.

3.4 ANALYSIS OF INVERSE MODEL

When the steps above have been taken, a first inverse model can be created. At this point the goal is not to obtain a model that is suitable for implementation, but rather to examine what difficulties that must be handled in order to achieve this goal. For this task a modeling environment where such an inverse can be created and analyzed is needed. When the inverse is obtained, the general behavior of the model is verified.

Furthermore is the formulation of the inverse analyzed. The most interesting part to look at is the occurrence of nonlinear equation systems. When an explicit formulation of the inverse should be obtained, explicit solutions to such systems are needed. Reformulating equations or using approximations are methods that can be used to remove or decrease the size of these systems, which would simplify the inverse modeling.

Another interesting phenomenon to look out for is index reduction, which means that equations are differentiated in order to obtain the inverse. Index reduction is a common phenomenon in dynamic modeling. A typical example when index reduction will occur for fluid systems is the connection of two volume models. This would mean that the states of each volume no longer are independent, making it necessary to manipulate the equations to obtain the independent states of the whole system. If the inversion results in multiple index reductions it will be hard to obtain an inverse model. This problem might be handled when the explicit formulation of the inverse is formulated.

3.5 CREATE EXPLICIT INVERSE

At this point the inverse model is formulated. This task consists of two steps; reformulating the DAE to have the desired output and input signals, and the formulation of the integration of the system, where approximations of derivatives are used to describe the development of the states in the model. The first step of this process is the hard one, as it is not trivial to determine whether it is possible to find the desired expression.

3.5.1 Model Inversion

We will follow the formulation in (Looye, Thümmel, Kurze, Otter, & Bals, 2005) to describe how the reformulation of the DAE to an inverse form is conducted. A general implicit DAE can be expressed as

$$0 = f(\dot{x}, x, y, u)$$

Where f is a set of functions, x is differentiated variables, y is the algebraic variables and u is input signals and disturbances. By solving systems of equations and possibly differentiating equations, this system is reformulated into the following explicit state space form

$$\begin{bmatrix} \dot{x}_1 \\ x_2 \\ y \\ w \end{bmatrix} = f_1(x_1, u)$$

Here the vector x is split into x_1 and x_2, where x_1 is the state vector which contain all independent variables and w contains derivatives of x and/or y which appear if f must be differentiated. The number of differentiations that are needed corresponds to the number of index reductions encountered for the system in Section 3.4

By choosing suitable input and output signals in the DAE formulation, the explicit inverse formulation is obtained, as the output and the state derivatives both are explicitly formulated as functions of inputs, disturbances and the current values of the states in the state space formulation.

The difficult part of this task is to calculate the function f_1 from the original formulation, so that an explicit formulation is obtained. Guidance for this task can be found in (Cellier & Kofman, 2006). There is no guarantee that this can be achieved explicitly for a general case, as the task might involve solving a system of nonlinear equations. Starting the analysis on simplified models is one method that can be used to clarify which kinds of models that can be inverted. The analysis of the inverse performed in the previous step should also provide guidance for this task. If problematic nonlinear equations are encountered, additional approximations in the model formulation can be used in order to simplify the derivation of the function f_1. Other alternatives are adding a one sample delay between different equations to break algebraic loops, or implementing a functionality for solving the equation numerically.

Index reductions can also prove problematic when the inverse is formulated, especially if there are more than one. This can make it necessary to include derivatives of functions used in the formulation, such as media properties, which might be hard to obtain. One approximation which would avoid this problem is to replace the analytical expression of the derivatives with approximations. This approximation will often also simplify the general formulation of the system, as formulations with partial derivatives would be simplified and the need for derivatives of various signals in the system would disappear. However, numerical differentiation can lead to problems with stability and accuracy, so care must be taken to ensure that the model is well-behaved.

3.5.2 Sampling

The states describe the dynamics of the process and these must be updated at each sample. A simple approach for approximating the integration of these is to use explicit Euler. This means that the time derivative of the state signal, which is calculated at each sample, is assumed to remain constant for the entire sample period. The state is then updated under this assumption. This means that an equation such as

$$\dot{T} = g(t)$$

Results in the update law

$$T(t_{n+1}) = T(t_n) + g(t_n) \cdot t_s$$

where t_s is the sampling time.

The inverse model does not need to be created in the environment where the final implementation will be used, but it is important to have the features and functionalities of this environment in mind when the formulation is created.

3.6 ANALYZE PERFORMANCE OF DYNAMIC FEEDFORWARD

Before implementing the inverse model in a real system, the performance can be evaluated in simulation using a model of the process. In the plant model, none of the approximations introduced in order to obtain better inverse properties are used, the model is instead as accurate and close to the real plant as possible. The feedforward model is then used to determine the input signal U_{ff} to the detailed model, simulating the situation in the real plant, when no additional control action from other parts of the control system is present. This gives the setup displayed in Figure 5. Using this kind of setup, various experiments can be conducted, examining the behavior of the feedforward control under different circumstances.

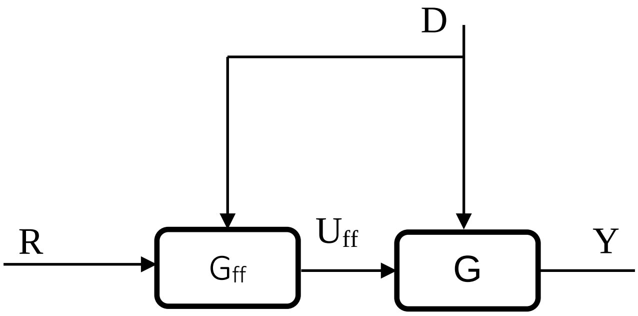

Figure 5. Model setup for performance evaluation, with a feedforward model G_{ff} and a process model G.

Important tests include analyzing the response of the system to typical input signal transients, and investigating the robustness against modeling error and measurement noise. As a result of the noise sensitivity analysis, suitable filtering of input signals to avoid high frequency content, can be considered.

3.7 ITERATION AND FINAL IMPLEMENTATION

Some steps described above might be performed iteratively due to difficulties encountered at later steps or in order to improve performance. It is also possible to consider several different modeling assumptions from the start and reject the ones that prove unsuitable as the project progresses. When an inverse model with satisfactory performance is obtained, it is implemented in the real process.

4 Tools

The main tool used in this project is Dymola. Dymola is a modeling and simulation program based on the equation based language Modelica. Although the final implementation of the feedforward system needs to be formulated in the programming environment used in a real plant, Dymola and Modelica prove very useful for various tasks throughout the project. This will be explained further below.

4.1 MODELICA

In Modelica, models are described by directly formulating the equations which govern the behavior of the system. Differential, algebraic and discrete equations can be used. The user does not need to adapt the formulation of the equations with regard to which signals are input and output, this will instead be the task for the simulation environment that is used. This non-causal modeling approach enables a very simple implementation of inverted systems. By handling a signal that is normally an output as an input instead, an inverted model is automatically obtained. In (Thümmel, Looye, Kurze, Otter, & Bals, 2005) this procedure is described, together with limitations of the method and possible pitfalls during implementation.

Another important feature of Modelica modeling is that it enables the user to base the created model directly on the actual physics it is supposed to mimic. To use physics-based modeling in this fashion has the main benefit that the parameter values and the mathematical relationships come directly from the formulation of the system, reducing the need for manual adjustment of the system.

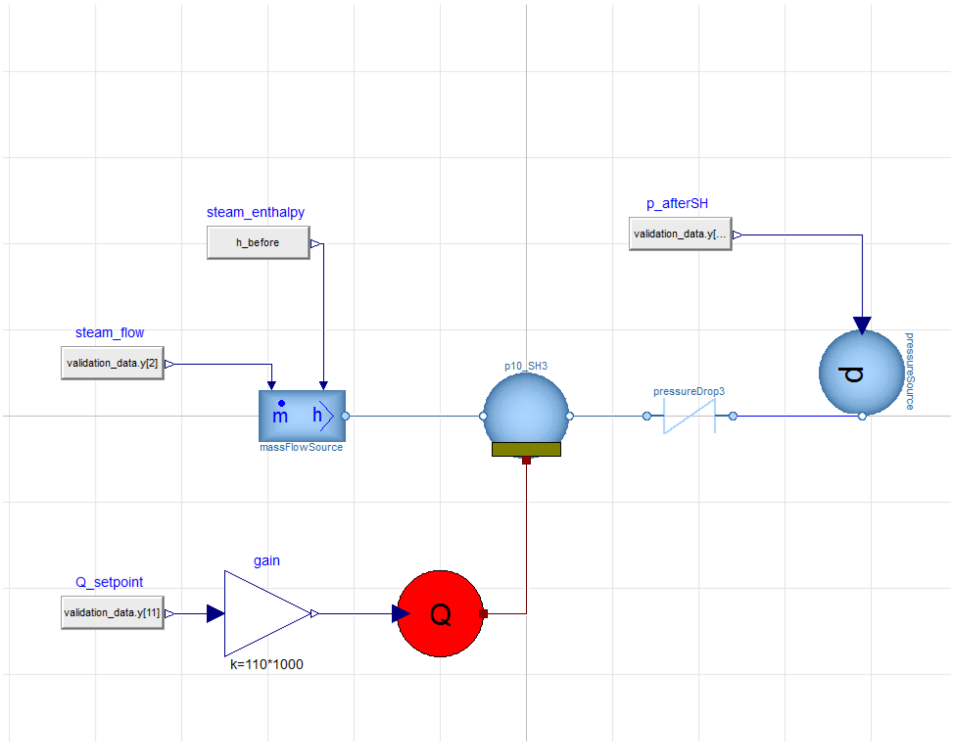

Figure 6. Graphical representation of a volume model with flowing steam and added heat from an external heat source in Dymola.

4.2 DYMOLA

Dymola provides an environment where Modelica models can be developed, compiled and simulated. For modeling, the Modelica code is complemented with a diagram layer, where the connections between subcomponents is visualized graphically, similarly to programs such as Simulink. Figure 6 shows a typical diagram representation of a Modelica model, consisting of several submodels. New models and experiment setups are typically constructed by connecting simpler models in the diagram layer, while the simpler models are imported from component libraries or written in Modelica code.

In order to simulate a Modelica model, it is first flattened and translated to C code. It can then be compiled and simulated using a suitable integration method, which can be selected by the user.

4.3 DYMOLA FUNCTIONS FOR MODEL INVERSION

This section contains descriptions of how Dymola and Modelica are used to solve different tasks during the process of deriving a dynamic inverse model. Even though Dymola cannot be used to derive the needed explicit inverse formulation, it has several functionalities that provide help when the model is developed and analyzed, according to the steps in the previous chapter.

4.3.1 Simulation

Simulations are very powerful tools to analyze and verify behavior of models during different parts of the inversion task. It is used to verify that the first modeling is correct, to analyze behavior of different inverted models and it can also be done to test the performance of the feedforward on more realistic plant models. Using the functionality of Dymola, it is possible to use either continuous models inverted by the tool itself, or models of the sampled inverse system that should be implemented in the feedforward in the real plant.

4.3.2 Linearization

The linear analysis function in Dymola creates linearized models so that the dynamics of a process can be analyzed. It is used for two purposes during the development of inverse models. Firstly, the speed of the dynamics of a model, which is to be inverted, is determined by looking at the characteristic time of the poles and zeroes of the system. Secondly, instability problems due to unstable zero dynamics can be detected by looking at the zeros of the model. A positive real part of any zero indicates that the inverse will be unstable.

4.3.3 Translation Log and Mof File

When a Modelica model is translated to c-code, data from the translation is collected in a log. This log contains information which is valuable when deciding the formulation of inverse models. In order to obtain the useful information, an inverse model formulated in Modelica is translated. The interesting parts of the translation log are the information regarding equation systems and information regarding index reduction, both marked in the translation log in Figure 7. Both of these can be used when the explicit formulation of the inverse is developed. Existence of systems of nonlinear equations means that the formulation of the model might need to be changed in order to allow for an explicit inverse to be formulated. Index reduction means that equations must be differentiated in order to obtain the inverse formulation.

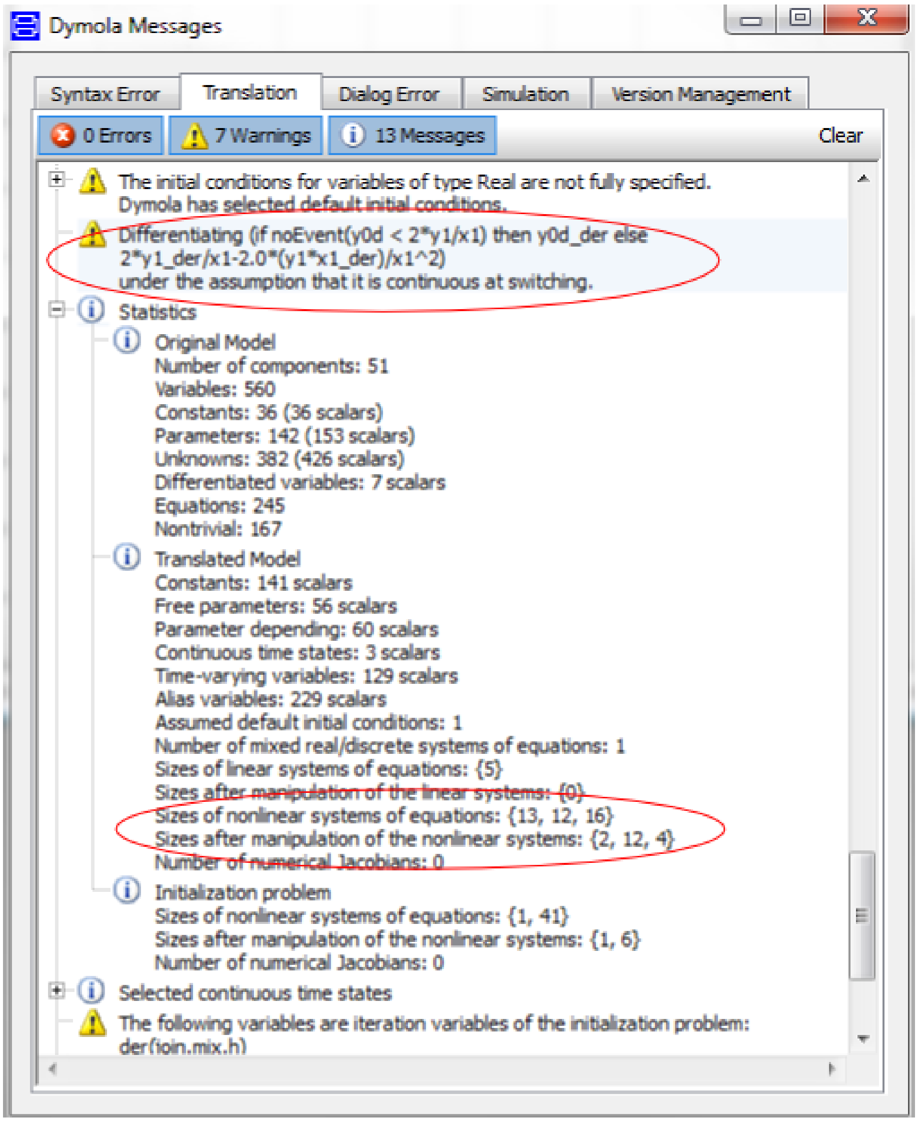

Figure 7. Dymola translation log with differentiated equations and nonlinear equation systems. The red circles mark that index reduction is performed (top) and the sizes of the nonlinear equation systems in the system (bottom).

The translated Modelica code can also be examined using a generated listing of the code, called dsmodel.mof. In this file information about how Dymola solves the differential algebraic equation is collected. This can give clues of how the explicit inverse model can be derived.

5 Superheater Temperature Control

5.1 CONTROL OBJECTIVE

Steam superheater temperature control in thermal power plants is well-known to be a challenging control problem (Moelbak, 1999). The reasons for this is both that the dynamics is load dependent with a non-negligible time delay, and it is exposed to major disturbances from the flue gas.

The superheater steam temperature is normally controlled by spraying water into the steam pipe before the superheater. The target steam temperature is limited by the creep point of the steel in the superheater tubing. Operating at temperatures above this point will shorten the life time of the boiler. Fast changes in tube temperature will also shorten the life span of the tube. On the other hand, higher steam temperature means more produced electrical power at low cost of fuel. Maintaining the steam temperature constantly at the target temperature is, therefore, critical to maximizing the electrical efficiency as well as the life span of the boiler and turbine (Huiyong, o.a., 2015).

5.2 BENEFITS FROM IMPROVED SUPERHEATER CONTROL

There are several advantages with improved steam temperature control. The main points are listed below (Moelbak, 1999).

5.2.1 Efficiency

If the disturbance rejection of steam temperature controller can be improved so that the largest “normal” variations can be reduced, the outlet temperature set-point can be increased without changing the probability for an off-spec temperature and accordingly the turbine efficiency will increase, see Figure 8. Feedforward offers this possibility since the feedforward can act directly to counteract the disturbance without any change in the controlled temperature. The feedforward also offers the opportunity to decrease the feedback gain and thereby decrease the noise sensitivity. This offers decreased noise in the control signal with increased disturbance rejection.

A rule of thumb says that a 10°C higher temperature on fresh steam will give 0.25% increase in efficiency at a 400 MW plant (Moelbak, 1999). In (Immonen, 2003) a case example is given from an U.S. pulp and paper mill where the standard deviation of the steam temperature was decreased from 5°C down to 2.3°C, and the annual savings from an increased steam temperature set-point were approximately $130,000 (in this case from increased backpressure power generation).

5.2.2 Life Span

The performance of the steam temperature control has a direct impact on the thermal stress of the plant, as noted in section 5.1. There are both constraints on the maximum and minimum permissible temperature and also on how rapid the temperature change is allowed to be. It is plausible to assume that all changes in temperature will decrease the expected life span of the tubes. The larger and faster the changes are, the shorter the life span is. The performance of the steam temperature controller is therefore of outmost importance, especially the performance regarding disturbance rejection.

The decreased noise sensitivity of the feedback, described in 5.2.1, will decrease the wear of the valves and actuators.

5.2.3 Boiler Stability

Improved steam temperature control improves the overall boiler stability. Boiler stability is crucial in situations such as starts and stops of the boiler, soot blowing, and a range of possible fault situations of the boiler.

Improved boiler stability in general can improve the load following capability of the plant significantly. This is an important aspect in an increasingly liberalized energy market but also from an increasing amount of intermittent wind power generation which adds extra power regulation requirements on power plants (Eng, Johansson, & Dahlström, 2014). The steam temperature normally limits the load change speed and improved steam temperature control will therefore directly have an effect on load following capability.

Improved overall stability of the boiler will result in reduced probability of boiler outage and therefore the availability of the plant which has a direct influence on the plant economy.

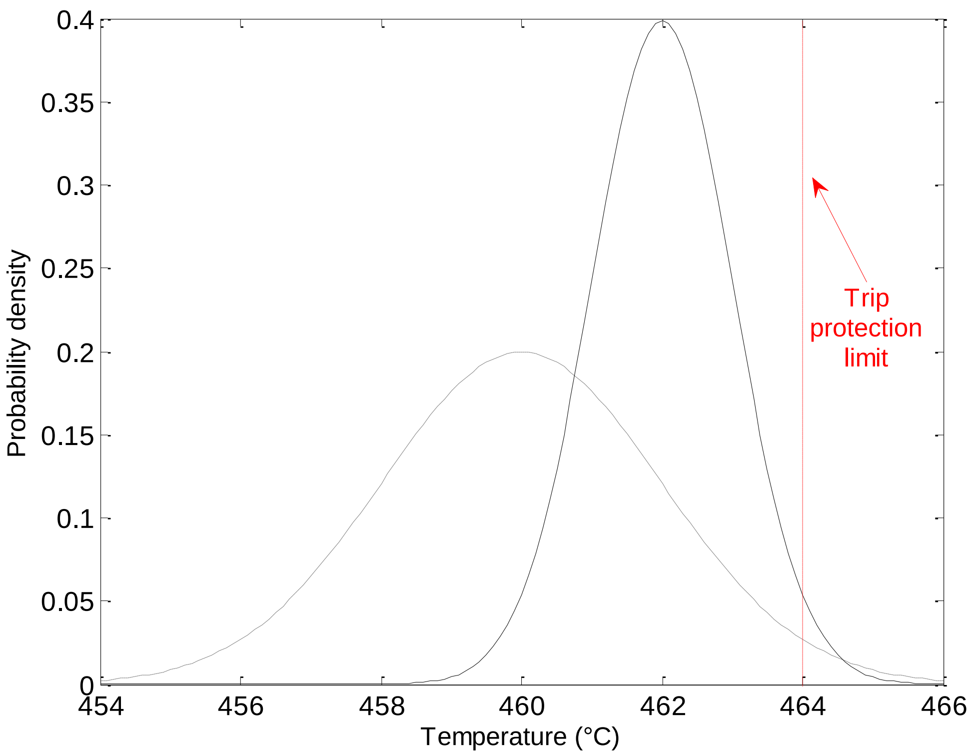

Figure 8. The reduction of temperature variance makes it possible to increase the set-point (target shift). The solid curve represents a condition where the variance has been reduced by a factor of four compared to the dashed curve. Because of this, it is possible to change the set-point from 460 to 462°C, without higher risk of boiler trip.

Large boilers are normally equipped with extensive measurement systems designed to detect all the relevant disturbances. During large disturbances the operator normally stabilize the boiler by manually manipulate the controller outputs. Thereby the operator uses their knowledge as the basis for a kind of manual feedforward. The feedforward proposed in this project utilize the same measurements for the automatic model based feedforward that is continuously active during the operation of the boiler.

5.3 CONTROL METHODS

The superheater control is typically structured as in Figure 9. It consists of two PID-controllers connected in a cascade loop where the outer controller (PID2) controls the temperature after the superheater, T_2, by manipulating the set-point for the inner controller (PID1). PID1 controls the temperature before the superheater, T_1, by manipulating the water injection valve. This structure is the conventional way to control the steam temperature at larger plants.

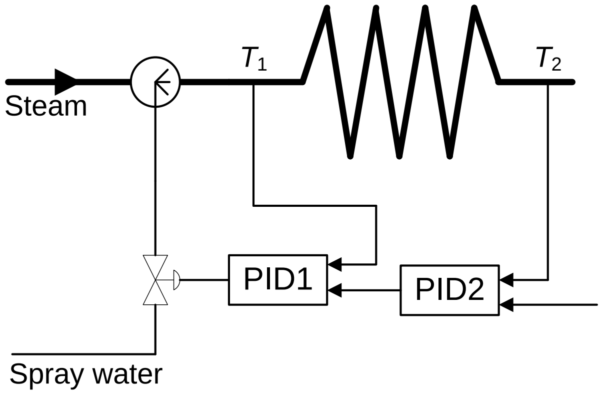

Figure 9. Cascade PID loop for a superheater.

There are variants that includes mass flow measurement of the injection water and an additional mass flow controller (giving a cascade loop with three controllers) to counteract flow disturbances i.e. pressure variations in the feed water system, see Figure 10. The difficulty with this solution is that PID1 and PID-F work in the same frequency band and might disturb each other. This is why sub alternatives of this is variant exists. The sub alternatives can be a configuration where PID1 and PID-F are combined or one of them are of reduced complexity (e.g. p-control only).

There are also variants that uses only the outer loop controller, PID2. The inlet temperature is then mixed in to the controller error by some kind of model.

The use of several controllers can improve the performance of the control system but it also increases the complexity and the amount of tuning time required. Some kind of feedforward is almost required for the solution with three feedbacks loops.

As noted in above, there are challenges with superheater temperature control. There are major disturbances that needs to be handled and they can be divided in two groups, by which loop they affect.

1. Disturbances that act on the outer loop are, among others, changing boiler load, varying heat flow from the flue gas, varying steam flow and steam pressure.

2. Disturbances that act on the inner loop are changing steam temperature from the previous superheater, steam flow, steam pressure, feed water pressure, feed water temperature.

One effective way to deal with the different disturbances is to add feedforward to the controllers, which is treated thoroughly in this report.

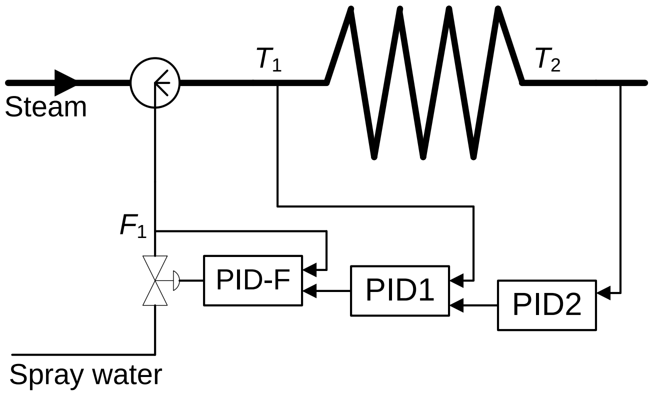

Figure 10. Alternative cascade loop with an inner flow controller.

5.4 SUPERHEATER CONTROL IN HELENEHOLMSVERKET

In this section the original steam temperature control at Heleneholmsverket, prior to this project, is described. The changes that are made because of this project are described in Chapter 7.

Figure 11 shows a schematic diagram of the superheater configuration at Heleneholmsverket. There are three control structures as the one shown in Figure 9, controlling the temperature after SH2a, SH2b, and SH3 respectively.

The controllers are connected through the temperature set-points. The temperature set-points are inherited downward through the cascaded superheaters. This is accomplished by adding 60 °C to the temperature set-point of the inlet temperature controller, PID1, and use this new value as the temperature set-point in the outlet temperature controller, PID2, in the previous superheater in the flow direction. Since PID2 has to be slower and the set-point has a maximum rate of change the previous superheater seeks to balance the allowable superheating to be cooled by the injection to 60 °C. None of the set-points are allowed to be lower than the saturation temperature plus a super heating margin of 20°C.

To speed up the control of the superheaters, stabilize them and to help them handle several disturbances, feedforward is used. There is a feedforward to each controller, see Figure 12 (to simplify the figure, feedforwards are only shown for SH3). These feedforwards were implemented, with a fair amount of engineering effort, in the control structure at Heleneholmsverket prior to this project and they are described in more detail in the following two sections.

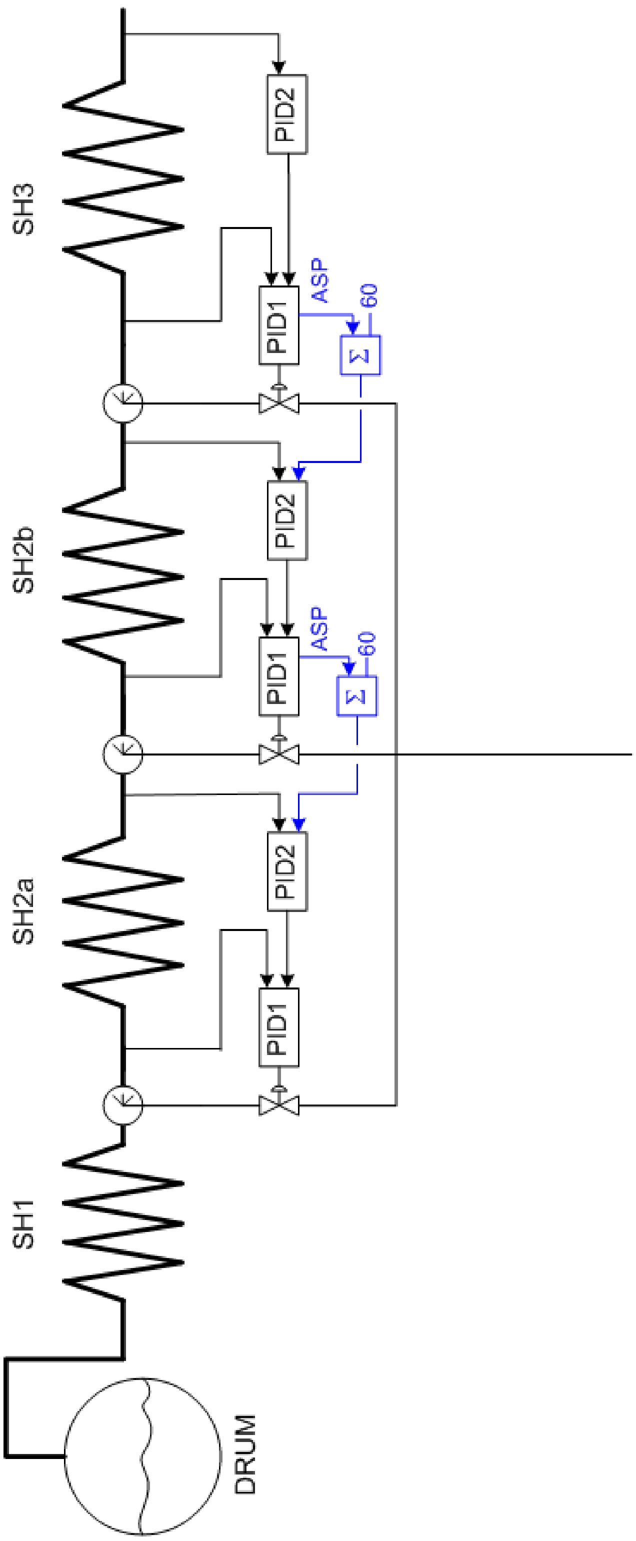

Figure 11. Steam temperature control at Heleneholmsverket. In this figure only the feedback controllers are shown. The cascaded controllers for each superheater are connected via the set-points. The external set-point used in PID2 for SH2a is the active set-point in PID1 in SH2b + 60 °C. The external set-point used in PID2 for SH2b is the active set-point in PID1 in SH3 + 60 °C. There is also a feedforward to each PID-controller, not shown in the figure.

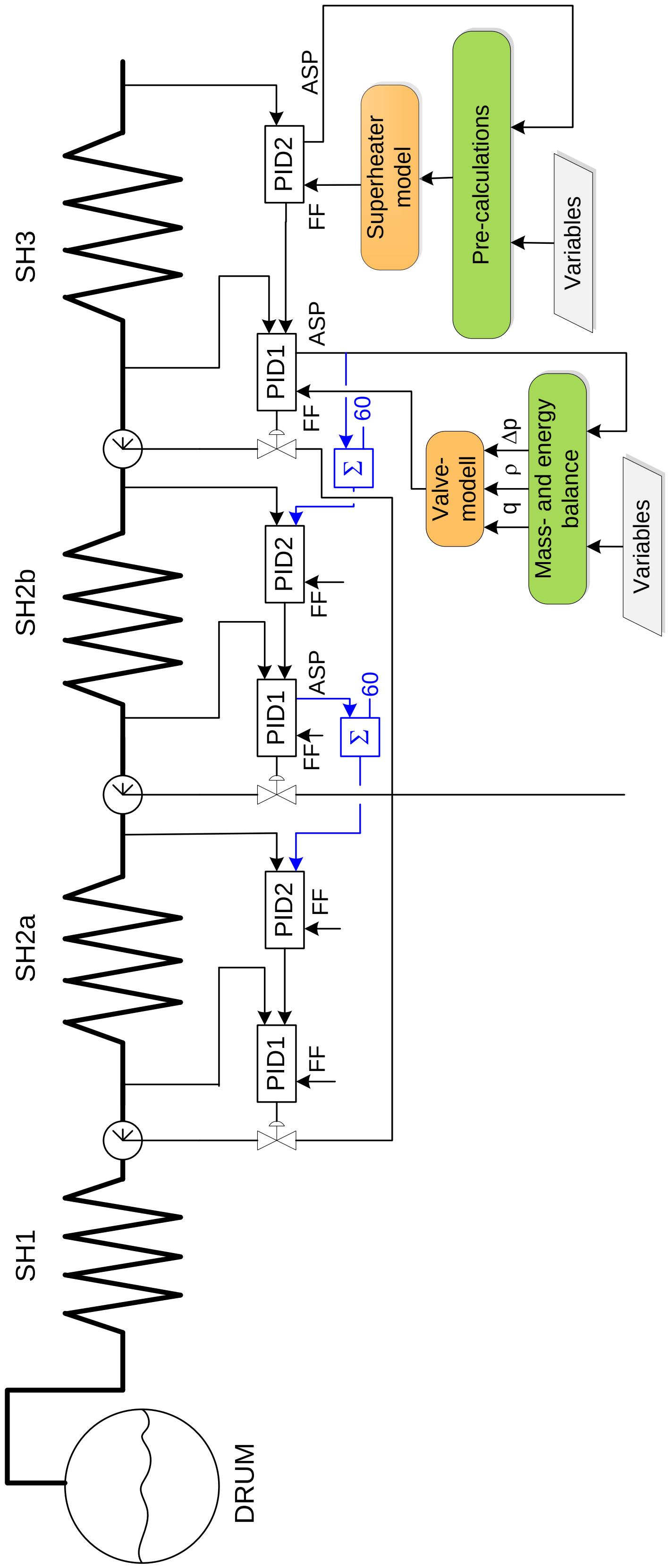

Figure 12. Steam temperature control at Heleneholmsverket. There is a feedforward to each PID-controller, but it is only shown for SH3 in this figure. Abbreviations: FF – feedforward, ASP – active set-point.

5.4.1 Feedforward to PID1 (the inner loop).

The feedforward to PID1 that controls the inlet temperature to the superheater by governing the injection valve consists of two major parts. First pre-calculations to determine the variables to be used in the second part, which is a valve model that gives the required valve opening, see Figure 13.

In the first part the required injection water flow is calculated from a mass and energy balance. The equation uses the temperature set-point into the superheater, actual value and temperature set-point out of the preceding superheater, and injection water temperature as well as steam and water pressure in the interesting points and the actual steam flow.

The usable pressure drop over the injection valve is also calculated. This is the available pressure drop that the valve can use to transport the desired flow. To determine this pressure drop the existing measurements are used and the pressure drop from the measuring points to the valve are estimated. First the pressure drop from the measuring point on the feed water to the injection valve is estimated based on the desired mass flow. From this, the pressure at the valve inlet is known. The pressure at the valve outlet is calculated based on the measuring points on the steam in the drum and the pressure at the outlet from the superheaters. The pressure drop is distributed between the superheaters and from this the pressure at the injection point is calculated, as there is a pressure drop caused by the steam flow through the injection nozzle. Finally the pressure drop of the water passing through the injection nozzle is calculated.

The water density is calculated from the injection water pressure and temperature.

Moving on from this, the calculated injection water flow, the usable pressure drop over the injection valve and the density of injection water flow are fed in to the second part, namely the valve model that calculates the valve opening required if the injection valve was linear. Besides the calculation of the required valve opening of a linear valve, the valve calculations also consists of a nonlinear estimation function which dynamically estimates the nonlinear valve characteristics from measurement data. This also reduces the effect of nonlinear repeatable model errors.

The calculated required valve position is then manipulated with a linear lead/lag filter that is empirically tuned to get the desired response of the feedforward. Each measured disturbance also has a linear lead/lag filter connected to its input to the feedforward to enable different dynamics for different disturbances.

The feedforward not only helps to eliminate the measurable disturbances but it also helps in handling set-point changes through the mass- and energy balance. This is a great advantage when cascaded controllers are used. Since the feedforward is stable faster set-point changes can be fed to the feedforward than to the feedback.

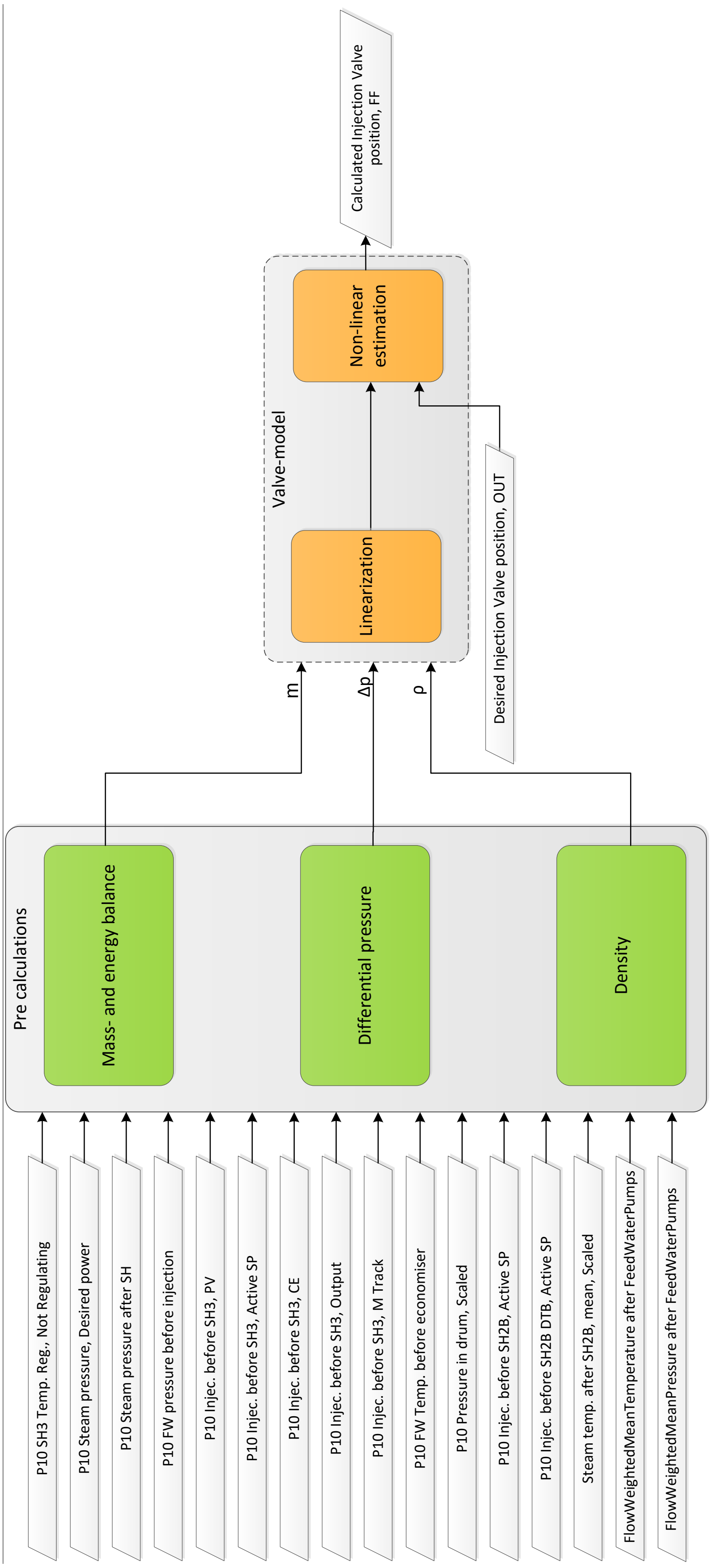

Figure 13. A simplified description of the calculation of required injection valve position given the actual process conditions, used as feedforward to PID1.

5.4.2 Feedforward to PID2 (the outer loop).

The feedforward to PID2 that controls the outlet temperature from the superheater by manipulating the set-point to the inlet temperature controller, PID1, is a calculation of the required temperature at the superheater inlet to keep the outlet temperature at the set-point, given the present conditions, see Figure 14.

First the steam pressure at the injection point is calculated using the steam pressure in the boiler drum and the steam pressure after superheater 3.

Then the heat flow to the superheater is calculated by multiplying the desired fuel power with a power depending factor. The factor is estimated using a nonlinear estimator. The estimator maps the static mass- and energy balance of the superheater to match with the total fuel power.

The last part of the calculation of the feedforward is the mass- and energy balance. This is a static mass- and energy balance where the calculated heat power is added to the energy balance. The calculated required inlet temperature is then manipulated with a linear lead/lag filter that is empirically tuned to get the desired response of the feedforward.

5.4.3 A Note on the Transport Delay

In the feedback loop there is often a dominant transportation delay by the steam flow through the superheater tube (Huiyong, o.a., 2015), (Gilman, 2010), (Grimble, 2006). The delay can typically be around a minute or more.

The modeling in this project however, shows that this dominating transportation delay does not exist in the studied superheater. The transportation delay can be calculated by dividing the tube length with the steam speed. The superheater basically consists of 108 parallel tubes that are approximately 26 meter in length. The tubes have an inner diameter of 27 mm. At 500 °C and 100 bar the density is 30.8 kg/m^3, at 40 kg/s this gives a steam speed of approximately 21 m/s. The time it takes for the steam to be transported through the superheater is approximately 1.2 seconds.

Higher order dynamics can obviously be interpreted as a transport delay in black-box modeling. For the inversion of the physics-based model this is a major benefit since a time delay cannot be inverted.

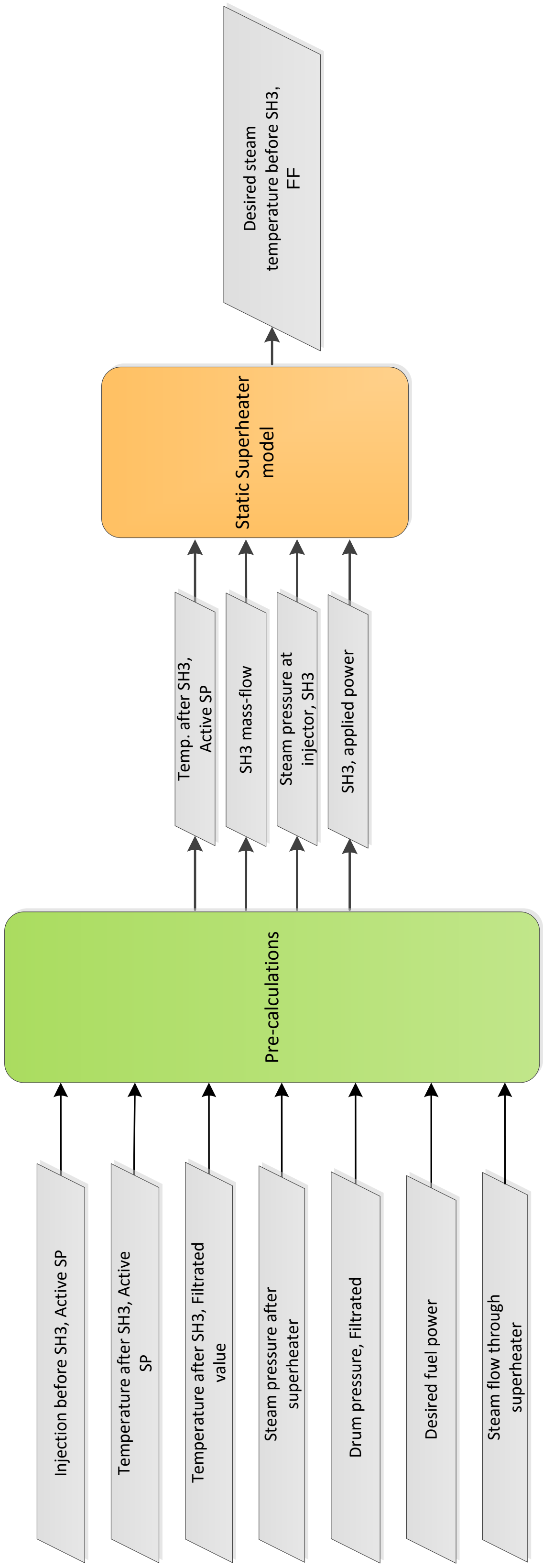

Figure 14. A simplified description of the calculation of required temperature into the superheaters given the actual process conditions, used as feedforward to PID2.

6 Inverse Modeling of Superheater Stage

6.1 MODELING ASSUMPTIONS

The model boundaries of the dynamic feedforward model are chosen to be the same as the previously implemented feedforward system, which is described in Chapter 5. The model is therefore based on the energy balance of steam with heat added from the flue gas, which is calculated based on the firing power set-point. Using a predefined set-point for the outgoing steam temperature, the needed incoming temperature of the steam reaching the superheater stage needs to be calculated by the feedforward. To achieve this, measurements of pressure and mass flow are used as input to the inverse model. The incoming steam temperature is then used as a set-point for the underlying control system which determines the cooling spray mass flow. This gives the control structure visualized in Figure 15, where the PID2 controller of the superheater and the feedforward to the inlet temperature controller has been removed from the figure for clarity.

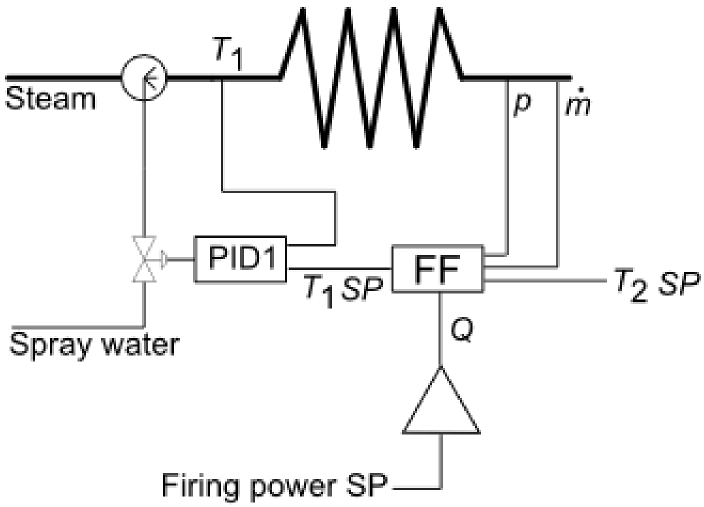

Figure 15. Schematic view of the feedforward model in the superheater temperature control system.

Using the same interface as is already used simplifies the implementation of the new feedforward in several ways. It guarantees that the feedforward fits into the rest of the control system of the plant, it means that the needed measurement signals are available and reliable as they have been used for feedforward purposes in the past, it makes it easy to switch between the two feedforward methods and it simplifies the validation of the new feedforward, as it can be directly compared with the old.

It is also concluded that increasing the boundaries of the feedforward would not necessarily improve the performance of the feedforward. Including the flue gas in the model would for example probably not be beneficial due to limited and unreliable measurements of this part of the process. The fast dynamics between firing power and flue gas temperature and mass flow also indicates that this simplification is reasonable. The filtering of the flue gas dynamics through the tube walls would furthermore conceal much of the effect of the dynamics anyway, if modeling of the flue gas dynamics was conducted.

The steam side of the superheater stage is modeled using standard assumptions, having steam flowing through volumes with mass and energy balance equations and the piping in the component modeled using a number of lumped wall segments. The temperature of each wall segment is calculated using dynamic energy balance, with heat transfer between wall and steam driven by the temperature difference between the two. Each wall segment is connected with a steam volume and these are connected in series forming a finite volume approximation of the steam pipes in the superheater stage. This setup is visualized in Figure 16.

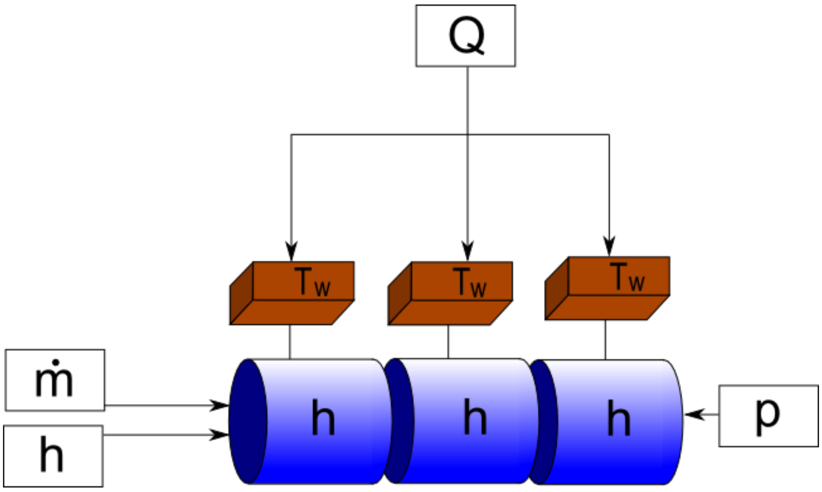

Figure 16. Schematic superheater model.

Three different assumptions regarding the dynamics of the steam volumes are considered; using dynamic mass and energy balance, using static mass and energy balance and using static mass balance with dynamic energy balance. If a dynamic mass balance is used, simple pressure losses are also added to the model. For the completely dynamic assumption, the following three equations govern the states of the model.

$$\dot{U} = \dot{m}_{in}h_{in} - \dot{m}_{out}h_{out} + Q_{w,s}$$

$$\dot{M} = \dot{m}_{in} - \dot{m}_{out}$$

$$\dot{T}_{wall} = \frac{Q_g - Q_{w,s}}{M_{wall}cp}$$

Where U is the internal energy of the steam in a volume, M the total mass of the steam and T_{wall} is the wall temperature. Furthermore, the following relation between internal energy and enthalpy H for a volume V is used

$$H = U + pV$$

When static mass balance is combined with dynamic energy balance, an additional assumption that the derivative of the mass is not affecting the derivative of the internal energy is made, which means that

$$\dot{U} = M\dot{u}$$

where u is the specific internal energy. For all models steam properties from IF97 tables are used. The result of using each of these assumptions in an inverse implementation is presented in the following sections.

6.2 ANALYSIS OF MODEL

The suitability of inverse implementation of different modeling options is analyzed in this section. First the speed of the dynamics is investigated.

6.2.1 Speed of Dynamics

As explained in Section 3.3.1, the sampling rate of the control system must be considered when the dynamic inverse model is created, as too fast dynamics will result in instability. In Heleneholmsverket the sampling rate is 2 Hz.

When analyzing linearized versions of completely dynamic volume models, using volume sizes and mass flows of the same magnitude as in a real plant it is revealed that the fastest dynamics of these components are approximately two orders of magnitude faster than what is possible to implement. It is the pressure dynamics, which is related to the dynamic mass balance, which is this fast. For this reason pressure dynamics cannot be used in any steam volumes, which implies that static mass flow balances must be used.

The second fastest dynamics in the model is the energy balance of the steam volumes, the characteristic time of this equation is a couple of seconds. This dynamic is slow enough to be considered for inverse implementation. The energy balance of the wall is the slowest dynamics of the system and for this reason it is the dynamics that will by most prominent in determining the overall behavior of the system. The characteristic time of this is in the range of one minute.

6.2.2 Unstable Zero Dynamics

The analysis of linearized plant models also reveals a case of unstable zero dynamics. Fortunately, this only occurs when dynamic mass balance is assumed, which has already proved unsuitable due to the fast pressure dynamics. However, it will nonetheless be presented for completeness.

The problem is visible when an implementation with three or more segments is considered. Then the system from input enthalpy to output temperature has unstable zero dynamics, which can be seen both from the linear analysis and also by investigating a step response for the model. In Figure 17, the step response for a dynamic pipe model with three elements and 10 MW of heat added to the wall is plotted. During the first 0.1 seconds following the step, the output temperature is decreasing.

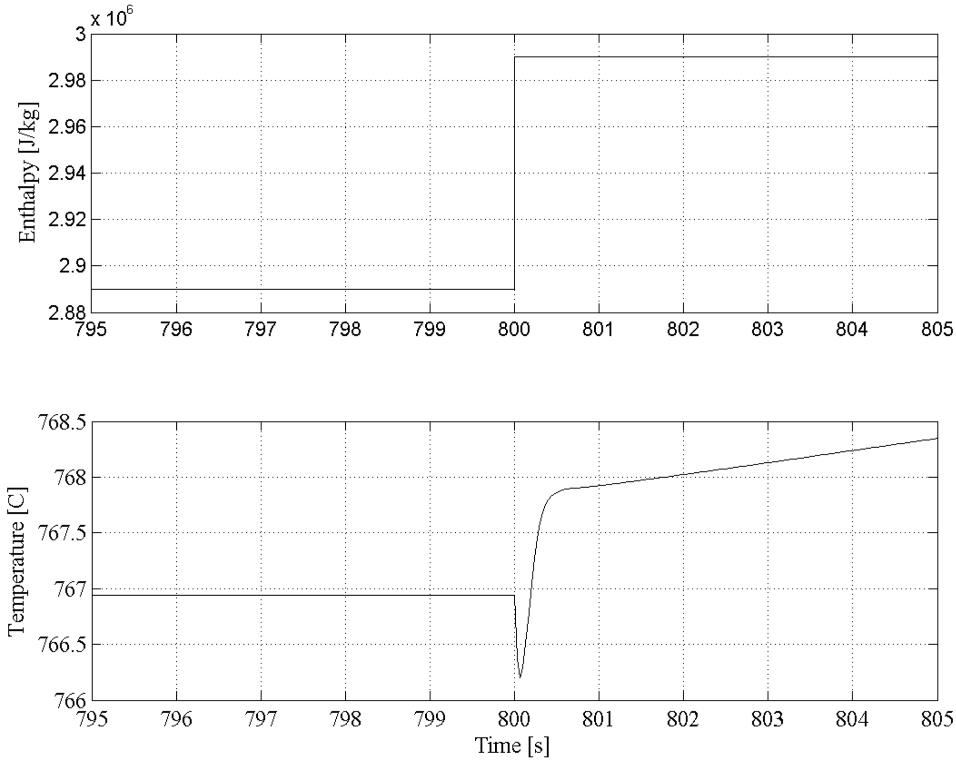

Figure 17. Step response of a dynamic pipe model with heat added through wall models.

To understand this, it is easiest to consider the step response for an implementation of the pipe with an arbitrary, large number of segments. It is first noted that the increase in enthalpy will result in a decreased density, which in turn will result in a temporary increase in mass flow out of all volumes. Secondly, with many segments, there will be a significant delay before the enthalpy change has a direct effect on the enthalpy reaching the last volumes. The increased mass flow from the first volumes, will therefore reach the final volumes before the incoming enthalpy to these has been changed significantly. Now, we look at the energy balance of the volume

$$\dot{U} = \dot{m}_{in} h_{in} - \dot{m}_{out} h_{out} + Q_{w,s}$$

As the dynamics related to the mass balance is very fast for a small volume, we can assume that the mass flows are approximately equal. Then we get

$$\dot{U} = \dot{m}_{in}(h_{in} - h_{out}) + Q_{w,s}$$

Now we note that the heat which is added through the wall makes the outgoing enthalpy higher than the incoming. This means that when the mass flow is increased, the derivative of the internal energy will become negative, which will lead to a decreased output temperature. This implies that the inverse system, which would correspond to an otherwise feasible model for feedforward control, is unstable. No analytical proof have been derived that the critical number of segments is three, instead linearizations and simulations have been used to verify this.

6.2.3 Non-Invertible Parts

The intended feedforward model setup does not contain any parts that are not possible to invert. There does exist a limitation of how fast the temperature set-point, which the feedforward calculates, is allowed to change, but this limitation lies outside the inversion problem and should be handled as a separate control problem.

6.2.4 Conclusion

From the analysis of the modeling approaches that are available for the dynamic inverse implementation, it is clear that only static mass balance assumptions can be used in the representation of the steam volumes. No other limitations to what can be implemented were found during this analysis, which means that the continuation of the modeling effort will be conducted with the goal to implement a finite volume model with a suitable discretization, using standard assumptions.

6.3 ANALYSIS OF INVERSE

The possible model setups for inverse implementation are inverted by reformulating the Modelica code to have the desired output temperature as an input signal, with the incoming enthalpy as an output. This procedure does not reveal any indications that an inverse using a static energy balance assumption could be derived, but when dynamic energy balance is assumed and more than one volume is used in the finite volume implementation, the model proves impossible to invert.

The reason for this is that the incoming enthalpy is calculated based on several derivatives, including the derivative of the outgoing enthalpy. Due to index reduction during the inversion it also contains partial derivatives of steam properties. If an implementation with more than one volume should be used, each extra volume would imply further differentiation of these expressions, making it impossible for Dymola to translate the model, as it demands higher order derivatives of steam properties, which are not implemented in the media functions. If an inverse implementation with dynamic energy balance is to be implemented, using an approximate expression for the derivative instead of the analytic expression seems necessary. Another noteworthy result of the index reduction in this model is that the state related to the dynamic energy balance is removed in the inverse model.

As the inverse model with static mass balance is displaying reasonable and expected behavior during simulation, and no additional complications regarding the inversion task are detected, derivation of a sampled explicit inverse model can be investigated.

6.4 EXPLICIT INVERSE FORMULATION

Volume implementations using both static and dynamic energy balance are considered for inversion, with the static volume inversion described first.

By formulating all equations governing the dynamics of one static volume connected with a dynamic wall with heat transfer, a formulation where the needed incoming enthalpy is calculated based on a desired output temperature can be obtained in a straight forward manner, assuming known mass flow, pressure and heat flow. The key equation is the energy balance equation, which in the static case reads

$$0 = \dot{m}_{in} h_{in} - \dot{m}_{ut} h_{in} + Q_{w,s}$$

in its original form. With identical incoming and outgoing mass flows, rearrangement gives the following expression for the incoming enthalpy h_{in}

$$h_{in} = h(p, T_{out}) - \frac{Q_{w,s}}{\dot{m}}$$

where h is the enthalpy as a function of pressure and output temperature. As the heat transfer $Q_{w,s}$ can be expressed as a function of T_{out} and the wall temperature state, the formulation is consistent with the formulation described in Section 3.5. Explicit Euler is used to update the temperature of the wall at each sample. By connecting several of these components serially, an inverted model of a superheater is obtained, using finite volume modeling. The possibility to achieve this is a powerful result as there is no increase in modeling complexity when the discretization of the model is increased, making it easy to implement an inverse model with a desired discretization.

Next, the volume with dynamic energy balance is considered. In order to circumvent the difficulty of differentiated equations described in the previous section, an approximation is used for the internal energy in this component. In an exact implementation, the the derivative of the internal energy would be expressed as a function of the derivative of outgoing enthalpy in the following way

$$\dot{u} = \frac{d}{dt}\left(h_{out} - \frac{p}{\rho}\right) = \dot{h}_{out} - \frac{\dot{p}\rho - p\left(\frac{\partial \rho}{\partial p}\dot{p} + \frac{\partial \rho}{\partial h}\dot{h}_{out}\right)}{\rho^2}$$

Here the partial derivatives of the density would be calculated using IF97 steam property tables. As the incoming enthalpy is expressed as a function of this derivative, having more than one volume would imply further differentiation of this expression, which would be very hard to handle as it would require further differentiation of the input signals and higher order derivatives of media properties.

The approximation is tocalculate the derivative using the finite difference approximation.

$$\dot{u}(t_n) = \frac{u(t_n) - u(t_{n-1})}{t_s}$$

By using this assumption the same kind of result is obtained as in the static case, with the incoming enthalpy calculated using the following explicit formulation

$$h_{in} = h(p, T_{out}) - \frac{Q_{w,s}}{\dot{m}} + d(p, T_{out})\dot{u}$$

It is therefore possible to use the model in a finite volume implementation. Simulations show that the error caused by the approximation is very small, and the error is furthermore most visible when derivatives of input signals are known. In a sampled implementation only approximations of these derivatives can be obtained and in this case the extra accuracy achieved by including the derivatives in the model formulation is even smaller.

Both static and dynamic energy balance modeling seems viable modeling alternatives for the explicit inverse model. This means that there is a possibility to combine the two in the feedforward model. In order to determine which modeling assumptions that are most suitable and to verify that the feedforward system works correctly, performance analysis using both energy balance alternatives and with different discretizations are conducted next.

6.5 PERFORMANCE ANALYSIS

The performance of the feedforward control is evaluated in simulation in Dymola, as described in Section 3.6. The goal of the performance evaluation is to analyze the general behavior of the feedforward, to investigate whether dynamic feedforward can be beneficial for the considered implementation and to analyze the effect of using different modeling setups, in terms of discretization level and energy balance assumptions.

A test case is created with changes in input signals roughly corresponding to what is expected during operation of the real plant. The trajectories of these signals are displayed in Figure 18. The response of the feedforward model in terms of input enthalpy is used to determine the incoming enthalpy of the steam in a process model. The process is modeled using a fully dynamic finite volume implementation with five elements. The flue gas side and heat transfer is modeled in the same way as in the feedforward model. The performance of the feedforward control is evaluated based on the difference between the output temperature set-point and the actual output temperature in this process model. Also the control signal to the process from the feedforward is observed, as too aggressive control cannot be realized in the real plant. A graphical representation of the test setup in Dymola is displayed in Figure 19. Apart from the process model and the feedforward block, the model also contains sources for the input signals and the superheated steam, and blocks for introducing measurement disturbances and handling control signal saturation.

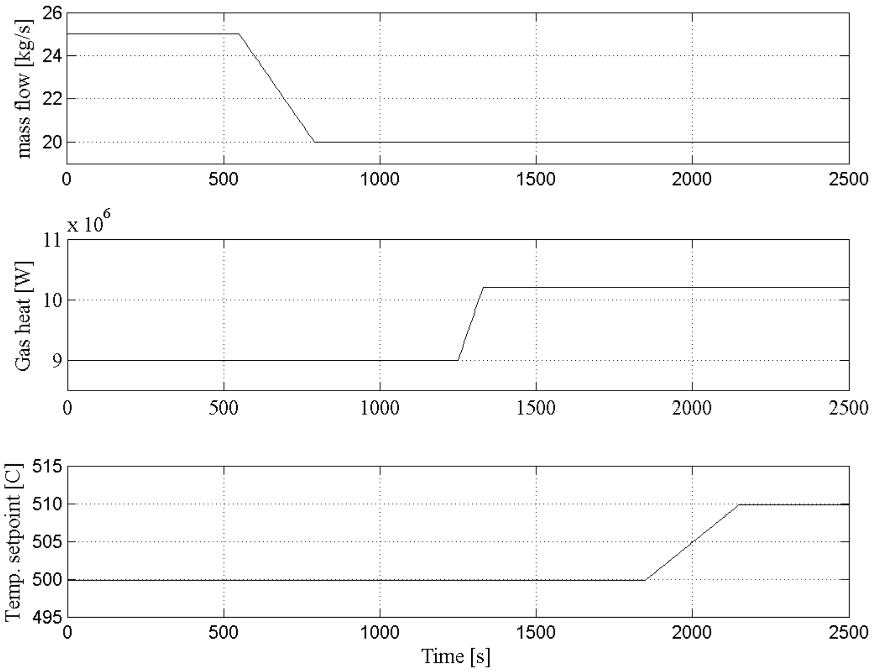

Figure 18. Experiment base case. During a 2500 seconds simulation, the mass flow, transferred heat and temperature set-point are ramped at different times.

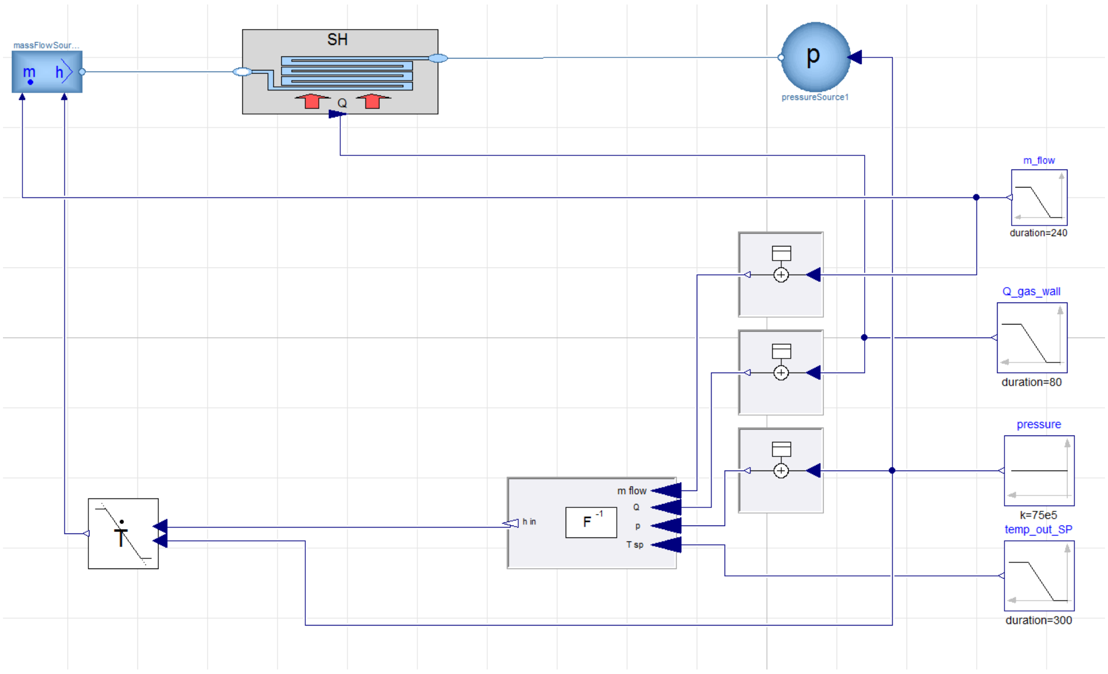

Figure 19. Feedforward experiment setup in Dymola.

6.5.1 Comparison with Static Feedforward

One standard feedforward implementation is to use a static inverse model. The previous feedforward control implemented in Helenholmsverket is an extension of this assumption, described in Section 5.4. For this reason the first test compares the performance of a completely static inverse model used for feedforward with a simple dynamic model. To obtain a static model, the wall component is removed from the superheater model, making the heat from the flue gas reach the steam without any filtering. Furthermore static steam dynamics is assumed. The performance of this feedforward model is compared with a feedforward using one semi dynamic volume, with the results shown in Figure 20. The performance of the two methods is identical for disturbances in mass flow, the static model is better for rejecting disturbances in heat and the dynamic model is faster when the temperature set-point is changed. The results indicate that there is no significant advantage of including the wall in the modeling, when only one volume is used to model the superheater. However, when a completely static model is used, the model cannot be improved by increasing the discretization, as this would not result in any change in the relationship between incoming and outgoing steam enthalpy. The performance of the dynamic model is on the other hand expected to improve for higher discretizations.

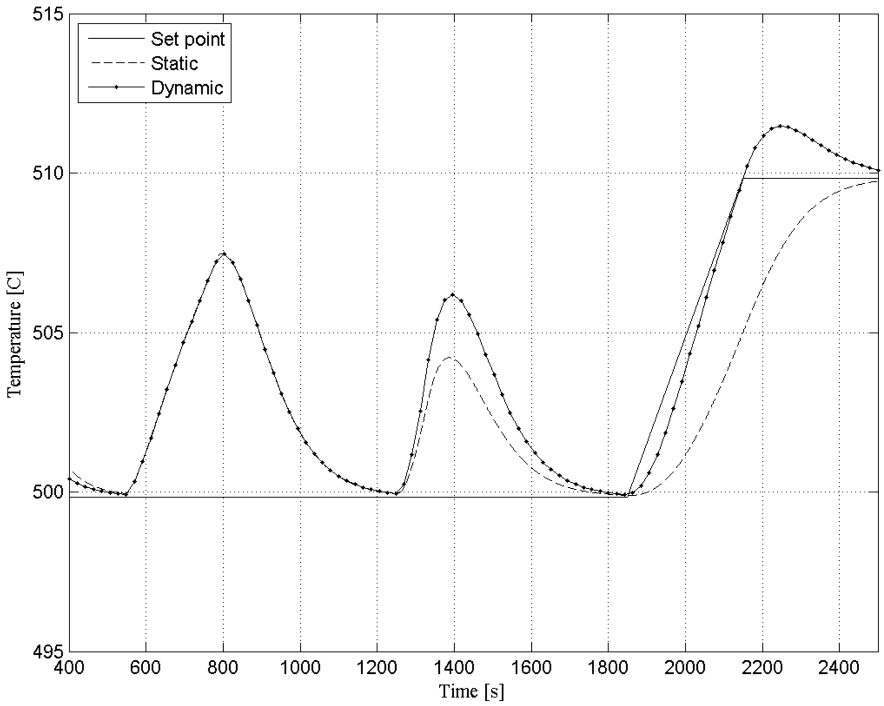

Figure 20. Process output temperature when a completely static feedforward is compared with a dynamic inverse model with one element.

6.5.2 Feedforward Energy Balance Model

This experiment compares the performance of static and dynamic energy balance assumptions in the feedforward model. First an implementation with only one volume in the feedforward model is examined.

As can be seen in Figure 21, the two methods give very similar steam temperatures in the process model. In Figure 22, the differences between the generated control signals and outputs of the two methods are displayed. Only during the temperature set-point ramp is there an observable difference between the methods, and even then it is less than 0.1° C.

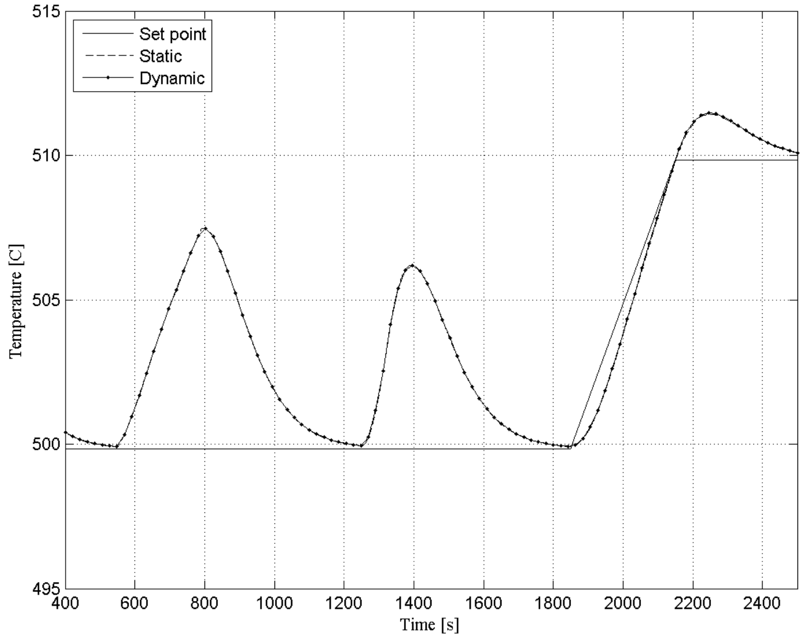

Figure 21. Process output temperature for one element feed forward models comparing static and dynamic energy balance assumptions.

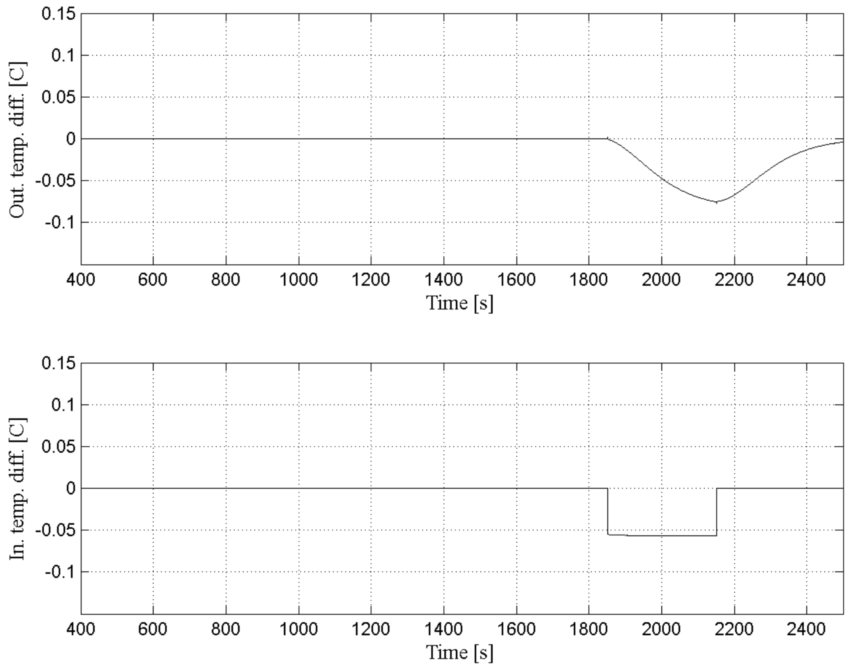

Figure 22. Output and input temperature differences when static and dynamic energy balance is compared for a one element feedforward model.

Results from identical tests with a discretization of three volumes in the feedforward is presented in Figure 23 and Figure 24. There is again only a very small difference in the output temperature between using static or dynamic assumptions, but the difference in the control signal is more significant than in the one volume case. However, the difference is still so small that no conclusion regarding which assumption performs better can be drawn.

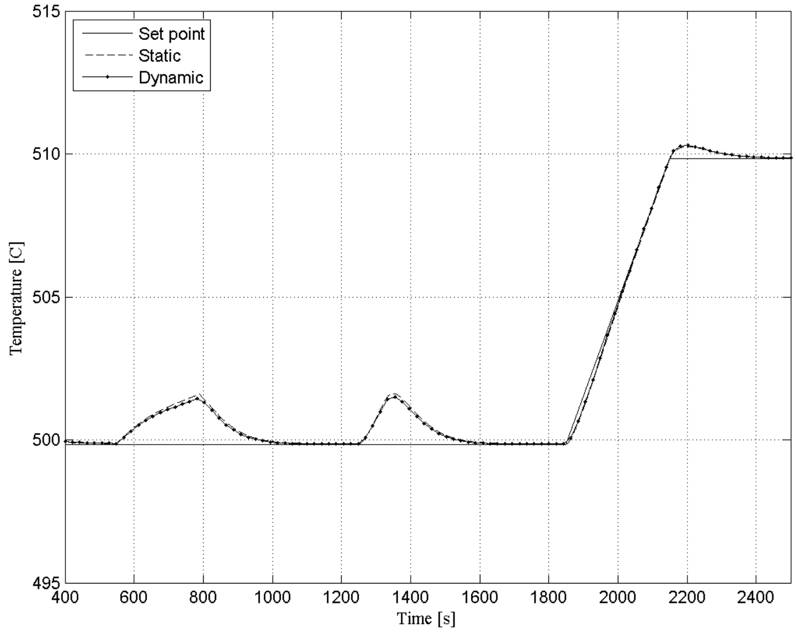

Figure 23. Process output temperature for three element feedforward models assuming static and dynamic energy balance.

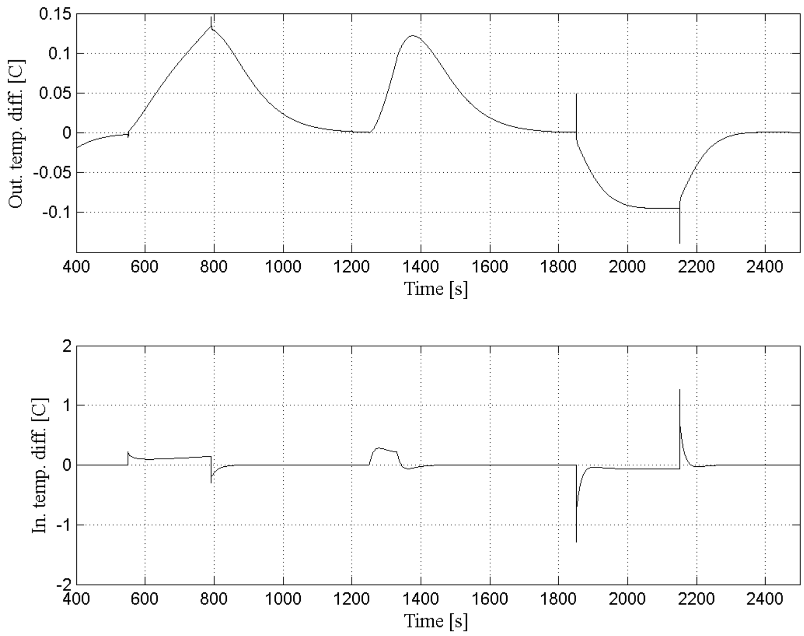

Figure 24. Output and input temperature differences when static and dynamic energy balance is compared for a three element feedforward model.

6.5.3 Discretization Level

Using semi dynamic volume assumption, different discretization levels of the feedforward model are investigated. Having one, two, three and four discretization of the control volumes in the feedforward system is tried.

Figure 25 to Figure 27 shows the response of the feedforward and the effect on the process model for the different transient scenarios. The figures show from top to bottom the output temperature of the superheater, the ramping input signal (not shown for the temperature set-point ramp), the input temperature calculated by the feedforward and an approximation of the derivative of this signal.

The expected result that increasing the number of discretized volumes increases the accuracy of the inverse model, but also results in more aggressive control signals, is visible for all transients. It can also be seen that the benefit of adding more volumes is decreasing when the discretization is increased, as there is only a small difference between the output temperature trajectories for three and four volumes. The trajectories displaying the derivative of input temperature reveals that higher discretizations also can result in saturation of the control signal, due to variations faster than the ramp limitations that are currently used in the real plant. This subject will be analyzed further in Section 6.5.7.

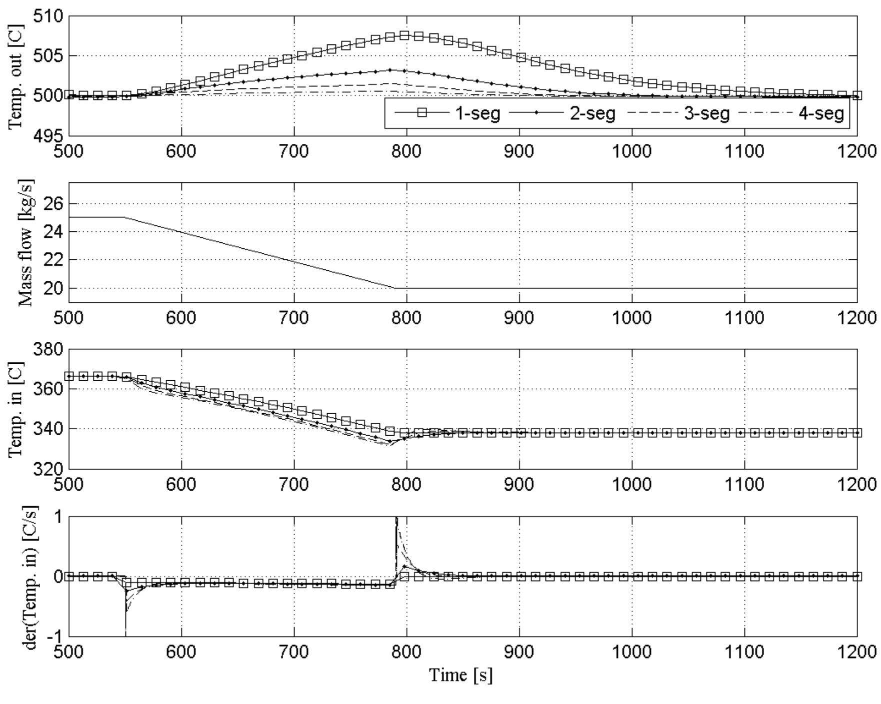

Figure 25. Results from ramping the mass flow for different feedforward discretizations in simulation.

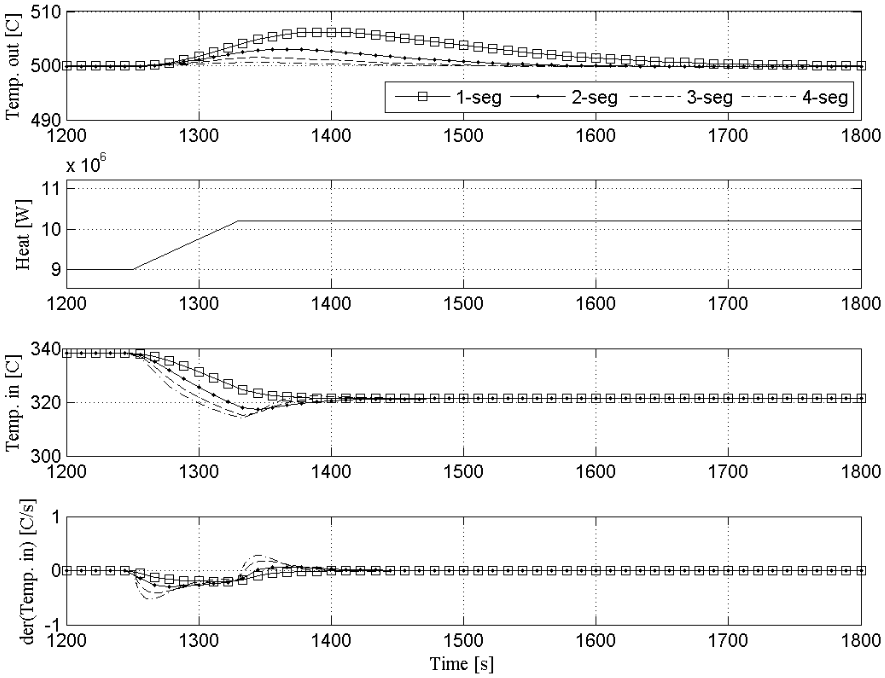

Figure 26. Results from ramping the flue gas heat for different feedforward discretizations in simulation.

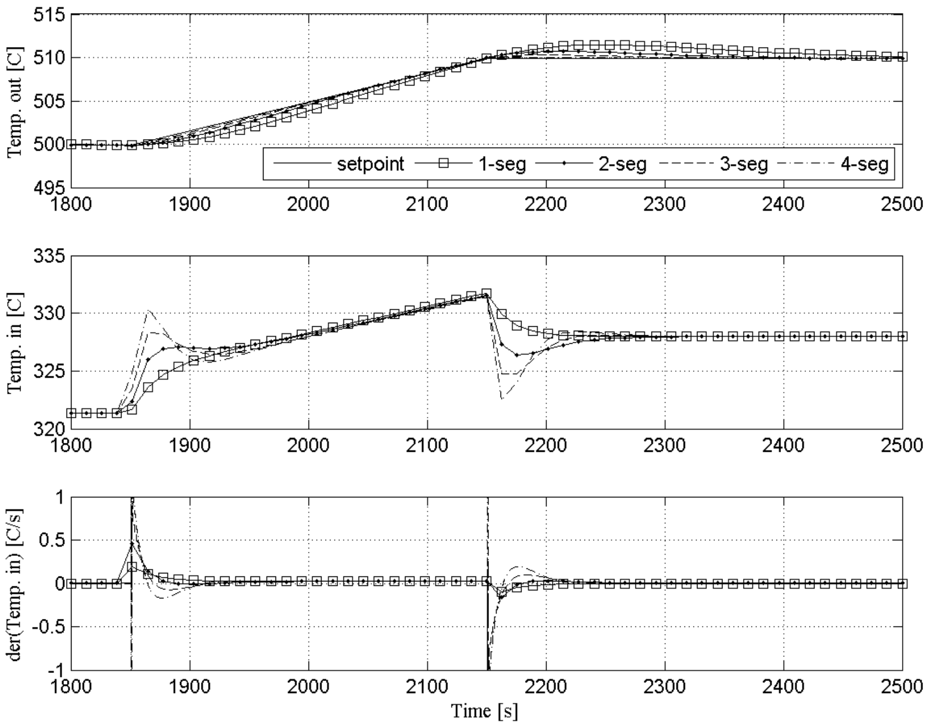

Figure 27. Results from ramping the temperature set-point for different feedforward discretizations in simulation.

6.5.4 Sampled-System

In this section the effect of having a sampled inverse rather than a continuous inverse model is investigated. This comparison can only be conducted using at most one semi dynamic volume in the feedforward model, as models with multiple volumes are not possible to invert exactly in practice, as explained in Section 6.3. For this reason models with the steam dynamics lumped into the last volume in the flow direction, and static mass balances in the other volumes, are compared. A discretized approach using three elements is still used for the representation of the wall and the heat transfer from the wall to the steam. A comparison is made between a continuous feedforward and two sampled feedforward implementations, using sampling times of 0.5 s and 3 s, respectively. Figure 28 shows that there is no detectable difference between performance of the sampled and the continuous implementation of the feedforward, when the sampling frequency of 2 Hz is used. For the slower sampling frequency small differences between the output temperature profiles can be seen, but these are still insignificant for the overall performance.

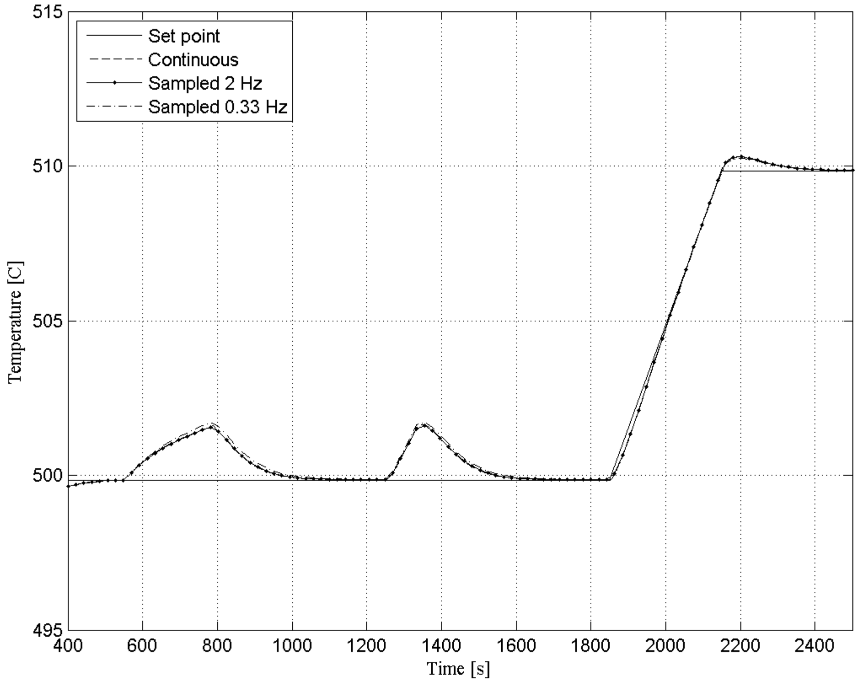

Figure 28. Process output temperature for three element feedforward models using continuous and sampled models.

6.5.5 Robustness against Measurement Noise

The noise sensitivity of the feedforward model is investigated by adding noise to signals used as input to the model. In the following experiment, white Gaussian noise sampled at 1 Hz is added to the pressure and mass flow signals reaching the feedforward. The standard deviation of the noise is 1 % of the value of each signal, which corresponds to 0.2^{o} C and 0.75 bar. The noisy input signals are displayed in Figure 29. The noise experiments are conducted using discretization levels between one and four in the feedforward model, with results on the output temperatures displayed in Figure 30. The main visible result is that the output noise level is increasing with the discretization level.

In order to estimate the standard deviation and the mean offset of the output temperature, simulations without ramping of input signals are conducted. The results of statistical analysis of these signals are presented in Table 1. Most notable is increase in standard deviation of the output when a higher discretization level is used, increasing the discretization with one approximately doubles the standard deviation of the output temperature. The noise also seem to introduce a small static offset with a similar dependency of the discretization as the standard deviation, but the absolute effect on the temperature is very small.

Table 1. Statistical results from noise experiment, depending on feedforward discretization.

Discretization	Average error [C]	Standard deviation [C]
1	-0.011	0.074
2	-0.025	0.15
3	-0.043	0.31
4	-0.089	0.58

In the control system of Heleneholmsverket, filters are implemented to avoid all unwanted noise in the measurement signals reaching the feed forward. The experiments in this section should therefore not be seen as scenarios that could occur in the real plant. However, the results are still relevant for the implementation of the feedforward, as they indicate the importance of filtering out the noise when a feedforward model of higher discretization level is used.

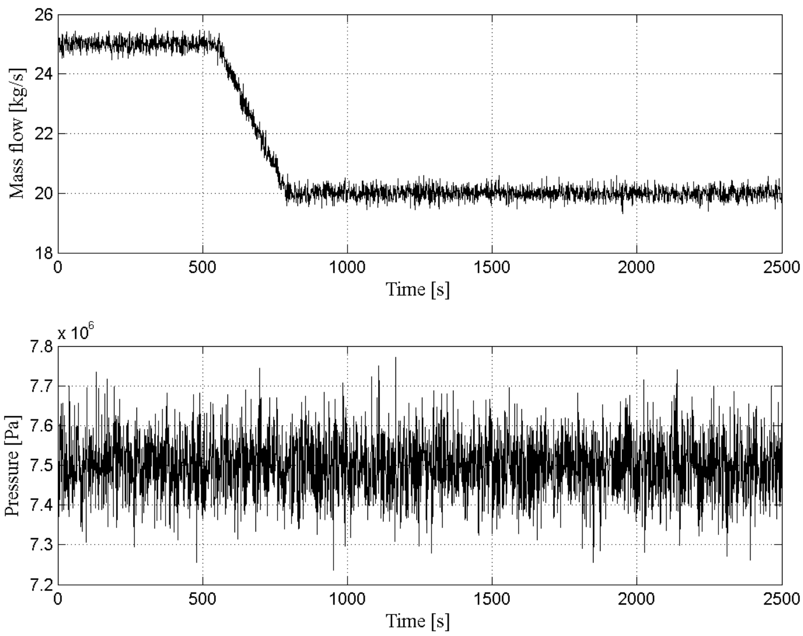

Figure 29. Pressure and mass flow signals with added noise.

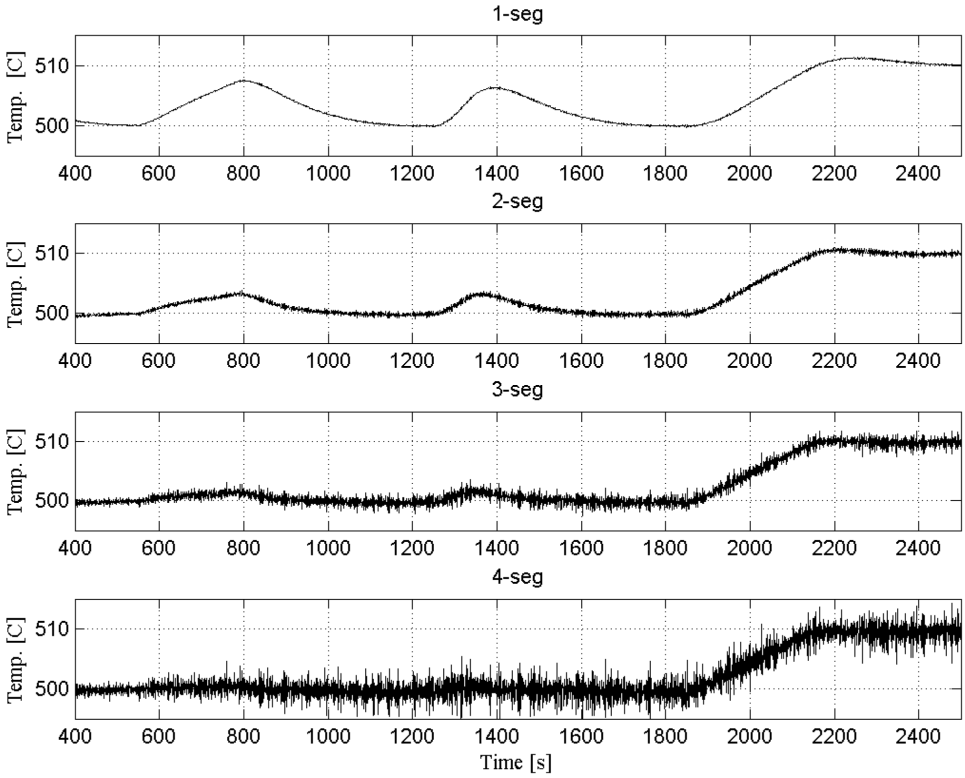

Figure 30. Process temperature output with noise added to measurements, with different feedforward discretizations. The output temperature contains noise and has a constant offset.

6.5.6 Robustness against Modeling Error

It is in practice impossible to construct a suitable feedforward model that matches the real plant exactly. For this reason the robustness against modeling errors is evaluated by using a process model with different parameter values than the feedforward model.

The most uncertain part of the feedforward model is the modeling of the heat transfer between the steam pipes and the steam itself. Therefore a plant model with a changed coefficient of heat transfer is used in simulation. Feedforward discretizations of one and three are used. Changing the process heat transfer coefficient from 1500 W/Km^2, which is the value used in the feedforward model, with 17 % to 1750 W/Km^2 or 1250 W/Km^2, does not alter the performance of the feedforward significantly, as can be seen in Figure 31 and Figure 32. In fact the performance is clearly better for the heat disturbance when the process model has a lower heat transfer coefficient and three segments are used in the feedforward, than when the models have the same parameter values. The reason for this is that the feed forward always gives too slow control action when it has a lower discretization than the process model. By having a lower heat transfer coefficient in the process model, the impact of the heat flow disturbance is slower in the process model as it takes a greater temperature difference between wall and steam to reach stationarity. This makes the models match better.

Another uncertainty is also related to the heat transfer from the flue gas to the steam, namely the modeling of the pipes. Here the thermal mass of the pipes is changed in the process model. Even though the pipe mass of each superheat stage is well known, the modeling of the pipes is simplified in the feedforward model compared to what is expected in a real plant. The assumption to distribute the total mass of tubes and headers evenly on a number of segments, is an approximation that is expected to result in some modeling error. The changed mass represents the model difference this could result in. The mass of the wall in the process model is increased with 10 % during one test, and decreased the same amount during a second test, resulting in the trajectories visualized in Figure 33 and Figure 34, for feedforward discretizations of one and three, respectively. Similarly to the heat transfer coefficient experiment, the performance is not greatly affected by altering the parameter value in the process model. The feedforward suppresses the mass flow disturbance more effectively for the process with a lower value on the mass, but the correct mass value gives the best performance for the set-point temperature ramp. For both modeling errors that were tried, the variations in performance depending on incorrect parameter value for the feedforward seems to increase when a higher discretization is used.

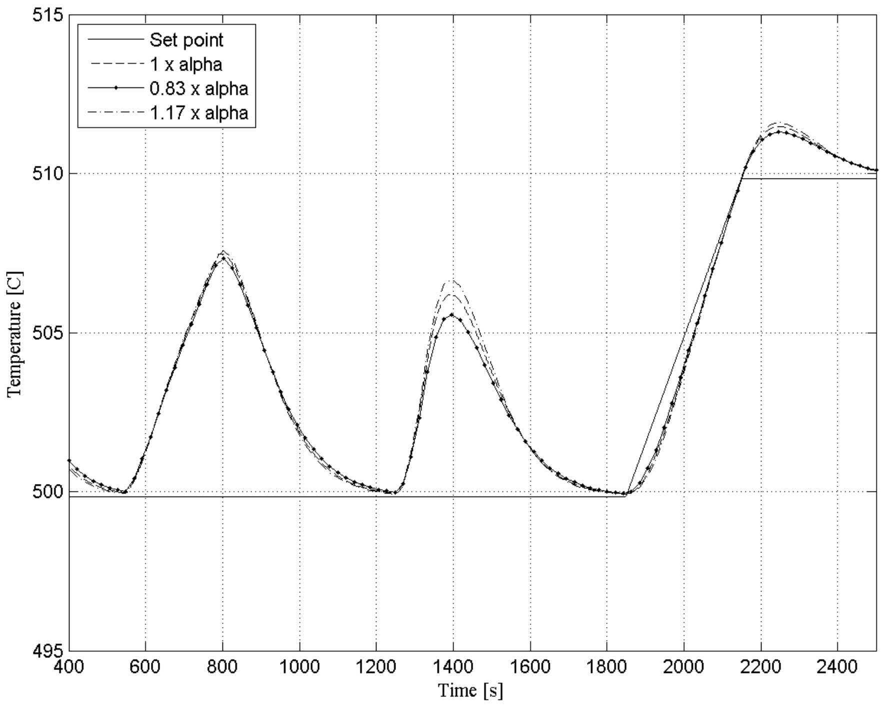

Figure 31. Process temperature output for different feedforward heat transfer coefficients, using one segment in the feedforward model.

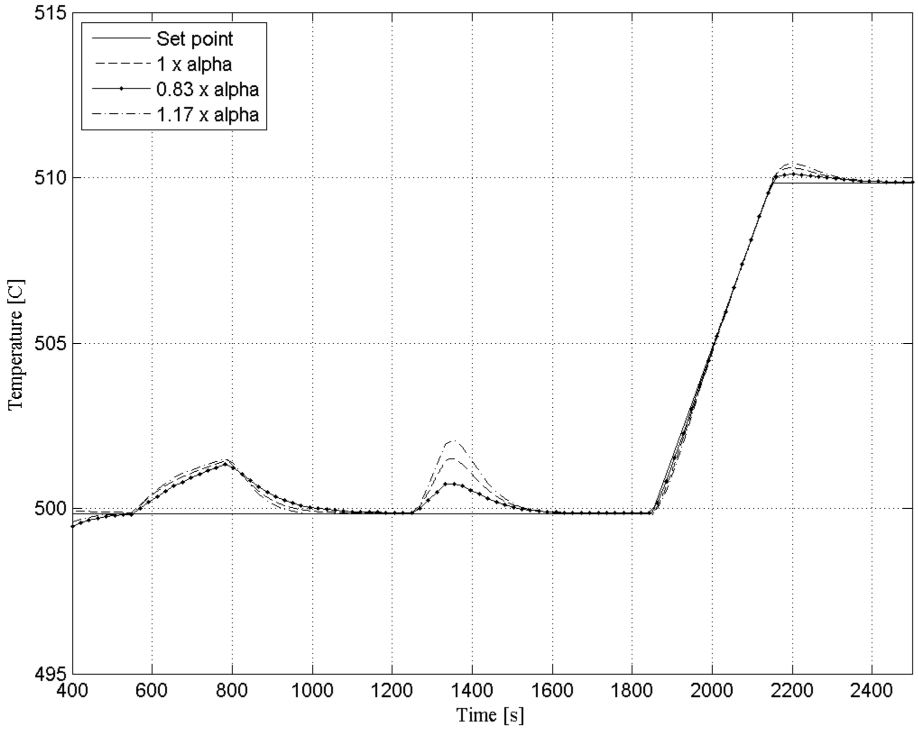

Figure 32. Process temperature output for different feedforward heat transfer coefficients, using three segments in the feedforward model.

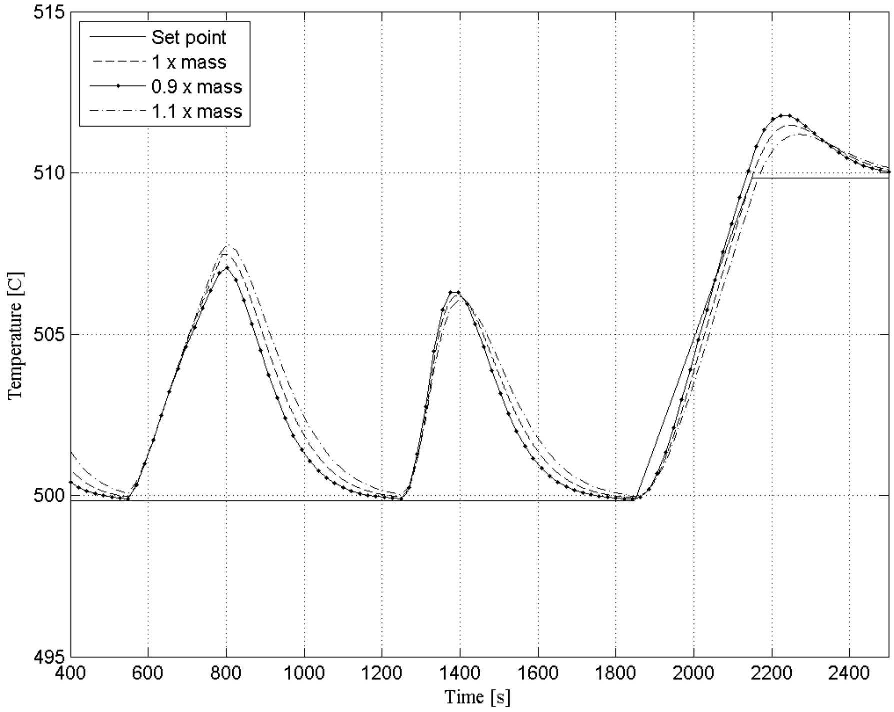

Figure 33. Process temperature output for different feedforward wall masses, using one segment in the feedforward model.

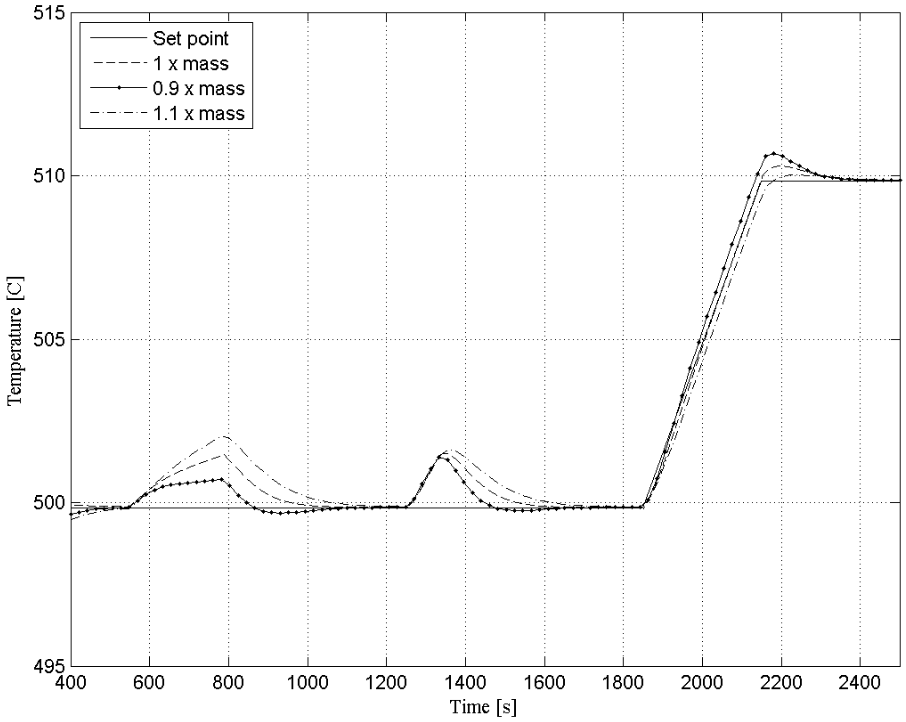

Figure 34. Process temperature output for different feedforward wall masses, using three segments in the feedforward model.

6.5.7 Temperature Limitation

In the real plant a limiter is implemented on the temperature set-point signal that the control system calculates, as explained in Chapter 5. This implies that the control signal can become saturated when the feedforward gives a control signal which changes too rapidly. This will affect the performance of the feedforward, as the saturation will result in a mismatch between the model and the process when the real plant does not get the control signal the feedforward system has calculated. The dynamics of the internal control loop in the real plant will also result in a mismatch. For the modeling assumptions in this project, the difference between the process and the feedforward model will be in the wall temperature. To analyze the effect of the saturation, a ramp limitation with the same maximal change rate of 0.33 K/s as used in the real plant is added to the experiment setup, limiting the signal reaching the process model. Experiments with a feedforward discretization of three are performed, first using the original experiment scenario. The result of this experiment, compared with a setup without the limitation, is displayed in Figure 35. The temperature limitation lowers the performance somewhat, which is explained by examining the input and output of the ramp limiter, visualized in figure. During the fastest transients, the ramp limiter becomes active, degrading the performance of the feedforward slightly.

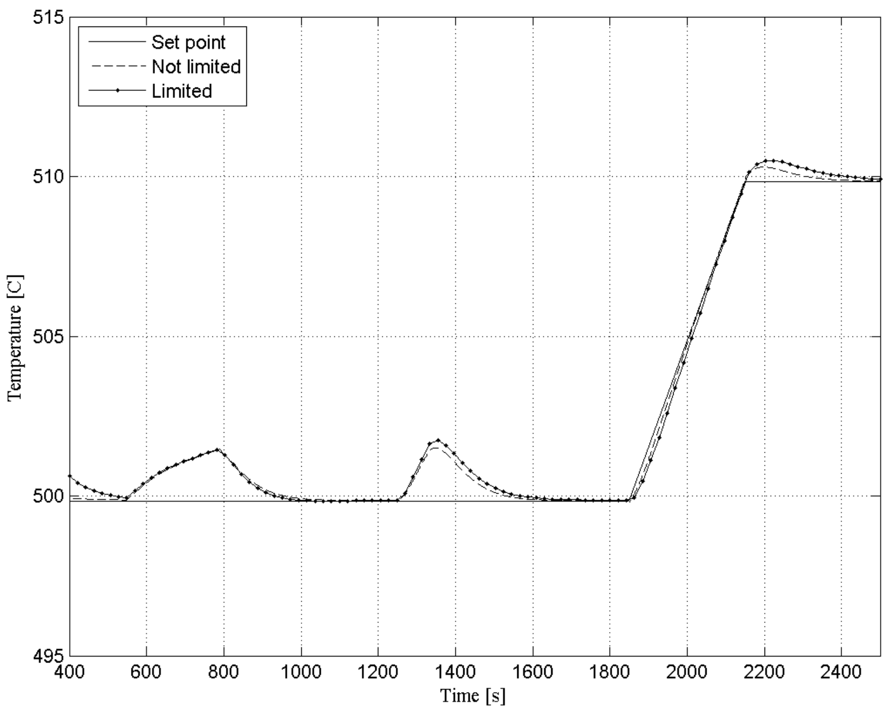

Figure 35. Process temperature output with and without ramp limitation of the control signal from a feedforward model with three elements.

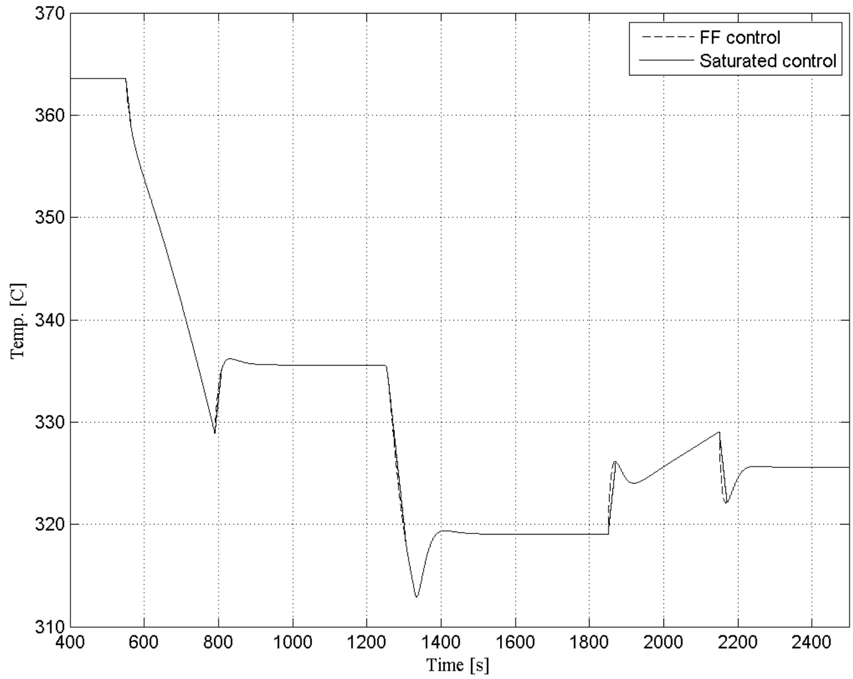

Figure 36. The control signal from feedforward is saturated by a ramp limitation, visible during fast transient.

To investigate the behavior for a more challenging case, faster ramps are used for the input trajectories. The mass flow is ramped 140 % faster, the heat is ramped 60 % faster and the temperature set-point is ramped 67 % faster, giving the trajectories shown in Figure 37.

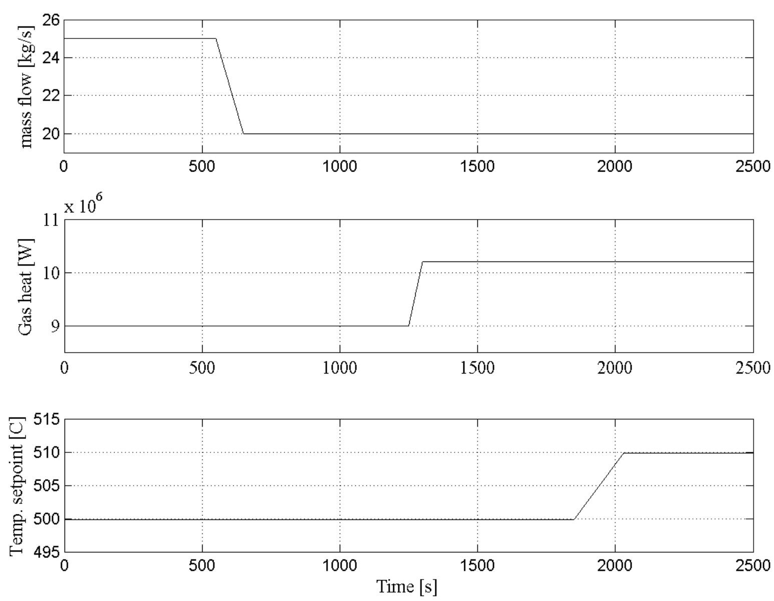

Figure 37. Faster input signals for control signal limitation experiments.

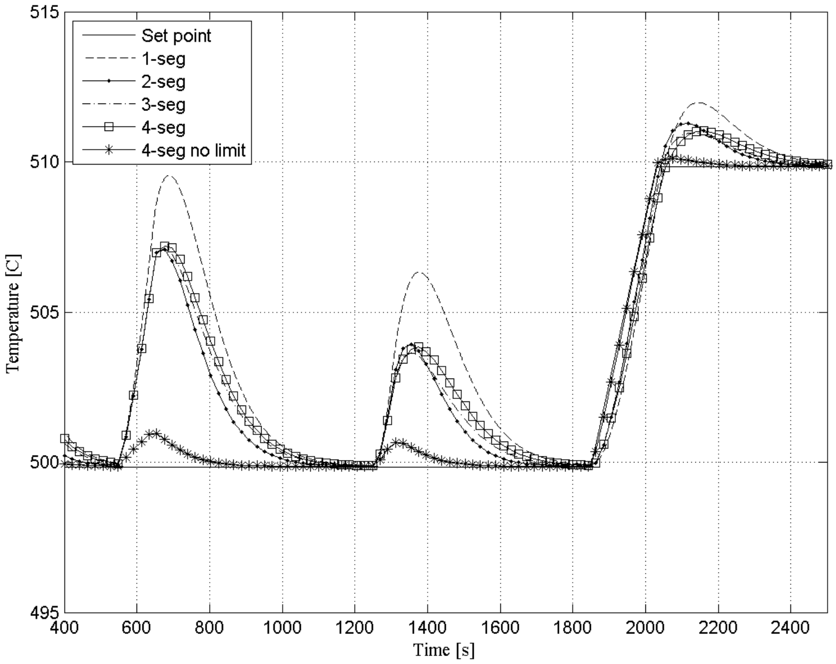

Figure 38. Process temperature output with ramp limitations on the control signal for a faster experiment scenario. Feedforward discretization between one and four. The temperature output for discretization four without the limitation is also included in the plot.

The output temperatures for different discretizations, when the ramp limitation of the control signal is active, is displayed in Figure 38. For comparison the output temperature for a four segment feedforward model, without using the temperature limitation, is also added to the plot. An interesting result can be seen, as the limitation makes the performance of the different feedforward discretizations very similar, except for when one volume is used, which still is clearly worst. The best performing feedforward is in this case the one with two segments. The reason for this can be seen in Figure 39. The slower control action of the lower discretized feedforward models means that a greater part of the control profile can reach the process, which improves the performance during the second half of each transient.

The experiments in this section show that control signal limitations and the expected input trajectories are important considerations when the feedforward design is determined. When there is a risk of control signal saturation, the smoother control action from lower discretizations can be beneficial. However, it is important to note that the feedforward will be implemented as a part in a larger control system. Having contributions from feedback control and using anti windup methods will improve the performance.

During the project, attempts were made to improve the performance of the feedforward with regards to signal saturation by using methods to estimate the energy difference between the inverse model and the process model caused by the saturation, and manipulate the control action based on this. However, no conclusive results were reached.

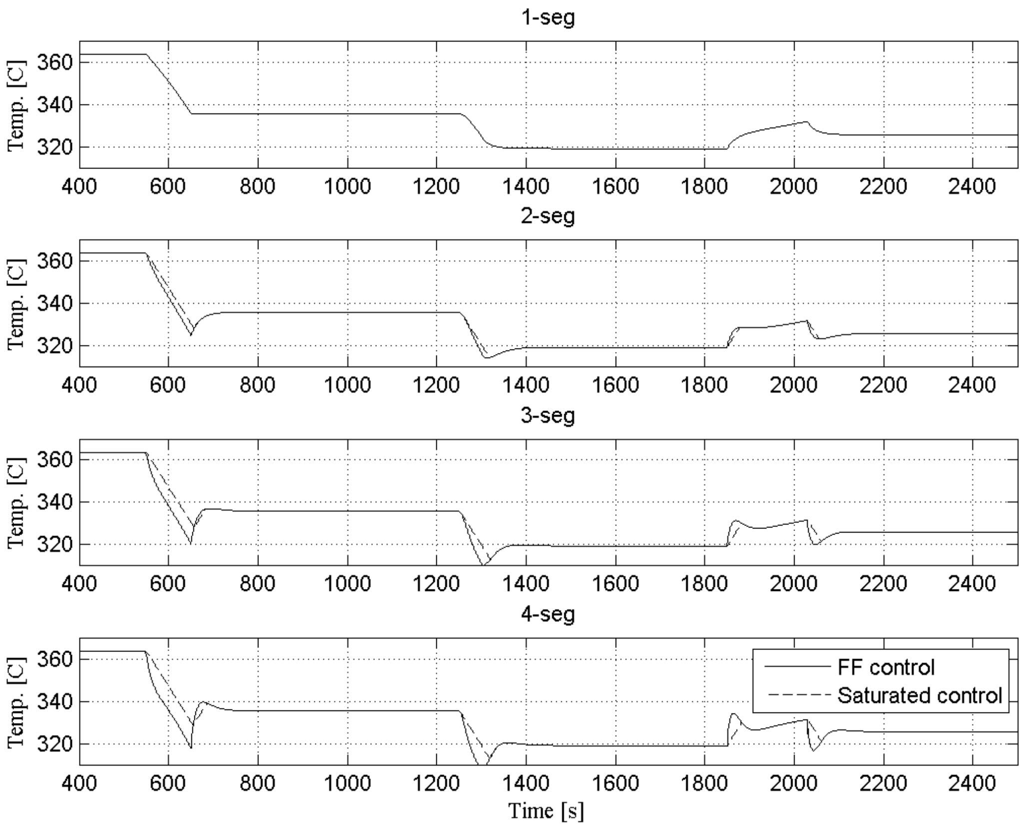

Figure 39. Saturated control signals from the feedforward for different discretizations of the inverse model.

6.6 CONCLUSION

From the performance evaluation, the following results can be seen

- It is only beneficial to use a dynamic model rather than a completely static nonlinear feedforward model when more than one element is used to represent the wall dynamics of the superheater stage.
- There is no significant difference in performance if dynamic energy balance is used rather than static energy balance.
- The implementation of a sampled system does not result in worse performance than a continuous system, for the sampling rate used in the considered process.
- Increasing the discretization of the feedforward model improves the tracking performance, but also results in more aggressive control action.
- The feedforward shows good robustness against measurement noise and modeling errors, but especially the robustness against noise is decreased when the discretization is increased, making it more important to filter out the noise before it reaches the feed forward.

- Saturation of control signals removes the benefit of using a feedforward model with a higher discretization, but only during fast scenarios.

When the modeling setup for the implementation in the real plant is considered, the main design choice that has to be made is the discretization of the feedforward model. Three different aspects need to be taken into consideration

1. For how fast dynamics should the feedforward be optimized? For faster dynamics, the discretization must be decreased.
2. How much measurement noise is expected? If the noise level is low, or the noise can be filtered away, higher discretizations can be considered.
3. How is the control signal saturation handled? If a system for compensating for this phenomenon is implemented, higher discretizations can be considered.

7 Implementation in Heleneholmsverket

7.1 FREELANCE MODELING

The Freelance implementation of the feedforward control system is created by combining function blocks previously implemented in the control system of the plant and new blocks developed especially to represent the dynamics of the inverted model. These are written in structured text, which corresponds to the Modelica code representing the process dynamics. As an example, the Modelica code for a static volume with a dynamic wall, which is run at each sample time, is presented in the text

```
when sample(t0, ts) then
  //Steam volume dynamics
  h = Modelica.Media.Water.WaterIF97_base.specificEnthalpy_pT(p,T_out);
  h_in=h+Q_s/m_flow_mixed;

  //Wall
  Q_s=(T_out-pre(T_wall))*A*alpha_steam;
  der_T_wall=(Q_s+Q_in)/(m_wall*cp_wall);
  T_wall=pre(T_wall)+ts*der_T_wall;

end when;
```

box below.

In the Freelance implementation in structured text the wall model is separated from the steam volume for a more flexible implementation. The feedforward model is then built by combining these block of structured text in a function block diagram as shown in Figure 40. The wall part is translated into the following code in structured text, shown

```
FUNCTION_BLOCK Wall_dyn_P

VAR_INPUT
    Q_in : REAL;
    T_steam : REAL;
END_VAR

VAR_OUTPUT
    Q_out : REAL;
    T_wall : REAL;
END_VAR

VAR t:REAL;
der_T:REAL;
END_VAR;

If t < 1.0 Then
    T_wall:=T0;
    t:=1.0;
END_IF;

Q_out:=(T_wall-T_steam)*Area*alpha;
der_T:=(Q_in-Q_out)/(mass*cp);
T_wall:=T_wall+der_T*ts;

END_FUNCTION_BLOCK
```

in the text box below.

The main difference between the two implementations is the method used to calculate steam properties. In Modelica, IF97 steam properties are used in functions that are table based. In Freelance polynomial approximations of the IF97functions are used instead, but the errors in the polynomial approximations are less than 1 % in the used region. The steam properties are calculated in function blocks in the Freelance implementation, rather than calling function as is the case in the Modelica models.

The final result in Freelance is a feedforward block which calculates the needed incoming steam temperature to the superheater stage, given measured pressure and mass flow, calculated heat flow from the flue gas and an output temperature set-point.

The two segment model used in the experiment is shown in Figure 40.

7.2 INTEGRATION WITH CURRENT SYSTEM

The derived Freelance function block has been integrated parallel to the existing static feedforward at Heleneholmsverket, see Figure 41. The feedforward that is derived in this project is the one that goes to controller PID2 for SH3, where the previous static nonlinear mass- and energy balance is replaced with a dynamic nonlinear mass- and energy balance. As the figure shows, both the old static mass- and energy balance and the new dynamic mass- and energy balance share a large part of the calculations.

A selector allows for switching between the two different feedforward calculations via a ramping function to allow for bumpless transfer. This makes it possible to compare the two feedforward strategies for evaluation. At steady-state, the output from dynamic feedforward equals the static feedforward and consequently the bumpless transfer is only active when switching during transient behavior.

As described in Chapter 5 the previous existing static feedforward is thorough and well-tuned. Also from the description here we can see that there is a small difference between the two feedforward implementations. The only difference is that one is static with empirically tuned dynamics and the other one dynamic. Therefore the new dynamic feedforward is evaluated by a challenging comparison.

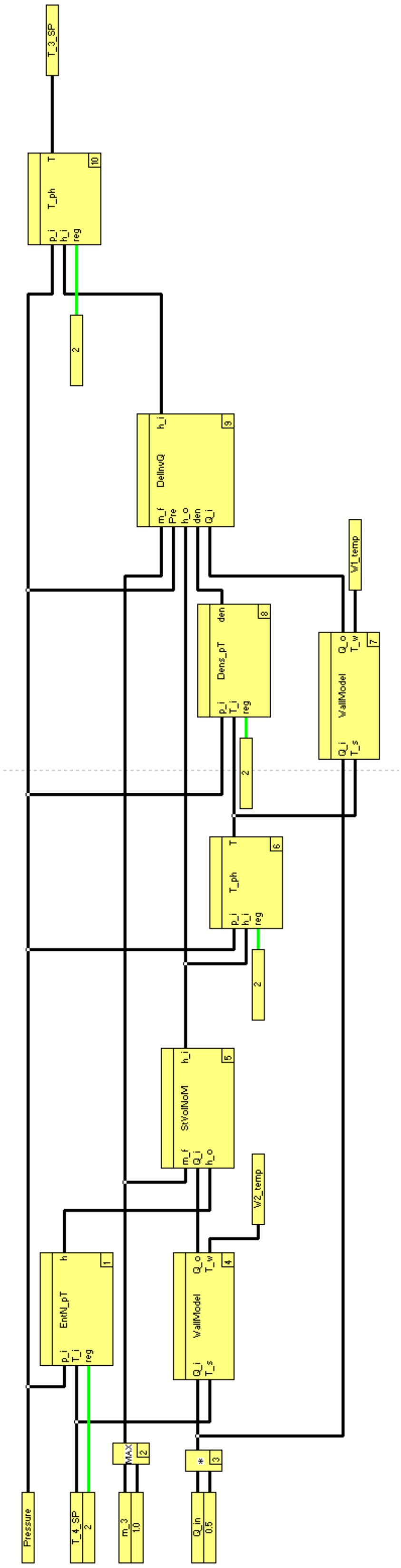

Figure 40. The two segment Freelance model used in the experiment.

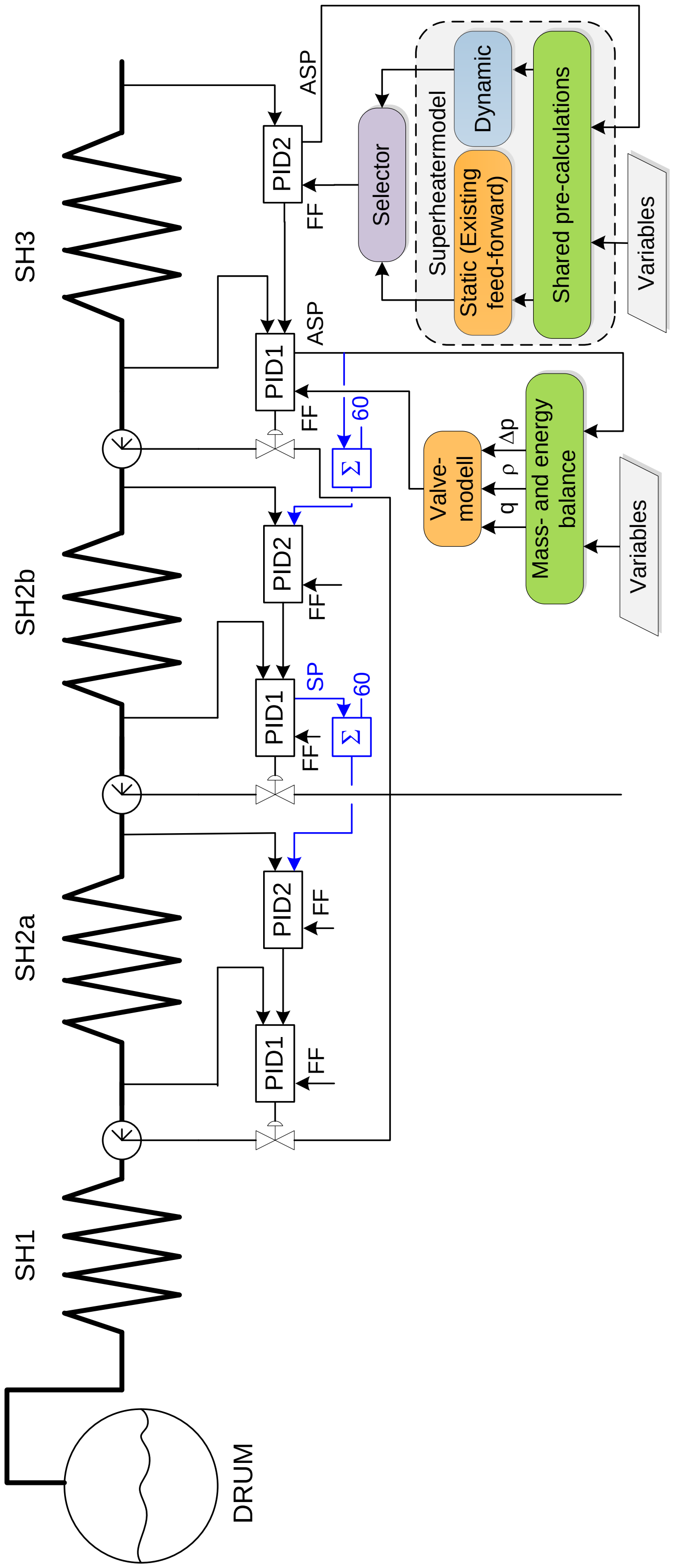

Figure 41. Implementation of new dynamic feedforward at Heleneholmsverket. There is a feedforward to each PID-controller, but it is only shown for SH3 in this figure. The feedforward marked “Dynamic” is only implemented for SH3 for the evaluation in this report. The other superheaters have only the static feedforward. Abbreviations: FF – feedforward, ASP – active set-point.

8 Results

8.1 INTRODUCTION

A number of tests to verify the theory of model inversion and feedforward in practice have been performed at one boiler at the heat and power plant Heleneholmsverket, namely boiler P10.

During the fall of 2015 when the tests were performed both of the turbines at the plant where out of operation. Therefore the tests had to be carried out with the direct heat exchangers instead. The direct heat exchangers takes high pressure superheated steam direct from the main steam line and uses a steam converter to change steam properties down to 10 bar and 275 °C before taking it into the heat exchanger.

The plant operation with direct heat exchangers differs from operation with turbines. With turbines in operation, the turbine governor controls the steam pressure and the boiler operates in open loop with fixed fuel power. During operation with direct heat exchangers without turbines, as in the test, the boiler controls the steam pressure by manipulating the fuel power and the steam flow is a result of the direct heat exchangers steam valves position. The steam valves controls the steam pressure in to the direct heat exchangers. The main control of the direct condenser is its power output to the district heating system. The output from the power controller is the condensate level set-point. This implies that different changes in power set-point are not equal since the resulting mass flow change is depending on the status of a multitude of states in the direct heat exchanger.

Normally the direct heat exchanger operation is limited to startup. This difference in operation gives a more challenging control problem for the superheater controller than during normal turbine operation since a changing mass flow affects the pressure that is controlled by manipulating the fuel rate. During the experiment, both the old static feedforward and the new dynamic feedforward has been tested. When switching from one feedforward to the other, nothing else has been changed (the same controller settings). In this way, the experiments on the two feedforward methods are completely comparable.

8.2 DESCRIPTION OF SIGNAL NAMES IN FIGURES

To avoid confusion, the different signals around the PID cascade loop in the superheater have been named with specific signal names. These signal names are then referred to in the following plots and text in this chapter, see Figure 42. For detailed description, see previous chapter on superheater control.

As in previous chapters, the inner temperature controller is called PID1 and the outer controller PID2. Obviously, the output from the outer controller is the external set-point for the inner controller. This signal has been named in relation to PID2, the outer controller.

To make it clear, the signals are:

PID2:asp – the active set-point for the outer controller
PID2:pv – the process value (measurement) for the outer controller
PID2:ff – the feedforward signal to the outer controller. This is where the

dynamic inverted process model comes in.

PID2:out – the output of the outer controller and set-point of the inner controller
PID1:pv – the process value for the outer controller.
PID1:ff – feedforward to inner controller
PID1:out – output of inner controller manipulating the water injection valve

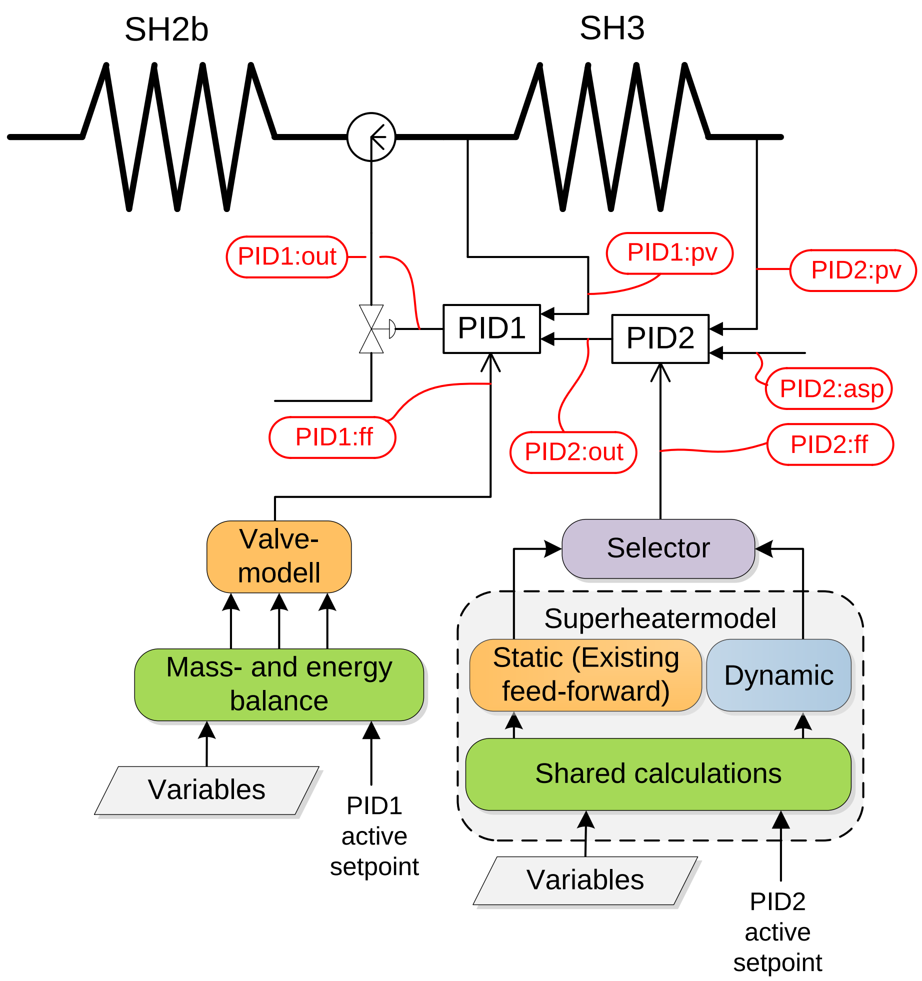

Figure 42. Definition of signal names, marked in red color, used in this chapter. The figure also generically shows the feedforward calculations and the switching between the old static and the new dynamic feedforward.

8.3 STEP AND DISTURBANCE TESTS AT BOILER P10

On the 23rd of September 2015 a series of tests were performed on boiler P10, producing steam to the district heating through the direct heat exchanger, as explained above.

The test is performed with a dynamic feedforward based on two discretization volumes, as described in chapter 6.

8.3.1 Step Change in Temperature Set-Point

Figure 43 shows a series of changes in the set-point for the outer temperature controller (PID2:asp). Normally this set-point is only changed during startup and in that sense this test is not a normal scenario. It will however clearly show the performance of the control loop.

Looking at the upper trend in Figure 43 we can see the temperature set-point (red) making a ramp instead of a pure step, between 450 and 460°C. The temperature has been entered as a step into the operator screens but there is a ramp function inside the controller that becomes active. The first two changes, from 0 to 30 minutes are with the old static feedforward and the second part, from 30 to 60 minutes is with the dynamic feedforward.

Two things are clear when comparing the static and dynamic feedforward. First, the dynamic feedforward performs much better as the process value (PID2:pv) is closer to the set-point (PID2:asp). Also, with the dynamic feedforward, the controller output (PID2:out) starts acting with a transient to accelerate the temperature change in the tube walls when the set-point change is made, this is not the case with the static feedforward.

The second to notice is that most of the changes in the controller output (PID2:out) comes from the feedforward (PID2:ff), both in the case of static and dynamic feedforward. This is as it should be, the feedback in the controller only has to take care of model errors and unmeasured disturbances. The dynamic feedforward acts more aggressively with the controller output, as expected since its performance is better.

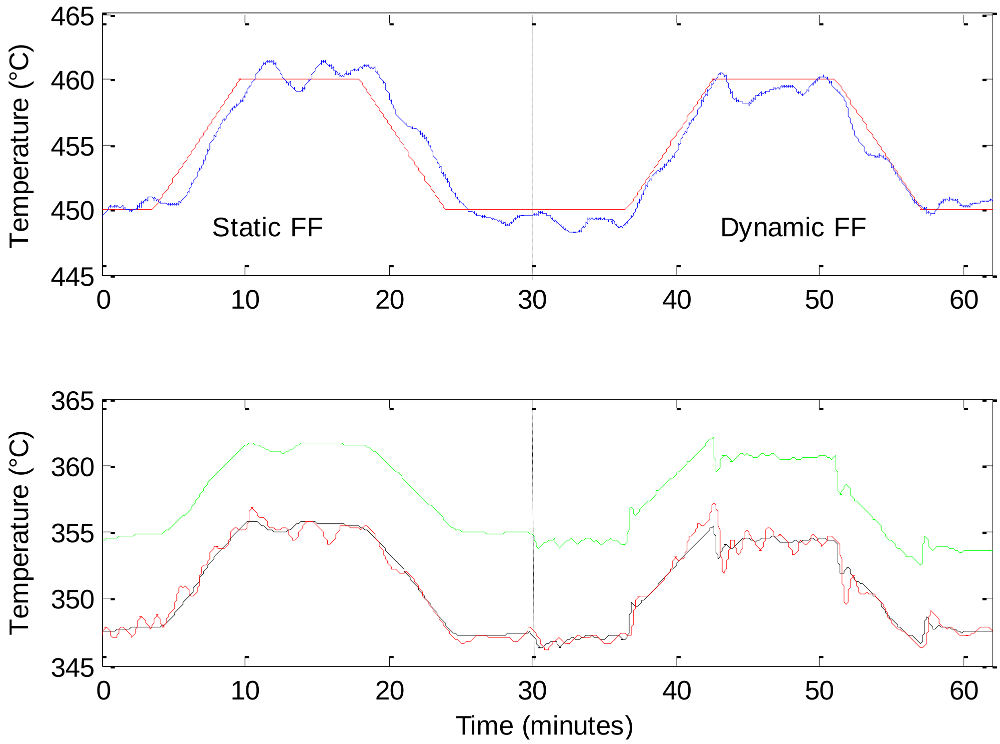

Figure 43. Step test in temperature set-point after SH3. Upper red – PID2:asp, blue – PID2:pv, green – PID2:ff, black – PID2:out, lower red – PID1:pv.

In Figure 44 the signals for the inner controller is shown, for the same test period as in Figure 43. Remember that the feedforward models we are evaluating in this project is connected to the outer controller. Still it is interesting to see how the inner controller performs.

The upper plot in Figure 44, shows that the inner controller follows the varying set-point well. The set-point is varying more aggressive when the dynamic feedforward is active, as noted in Figure 43.

Signal PID1:out is the output to the water injection valve. The more aggressive acting with the dynamic feedforward can be seen all the way down to this valve. This is natural, if we want to have quick changes in temperature then the injection valve much work harder.

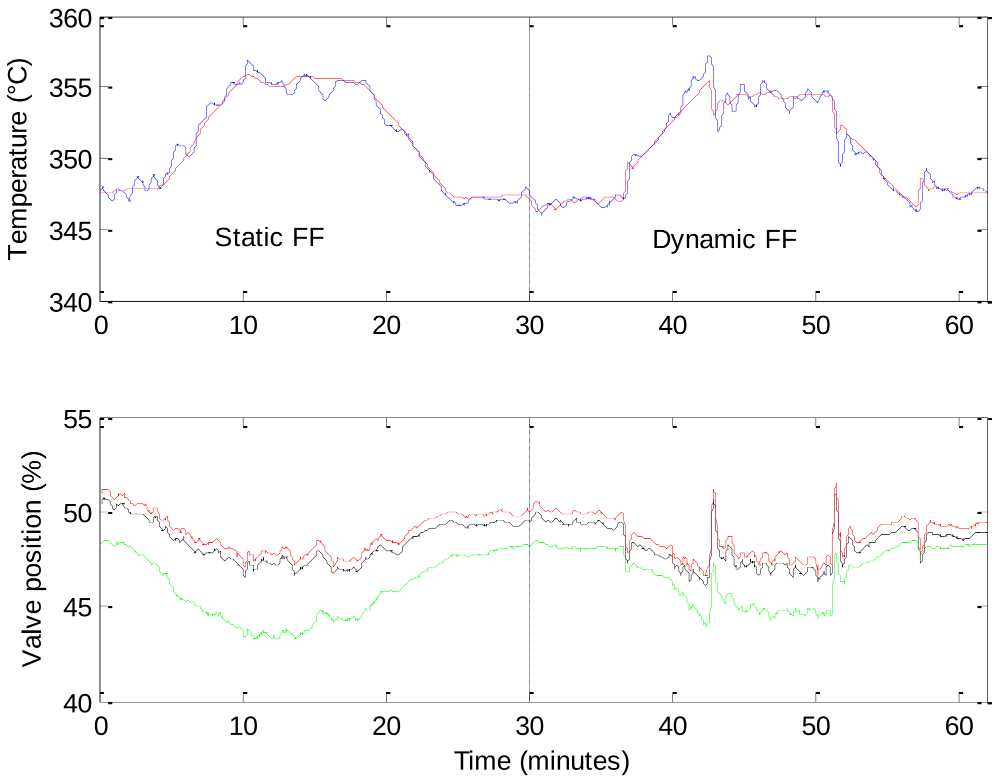

Figure 44. Changes in temperature before SH3. Upper red – PID1:asp, blue – PID1:pv, green – PID1:ff, black – PID1:out, lower red – actual valve opening.

8.3.2 Disturbance Test by Changing the Boiler Load

In order to make a disturbance test to the feedforward, the boiler load was changed. This is done by changing the set-point of produced power in the direct heat exchanger to the district heating. This will lower the steam pressure in the direct heat exchanger and the steam valve opens. Since the boiler controls the steam pressure at the boiler outlet it will follow this change in load.

Figure 45 shows the load change test. The first change in the set-point for heat power output from the direct heat exchanger is with the dynamic feedforward active. During this step change there was a significant deviation in the direct heat exchanger level control, affecting the result negatively. Subsequently the power and level controller parameters where changed before the next test,

At time 20 minutes a new change in set-point to the direct heat exchanger is done, this time with the old static feedforward switched in. There is a substantial deviation in temperature after the superheater.

At about time 33 minutes the dynamic feedforward is switched in.

At about time 41 minutes the boiler pressure falls under the boiler pressure controller's hysteresis and the boiler starts to increase the fuel rate. At about time 44 minutes the steam valve feeding the direct heat exchanger opens and increases the steam flow. These changes in the superheaters environment are handled by the feedforward basically without any changes in the feedback signal. The required change in inlet temperature is approximately 2.5 °C and the variations in controlled temperature after the superheater are negligible. Note the different scale in above and middle trend in Figure 45

At about time 50 minutes a change in the set-point for heat power output from the direct heat exchanger from 66 MW to 70 MW is initiated. This change, that require a change in inlet temperature in excess of 3 °C, see Figure 46, can take place without a change in outlet temperature larger than 1 °C. It is virtually impossible to see the disturbance in the outlet temperature, which is remarkably good performance.

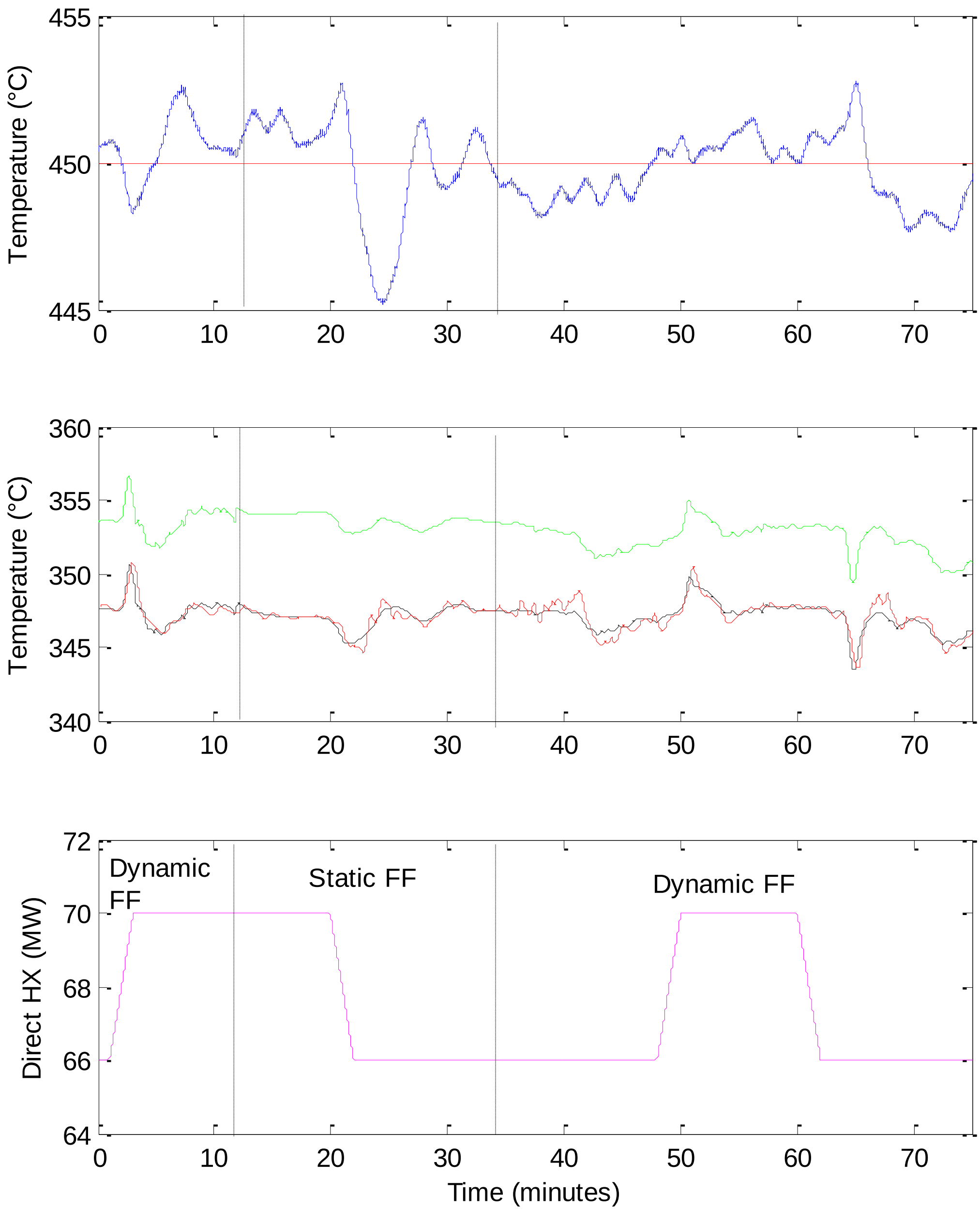

Figure 45. Load change in boiler. Upper red – PID2:asp, blue – PID2:pv, green – PID2:ff, black – PID2:out, middle red – PID1:pv, pink – direct heat exchanger power set-point.

At time 60 minutes a change in the set-point for heat power output from the direct heat exchanger from 70 MW back to 66 MW are initiated, still with the dynamic feedforward. This change, are more aggressive because of the position of the steam valve that feeds the direct heat exchanger at the start of the experiment. This disturbance require a change in inlet temperature in excess of 4 °C and faster than the previous change in heat exchanger power. The change required by the feedforward calculations are faster than maximum speed for the set-point ramp in the inner controller. This is the reason for the remaining controller error (PID2) of approximately 1.5 °C.

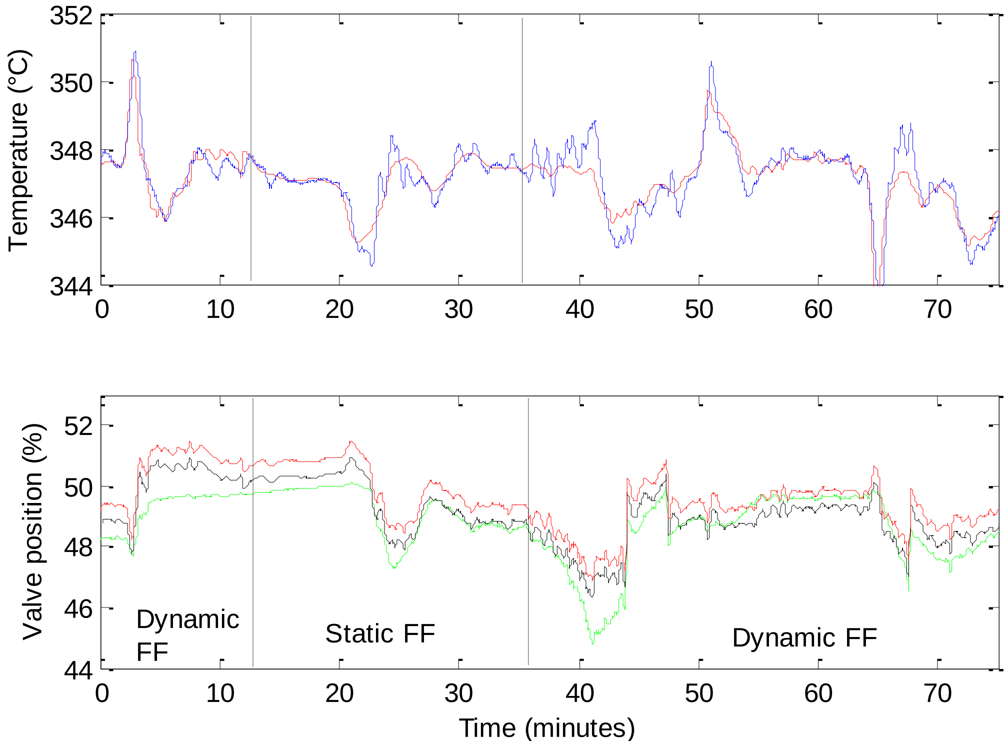

Figure 46. Changes in temperature before SH3 during load changes. Upper red – PID1:asp, blue – PID1:pv, green – PID1:ff, black – PID1:out, bottom Red- PID1 actual actuator position.

8.3.3 Boiler Shutdown

The boiler was shut down after the tests described above. During the shutdown the new dynamic feedforward was active, see Figure 47 and Figure 48. The superheater controllers were active during the whole procedure. Without going into details of the boiler shutdown procedure, it is clear that the feedforward handles the large disturbance caused by the stop. The feedforward signal reaches a steady state value at 500°C, which is a maximum-limitation in the Freelance program. This high feedforward temperature is natural since the controlled temperature after the superheater drops well below its set-point.

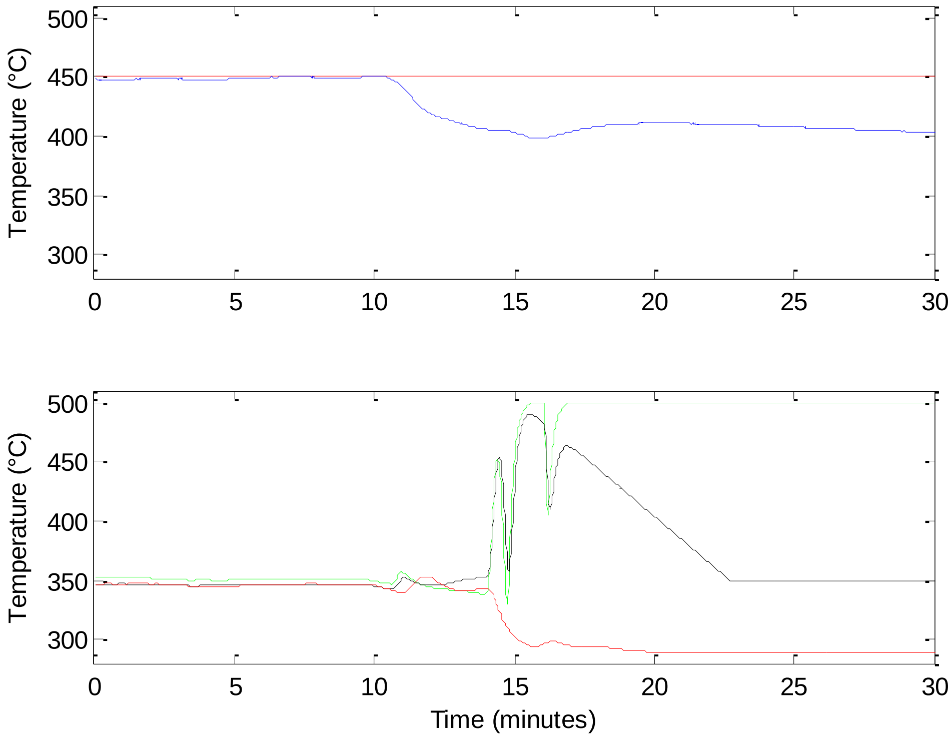

Figure 47. Boiler shutdown. Upper red – PID2:asp, blue – PID2:pv, green – PID2:ff, black – PID2:out, lower red – PID1:pv.

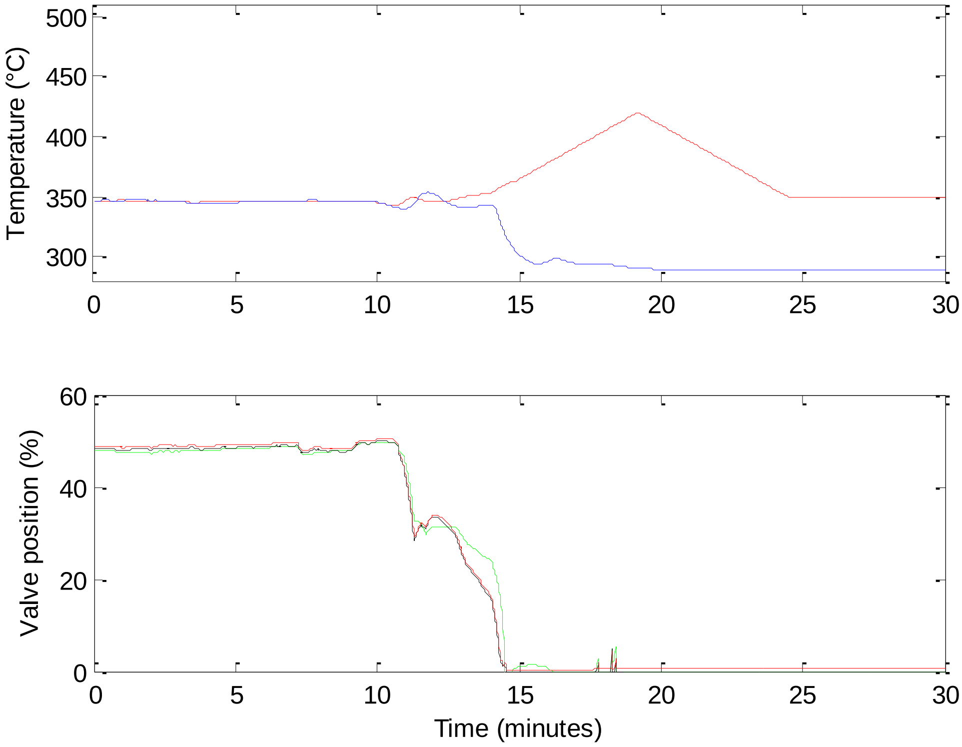

Figure 48. Boiler shutdown. . Upper red – PID1:asp, blue – PID1:pv, green – PID1:ff, black – PID1:out, bottom Red- PID1 actual actuator position.

8.3.4 Conclusions from Tests

The result shows that the dynamic feedforward performed much better that the older static feedforward, both in disturbance rejection and set-point following. This might be a surprisingly result regarding the small change we have actually made in the two different feedforward models, compare with Figure 42. There is only a change from a static to a dynamic model of the superheater.

8.4 ESTIMATION OF BENEFITS FROM THE CHANGES

Since the turbines where out of commission, no real tests of the benefits could be conducted. Instead the benefits where estimated by the use of a plant model.

The main benefit studied here is the possibility to increase the steam temperature set-point. Based on the tests and the current trip limits it is estimated that the steam temperature set-point can be increased from 510°C to 520°C.

8.4.1 Evaluation of the Possible Safe Steam Temperatur Increase

The first thing to take into consideration is the design temperature of the superheaters. For the superheaters of Heleneholmsverket, the superheater design is based on a normal operation temperature of 530 °C. The second consideration is the implemented trip limits. The approach here is to evaluate the limits and either change the limits if it is found that they are too narrow or relate the increase in steam temperature to them. If it is found that the limits should be changed it is very important to perform material analysis and design calculations to validate the changes, and a new validation of the plant safety should be conducted by the notified body In this case there are two trip limits; 530 °C during 3 minutes or directly when passing 550 °C. These are the limits one have to consider when increasing the steam temperature set-point.

The third consideration is harder to assess; it is the long term stress of the superheater tubes. Higher temperatures give greater superheater tube material stress. But variations in temperature also increase the superheater tube material stress. Amplitude, temperature changing time and number of cycles all affect the superheater tube material stress. The consideration is that the improved control decrease the amplitude, the temperature changing time and the number of cycles so that it enables the thermal level to be increased and still retain the same expected lifetime of the superheater tube material.

The consideration made in this project only reflects the two first points (design temperature and trip limits) since the third (thermal stress) is much harder to evaluate. The first point is a check if it is possible at all to increase the temperature based on the design data. This is of course necessary to investigate prior to the start of the project. The normal superheater temperature set-point at Heleneholmsverket is 510 °C and superheater design is based on a normal operation temperature of 530 °C. This allows for a possibility to increase the temperature set-point. The second point sets the limits for the amplitudes of normal variations to 530°C minus the set-point. Based on the test data, the amplitude caused by the tested disturbance are less than 3 °C. But since the turbines were not in operation, the fast mass flow changes caused by the turbines cannot be tested and an estimated extra margin is added. The third point is only handled as an approximation based on the behavior of the temperature. This is the background to the selected increased temperature set-point to 520 °C.

8.4.2 Thermal Calculation of the Benefits of an Increased Steam Temperature

Since the turbines where out of commission during the tests of this project the impact of increased temperature set-point cannot be tested. Instead the change is tested in simulation. This simulations are described in this chapter. The model used for this project is not completely in accordance with the Heleneholmsverket plant but the error is assessed to be small enough to make reasonable assumptions of the real plant performance. The plant calculations conducted by Mikael Bjärhamn at Grontmij.

The parts of the Heleneholmsverket plant that are assessed are two boilers connected to the large turbine, G12. The G12 is a DURAX-turbine from ABB-Stal. It consists of a high pressure counter rotation radial turbine part connected to two low pressure axial parts. The radial turbine has four extractions that is used to pre heat the condensate from the single district heating condenser and the feed water from the plants three feed water tanks. The condensate preheating uses two surface preheaters that is connected to each other so that the drainage flashes in the heater downstream and the drainage ends in the condenser. After the condensate preheaters the condensate reaches the three feed water tanks. The feed water tanks are pressurized and deaerated by fresh steam, steam from extraction three or steam from extraction two depending on the extractions pressure and subsequently the turbine load. From two feed water tanks feed water is pumped through the four feed water preheaters, two in series. There are two feed water heaters connected to each of the first extractions. The feed water preheating also uses two surface preheaters in series that is connected to each other so that the drainage flashes in the heater downstream and the drainage ends in the feed water tanks.

The model uses a turbine with five exactions. The model however uses two district heat condensers with different condensation pressure. The last condenser in the district heating flow uses the last extraction. The last extraction is also used as a mixing preheater of the condensate from the condensers. The forth is used for preheating of condensate with a surface preheater. The condensate is led to the preceding mixing preheater. The condensate after the condensate preheater is led to the feed water tank. The feed water tank is pressurized and deaerated by steam from extraction three. Extraction one and two are used to preheat the feed water prior to the boiler with two surface preheaters. The drainage from the preheaters are connected to each other so that the drainage flashes in the heater downstream and the drainage ends in the feed water tank.

The main difference is that the modeled process uses one additional extraction and an additional district heating condenser to be able to expand the steam further than is dictated by the distribution temperature of the district heating system. The preheating of condensate and feed water has an additional extraction to utilize and uses two mixing preheaters, the feed water tank and the one after the district heating condensers. The feed water tank also has its own extraction. This increased complexity increase the electrical efficiency of the plant. It is however not deemed to have a greater influence on the evaluation of the result. In addition this reports focus is on the model based feedforward approach and not specifically on the implementation in Heleneholmsverket.

The simulation setup is based on the scenario that the plant tries to meet a specific district heating load and temperature. The electrical power is a result of the need for heat flow in the district heating condenser. During the same operational conditions change the superheating temperature from 510 to 520 °C and change operational conditions to generate the same temperature and amount of district heat as previously.

This results in an additional 601 kW electricity through an increase of 635 kW in boiler thermal load. This implies that if we assume that the increase in boiler load has a fuel efficiency of 90 % the additional 601 kW electricity requires 706 kW of fuel power. The fuel to electricity efficiency for the increase in steam temperature is 85.1 %. It is this very high figure that is the basis for the whole project. The calculations can be viewed in Figure 49 and Figure 50.

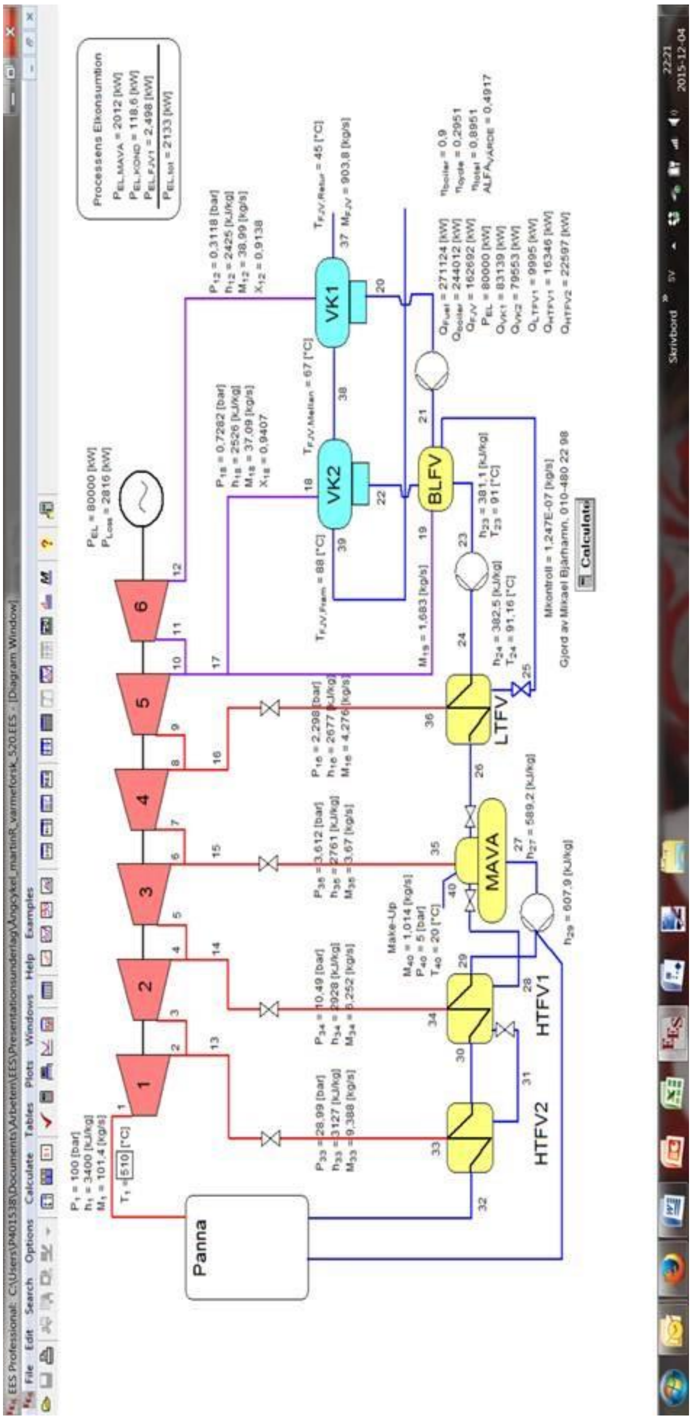

Figure 49. Reference case with a superheater temperature of 510 °C, tuned to hit 80 MW electricity. Plant calculations conducted by Mikael Bjärhamn.

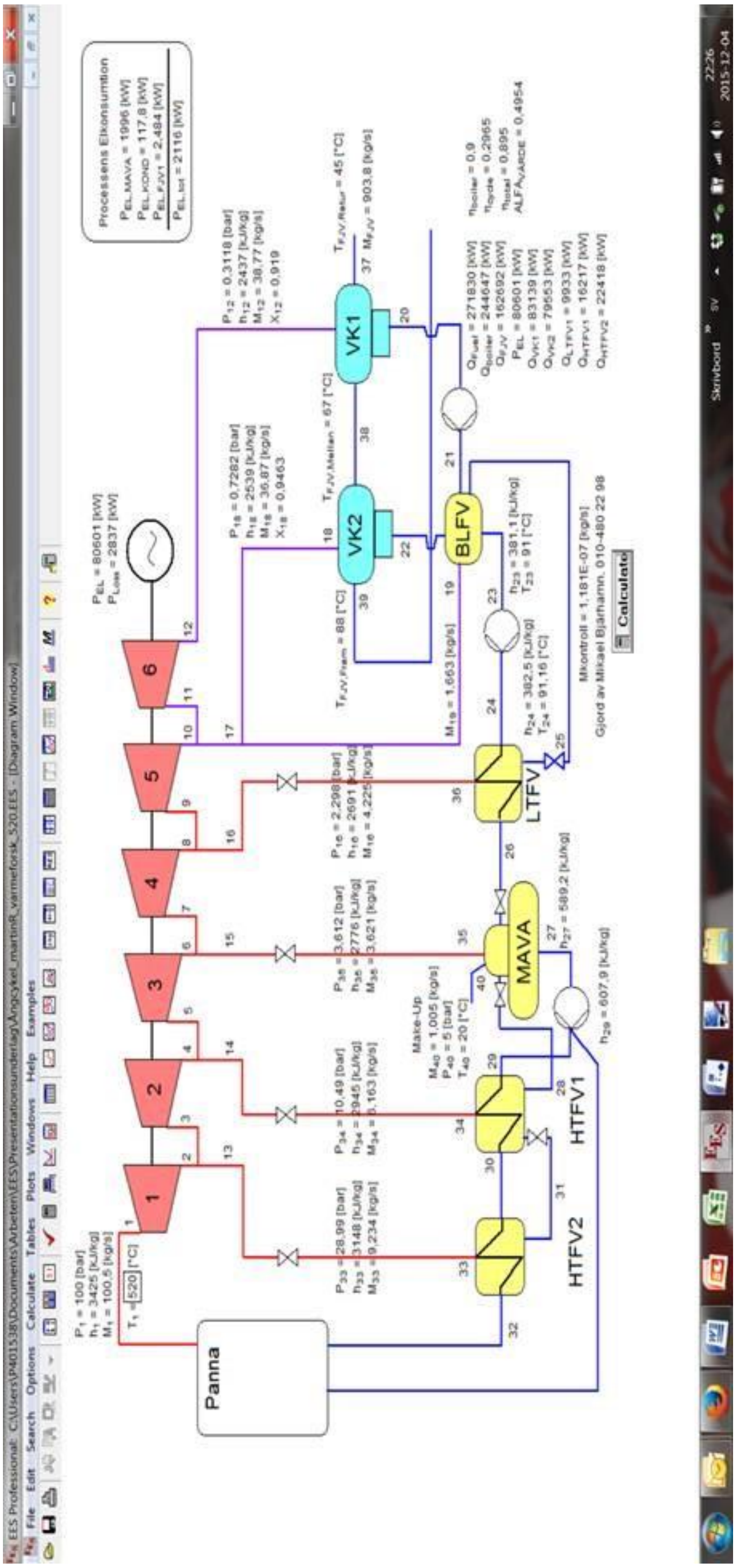

Figure 50. Increased superheater temperature case with a superheater temperature of 520 °C with the same district heat load as the reference case. Plant calculations conducted by Mikael Bjärhamn.

8.4.3 Econmical Benefits of an Increased Steam Temperature

In the case at Heleneholmsverket that uses natural gas to fire its boilers it is the relation between the price of a kWh of gas verses the price of a kWh of electricity and the operational time at that power level that determines the increase in revenue. If we for simplification assumes that the gain of the higher superheating temperature is linearly scalable to heat power the heat produced at Heleneholmsverket yearly can be converted to yearly hoers at the simulated district heating power level. This yearly operation time can be multiplied with the gain per hourly operation at the simulated case.

$$Gain =$$

$$\left(601\ kW * \frac{El\ price}{kWh} - 706\ kW * \frac{Gas\ price}{kWh}\right) * Equivalent\ Operation\ Time\ h$$

If we assume 500 GWh district heat yearly at 163 MW we get 3067 hour equivalent operational time yearly. If we assume an electrical price of 0.03 euro/kWh_{el}, and a gas price of 0.02 euro/kWh_{gas} we get 12 021 euro yearly. The electrical price can vary very much up to 1 euro/kWh_{el} and down to 0.01 euro/kWh_{el}. This implies that higher steam temperature can be very profitable during certain operation conditions and it can be counterproductive in other operational conditions. During the conditions with negative gain the steam temperature is lowered to counteract the negative gain.

If the boiler uses a less pricy fuel, like wood chip, the gain is much higher per operational hour and the operational time is normally greater for plant with less pricy fuel.

9 Discussion

9.1 POTENTIAL OF METHOD

No guarantees can be given regarding the possibility to utilize the methods presented in this report on other processes. The reason for this is that the DAE from which the inverse formulation should be calculated in the general case is implicitly formulated and could include nonlinearities from which it could be impossible to derive the desired explicit formulation. However, in this project an inverse formulation was obtained without very complicated calculations or removal of any significant dynamics from the model. Based on the experiences from this inversion task it therefore seems likely that such a formulation can be obtained for other processes of similar complexity as well, and probably also for more complex models, at least if suitable approximations are used.

This project also indicates that if the dynamic inverse model is used for feedforward, improved performance compared to standard solutions can be expected, at least for nonlinear processes with slow dynamics compared to the sampling rate of the control system.

It is also concluded the non-causal modeling language Modelica, together with a simulation environment such as Dymola is very useful when the inverse model is created. Especially analysis of linearized process models and the possibility to evaluate the performance of the feedforward in simulations have been crucial for the development of the inverse model.

In order to create the dynamic inverse model for feedforward, knowledge of the physics-based process and general understanding of dynamic systems is essential. It is also important to have a grasp of the mathematics involved in deriving the inverse formulation. For this reason an educational level of Master of Science or similar is recommended if one is to perform this task.

9.2 IMPLEMENTATION IN HELENEHOLMSVERKET

The dynamic feedforward model displays improved performance compared to the previous feedforward implementation at site, even though the modeling is very simple. This indicates that this method could be worthwhile to implement in thermal power plants, for the task of superheater control. It should however be noted that the procedure of implementing this feedforward was simplified by the existence of the previous feedforward model, which is based on similar energy balance assumptions and steam calculations as used in the new implementation.

To implement the feedforward correctly, secure the measurements and tune the different filters on the signals used by the feedforward together with controller require both control engineering and thermodynamic knowledge to an educational level of Master of Science as well as practical process knowledge, as noted above.

As mentioned, the method increases the performance far beyond that of an already implemented advanced process based feedforward. In the gas fired boilers at Heleneholmsverket the economic benefits is estimated to be greater than 12 000 euro per year. In a power plant with a greater difference between electrical price and fuel price together with the longer yearly operation time the benefits will be even greater.

9.3 BIO AND WASTE FUEL BOILERS

When developing the physics-based model of the superheater it has been assumed that it is a gas fired boiler. This has been utilized in the way that the model of furnace is greatly simplified since the dynamics from fuel input to heat power is more or less direct. This simplification might not be possible when dealing with waste or bio fuel boiler.

Different type of boilers are described below and at Section 9.3.3 the difference in physics-based modeling is discussed.

9.3.1 Bio Fuel Boilers

There are several different ways of burning bio fuels, the following technologies can be distinguished.

- Fixed-bed combustion
- Bubbling fluidized bed combustion (BFB)
- Circulation fluidized bed combustion (CFB)
- Dust combustion

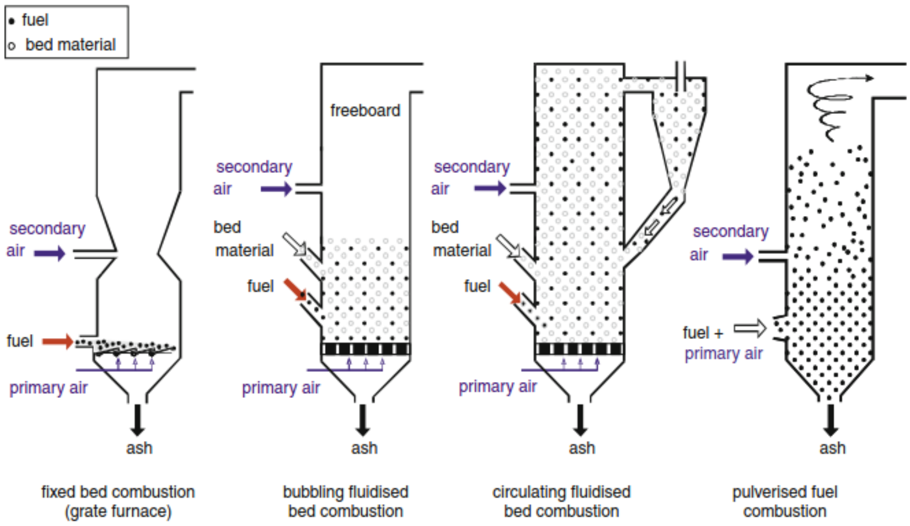

Figure 51. Combustion technologies for biomass. Picture borrowed from (Obernberger & Biedermann, 2012).

Each of the technologies above have different characteristics regarding fuel-type and combustion.

Fixed bed combustion

Fixed-bed combustion systems include underfeed stokers and grate furnaces. Primary air passes through a fixed bed, in which drying, gasification, and charcoal combustion takes place. The combustible gases produced are burned after secondary air has been added, usually in a combustion zone separated from the fuel bed.

Bubbling fluidized bed combustion (BFB)

As seen in Figure 51, the bed is located at the bottom part of the furnace. Primary air is supplied from below via a distributor plate and fluidizes the bed. The bed material is usually silica sand with a diameter of 1.0 mm. The fluidization velocity of the gas is approximately 1.0-2.5 m/s. Secondary air is blown in above the bed in the freeboard, this is to ensure a staged-air supply to reduce NOx-emissions. The amount of fuel should only be 1–2% of the bed material and the bed must be heated (internally or externally) before the fuel is introduced.

The biggest advantages of a BFB furnace is its large flexibility when it comes to fuel particle size and the moisture content. This makes it possible to mix different fuels or to fire it with other types of fuel. (Obernberger & Biedermann, 2012).

Circulating fluidized bed combustion (CFB)

As can be seen in Figure 51, a CFB furnace is a bit different from a BFB. By increasing the fluidizing velocity to 5–10 m/s and using smaller sand particles (0.2–0.4 mm in diameter) a circulating fluidized bed combustion system is achieved. The sand particles are carried along with the flue gases and separated in a hot cyclone or a U-beam separator, and feed back into the combustion chamber via a sand lock (not illustrated in the figure), however this is a perfect place to put a super heater; due to the nature of the sand lock it is possible to get a BFB environment by injecting air in the bottom giving it a very high heat transfer coefficient. The bed temperature (800 – 900°C) is controlled by external heat exchangers cooling the recycled sand (ex. sand lock), or by water-cooled walls. The higher turbulence achieved in a CFB furnaces leads to a better heat transfer and a very homogeneous temperature distribution within the furnace.

This is advantageous for stable combustion conditions, the control of air staging, and the placement of heating surfaces in the upper part of the furnace, however with a high flue gas temperature the heating surfaces in the furnace are more exposed to corrosion.

The disadvantages of CFB furnaces are their large size and therefore high price, making them suitable for outputs of $> 30\ MW_{th}$. In Scandinavia and other cold-climate regions this can be justified by using co-generation, flue gas condensation and steam superheating in the sand lock. Partial loads are problematic due to lack of turbulence. (Obernberger & Biedermann, 2012).

Dust combustion

Dust combustion is suitable for fuels available as small particles (average diameter smaller than 2 mm), e.g. saw dust. A mixture of fuel and primary combustion air is injected into the combustion chamber where the combustion takes place while the fuel is in suspension. The gas burnout is achieved after secondary air addition.

Fuel quality in dust combustion systems needs to be quite constant. A maximum fuel particle size of 10–20 mm must be maintained and the fuel moisture content should normally not exceed 20%.

9.3.2 Waste to Energy Boilers

Waste incineration plants are designed to treat waste with great variation in the composition of the incoming waste. This is the primary difference between waste incineration and other combustion systems. Waste is not an ideal fuel and there is a large variation in the energy content depending on the type of waste, from organic waste with an energy content of 4 MJ/kg to plastic with 35 MJ/kg (Tobiasen & Kamuk, 2013).

Modern waste boilers are equipped with a moving grate. The moving grate enables the movement of waste through the combustion chamber to give way for complete and effective combustion. The primary combustion air is supplied through the grate from below. This air flow also has the purpose of cooling the grate itself. Cooling is important for the mechanical strength of the grate, and many moving grates are also water-cooled internally.

Other types of incinerators are:

- Fixed grate
- Rotary kiln
- Fluidized bed

9.3.3 Modeling Difference between Bio/Waste Boilers and Gas Boilers

The main difference between a gas fired boiler and bio/waste boilers when modeling the super heater, is the dynamics from fuel input to delivered heat energy to the super heater.

When using a BFB, CFB or dust combustion boiler it can probably be assumed that the fuel will reach a gasified state without significant time delays, giving it similar characteristics as natural gas. In that case there is no large modeling difference. With the superheater in the sand lock the modelling will be more complex since the heat transferred to the superheater is separated from the fuel rate by some dynamics.

For bio fuel boilers with fixed bed and especially waste boilers the modeling will be of more complex nature. The varying fuel parameters (size, humidity, energy content and material) for the waste will be difficult to measure. Measuring the heat flow in real-time is difficult because of the extremely harsh condition inside the combustion chamber which does not allow the installation of temperature sensors (Liu & Chan, 2006). A possible solution is to compute the released heat energy in the furnace from measurements in the flue gas (e.g. O_2, CO, CO_2), in combination with stoichiometric calculations. The inherent filter times caused by the gasification of the fuel, heating and transport of the flue gas should be scalable to the air and fuel rates. Another possible solution is to use cameras of the bed and image processing to determent actual power output of the bed.

9.4 FUTURE WORK

In order to investigate the potential of the method presented in this project, the method has to be tried on other processes. This would give a better understanding of its limitations and usefulness.

It would also be interesting to perform a more rigorous theoretical investigation of the feedforward method presented in this project. This would include thorough analysis of sensitivity, frequency responses and the effects of sampling and approximations for the inverse model. This would give a better understanding of the potential and limitations of the method, and could provide guidance for which approximations and modeling assumptions that are suitable to implement.

During the project, attempts were made to improve the performance of the feedforward with regards to signal saturation by using methods to estimate the energy difference between the inverse model and the process model caused by the saturation, and manipulate the control action based on this. However, no conclusive results were reached and this should be further analyzed. This is very interesting since there are always limitations in actuators and other process parts and a systematic way to handle this by the inverted model would be very beneficial. Higher order models with better response would be feasible sins the actuator saturation as well as restricted areas of operation would be handled in a correct way to maximize the plant control performance with actual process limitations.

For the specific implementation in Heleneholmsverket, additional testing would be beneficial to evaluate which order of model should be implemented and how to handle actuator saturation. There is also a need to consider which adaptations of the rest of the control system that can be made, in order to maximize the performance using the improved feedforward method.

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IMPROVED SUPERHEATER CONTROL WITH FEEDFORWARD FROM PHYSICS-BASED PROCESS MODELS

Framkoppling är en av de mest fundamentala reglerstrukturerna inom reglertekniken och används främst för att hantera störningar i den industriella processen.

Den här rapporten beskriver en ny metodik för att härleda framkoppling utifrån fysikaliska modeller av den styrda processen. Modellerna kan, med fördel, vara både olinjära och dynamiska. Med hjälp av modelleringsspråket Modelica så kan man generera en framkopplingsmodell som sedan, efter handpåläggning, kan implementeras i ett industriellt styrsystem. Tester på en ångpanna visar en klar förbättring på reglerprestanda då man använder denna metodik.