Bumpless Transfer Between Advanced Controllers with Applications to Power Plant Control

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Abstract—This paper deals with bumpless transfer between a number of advanced controllers, e.g. in a gain-scheduling architecture. Linear observer-based controllers are designed for a number of linear approximations of the system model in a set of operating points, and gain scheduling control can subsequently be achieved by interpolating between each controller. We use the Youla-Jabr-Bongiorno-Kucera parameterization to achieve a differentiable scheduling between the controllers. This approach produces a controller and a scheduling parameter. In this paper we propose a systematic approach to achieve bumpless transfer between different nominal controllers. The approach is tested on a simple, but highly nonlinear model of a coal-fired power plant.

I. INTRODUCTION

In the power generation industry, the current trend toward market deregulation, coupled with increasing demands for maximization of natural resources and minimization of environmental impact, places greater and greater focus on effective plant-wide operation and control systems. Load following, i.e., the ability of the power plant to meet the power production demands at all times without wasting resources, is becoming a major concern due to the growing competition between power companies and other market forces, c.f. [3] and the references therein.

Power plant processes are complex, of high order, highly nonlinear, and noisy, which implies the necessity for employing multivariable control principles in order to obtain good stability and performance [11]. Conventionally, power plants have been operating for extended periods of time in, or close to, steady state, and the transitions from one operating point to another, when required, are typically fairly slow. However, with the increasing demand for load following capability outlined above, the ability of the power plant to perform stable and fast transitions between different operating points is becoming more and more important, a task that must be addressed by the power plant control system.

Gain scheduling control is a celebrated approach to tracking control of "well-behaved" nonlinear systems, which has been employed in several power plant control applications, e.g., [5], [8], and [13], as well as in numerous other practical applications in diverse fields such as flight control systems [7], [10], automotive control [6], and process control [2]. See also [15] for a general survey of gain scheduling. Gain scheduling schemes involve linearization of the system model in an appropriate set of operating points, followed by synthesis of one or more linear controllers for the system in these points, for instance using robust or optimal design methods (see e.g., [16]). However, it is important to note that, even if two controllers K_1 and K_2 are designed for the same linear system, there is no guarantee that a simple linear combination of the two controllers $K = \alpha K_1 + (1 - \alpha)K_2$, where $\alpha \in [0, 1]$ is a scheduling variable, stabilizes the system for $0 < \alpha < 1$.

[12] provided a framework for gain scheduling control based on the Youla-Jabr-Bongiorno-Kucera (YJBK) parameterization of all stabilizing controllers. By using the YJBK parameterization of all stabilizing controllers for the interpolation it is possible to switch between individual stabilizing controllers in a stable manner. [1] elaborated upon this idea by proposing a scheme that, based on several linearized models extracted from an artificial neural network, provided the basis for the design of a number of controllers in different operating points and gain scheduling using the YJBK parameterization.

In this paper we expand upon the work done in the aforementioned papers [12] and [1] by demonstrating how to switch between different nominal controllers, based on which the continuous gain scheduling takes place, after a new operating point has been reached. This switching should of course take place without introducing disturbances from the switching itself, i.e., via bumpless transfer. This issue is relevant when several controllers have been designed for different operating points, and it is desired to keep the order of the resulting controller reasonably low.

In some previous approaches, such as [4], bumpless transfer is achieved by introducing a feedback that continuously forces the output of the 'next' compensator to stay close to the actual compensator output. In the present approach, a similar structure is introduced based on the YJBK parameterization, which allows for handling stability in a more systematic way.

We also go into details with how to handle integrators in this framework. The gain scheduling approach proposed in this paper is tested on a simple, but highly nonlinear model of a coal-fired power plant.

The outline of the paper is as follows. Section II provides an overview of the YJBK parameterization and controller scheduling framework. In this section we also present the proposed approach to gain scheduling with bumpless transfer and discuss the actual implementation of the gain scheduling control method in details. Section III illustrates the usage of the method on a simulation model of a coal-fired power plant. Finally, Section IV sums up the conclusions of the work.

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II. GAIN SCHEDULING CONTROL

In this section, we first provide a brief review of the framework established in [12], on which we base the controller synthesis. Following that, we discuss how to achieve bumpless transfer to new nominal controllers and some accompanying implementation issues. We will provide all results in this section in discrete time, although they are equally valid in continuous time.

A. Basic Controller Parameterization

Consider the system G with the state space realization

$$G(z) = \begin{bmatrix} A & B_w & B_u \\ \hline C_v & D_{vw} & D_{vu} \\ C_y & D_{yw} & D_{yu} \end{bmatrix}$$
(1)

where $y \in \mathbb{R}^{p_y}$ is the measurement vector, $u \in \mathbb{R}^{m_u}$ is the control vector, $v \in \mathbb{R}^{p_v}$ is the signal to be controlled (which may coincide with y) and $w \in \mathbb{R}^{p_w}$ is a disturbance vector containing noise and command signals. If the subsystem G_{yu} given by the matrices (A, B_u, C_y, D_{yu}) is stabilizable and detectable, G can be stabilized by an observer-based feedback controller (see e.g. [16]). This setup is illustrated in the left part of Figure 1.



Fig. 1. Left: The interconnection of the system G and the observer-based controller $K(Q) = \mathcal{K} \star Q$, where \bullet denotes the star product [16]. Right: The controller is implemented using coprime factorizations of the controller and system.

Let $G_{yu}(z) = C_y(zI - A)^{-1}B_u + D_{yu}$ be written using coprime factorization as

$$G_{yu}(z) = NM^{-1} = \tilde{M}^{-1}\tilde{N}$$
⁽²⁾

with $N, M, \tilde{M}, \tilde{N} \in \mathcal{R}, \mathcal{H}_{\infty}$. Further, let a number of controllers for $G_{\gamma\mu}$ be given by

$$K_i(z) = U_i V_i^{-1} = \tilde{V}_i^{-1} \tilde{U}_i, \ i = 0, \dots, \nu - 1$$
(3)

where $U_i, V_i, \tilde{U}_i, \tilde{V}_i \in \mathcal{RH}_{\infty}$. These coprime factorizations can be chosen to satisfy the double Bezout equation

$$\begin{bmatrix} \tilde{V}_i & -\tilde{U}_i \\ -\tilde{N} & \tilde{M} \end{bmatrix} \begin{bmatrix} M & U_i \\ N & V_i \end{bmatrix} = \begin{bmatrix} M & U_i \\ N & V_i \end{bmatrix} \begin{bmatrix} \tilde{V}_i & -\tilde{U}_i \\ -\tilde{N} & \tilde{M} \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix}$$

for i = 0, ..., v - 1. All stabilizing controllers for G_{yu} based on any particular stabilizing, *nominal* K_0 can now be written according to the YJBK parameterization

$$K(Q) = \mathcal{K} \star Q = K_0 + \tilde{V}_0^{-1} Q (I + V_0^{-1} N Q)^{-1} V_0^{-1}$$
(4)

i.e., the linear fractional transformation setup depicted in the left part of Figure 1. We then have the following result from [16].

Theorem 1: Let a number of stabilizing controllers (3) be given for a system (2). Then $K_{i,i} = 0, \ldots, v-1$ can be implemented as $K(Q_i) = \mathcal{K} \star Q_i$, with $Q_i \in \mathcal{RH}_{\infty}$ given by

$$Q_i = \tilde{U}_i V_0 - \tilde{V}_i U_0 = \tilde{V}_i (K_i - K_0) V_0.$$

Proof: Follows by inserting $Q_i = V_i(K_i - K_0)V_0$ in (4), rewriting the expression as

$$K(Q_i) = K_0 + \tilde{V}_0^{-1} \tilde{V}_i (I + (K_i - K_0) N \tilde{V}_i)^{-1} (K_i - K_0)$$

and using the Bezout identity to show that $I + (K_i - K_0)N\tilde{V}_i = \tilde{V}_0^{-1}\tilde{V}_i$. Theorem 1 states that it is possible to implement a con-

Theorem 1 states that it is possible to implement a controller as a function of a stable parameter system Q based on another stabilizing controller, as depicted in the right part of Figure 1. This implies that it is possible to change between two controllers online, say, from a nominal controller K_0 to another controller K_i , in a smooth fashion by scaling the Q_i parameter by a factor $\alpha \in [0; 1]$.

In this paper we employ the YJBK theory to change from one controller designed in one operating point to another controller designed in a different operating point of a nonlinear system. Thus we implicitly assume that the nonlinear system is sufficiently well-behaved for the resulting gain scheduled controller to stabilize it in between the operating points. This is not explicitly guaranteed by the YJBK-parameterization, which only ensures stability while changing controllers in one operating point.

We shall also exploit some specific properties of a state space implementation of the YJBK parameterization to transfer not only parameters but also state information from one compensator to another.

B. Bumpless Transfer

If controllers have been designed in many operating points, the order of the controller K(Q) may become prohibitively large. If, for instance, there are v controllers in v operating points, all of order n, the order of K(Q) would typically be (2v - 1)n. Thus, it is desirable to switch to a new nominal controller, whenever the plant state has reached a new operating point, and base further gain scheduling on this controller. In that case, the order of K(Q) would be maintained at 3n at all times, at the expense of having to replace K and Q during operation.

Now assume we wish to construct such a gain scheduled controller, which includes integral action in order to remove any steady state errors that might arise from unmodelled dynamics, etc.

The integrator is included in the controller by augmenting the controller by an extra state defined as the integral of the control error $e = y - y_{ref}$, which corresponds to placing a pole in z = 1. However, we observe that both of the coprime factors U_i and V_i in (3) must be stable. This means that including an integrator on either side of the summation point in the middle of Figure 1 will add a pole in z = 1, violating the conditions for Theorem 1 to hold. However, it is possible to circumvent this difficulty by factorizing the integrator into the following coprime factorization:

$$\frac{z^{-1}}{1-z^{-1}} = \left(\frac{1-z^{-1}}{1-rz^{-1}}\right)^{-1} \left(\frac{z^{-1}}{1-rz^{-1}}\right) = V_I^{-1} U_I \quad (5)$$

where 0 < r < 1, yielding $V_I, U_I \in \mathcal{RH}_{\infty}$.

It should be noted that a compensator with control action composed by observer based feedback and by integral action can be designed under the usual separation principle paradigm. Although not mentioned in all undergraduate textbooks, the principle is simple: the observer gain is designed for the original system parameters, an (extended) feedback gain is obtained for an extended system model including the integrator, and the two actual feedback gain matrices - state feedback and integral feedback - is obtained by partitioning the extended feedback matrix consistently with the extended state space model. The proof of separation proceeds as usual.

Next, we present how to find Q once a number of controllers have been found in individual operating points. The following calculations should be carried out for each pair of two adjacent operating points, between which gain scheduling should take place.



Fig. 2. The interconnection of the controller $K(\alpha) = \mathcal{K} \star \tilde{\mathcal{K}}(\alpha) \star K_1$. The scheduling parameter α , thus appears in the middle block only.

Figure 2 illustrates the interconnection of the controller. Let \mathcal{K} , the augmented controller on which we base the YJBK scheduling, be given as (see e.g. [16])

$$\mathcal{K} = \begin{bmatrix} A + B_u F_0 + L_0 C_y & B_u & -L_0 & B_u \\ 0 & I & F_{I0} & rI \\ \hline F_0 & I & 0 & I \\ C_y & 0 & -I & 0 \end{bmatrix}$$
(6)

where $A + B_u F_0$ and $A + L_0 C_y$ are stable matrices (i.e., the norms of all eigenvalues are less than one), and $rI \in \mathbb{R}^{p \times p}$ represents the integrators included for each measurement output channel, factorized as described above. \mathcal{K} takes the signals *e* and u_q as inputs and yields the outputs *u*, which is applied to the plant, and e_q , which is fed to *Q*. Note that, for $\alpha = 0$, the resulting controller becomes

$$K_{0} = \begin{bmatrix} I & 0 \end{bmatrix} \mathcal{K} \begin{bmatrix} I \\ 0 \end{bmatrix}$$
$$= \begin{bmatrix} A + B_{u}F_{0} + L_{0}C_{y} & B_{u} & -L_{0} \\ 0 & I & F_{I0} \\ \hline F_{0} & I & 0 \end{bmatrix}$$
(7)

which can be recognized as a standard observer-based controller. As depicted in Figure 1, $K(\alpha)$ is formed as a linear fractional transformation of \mathcal{K} and Q scaled by α , i.e., $K(\alpha Q) = \mathcal{K} \star (\alpha Q)$. When $\alpha = 1$ we must have $K(Q) = K_1$ where

$$K_{1} = \begin{bmatrix} A + B_{u}F_{1} + L_{1}C_{y} & B_{u} & -L_{1} \\ 0 & I & F_{I1} \\ \hline F_{1} & I & 0 \end{bmatrix}$$
(8)

Note that, in the LFT setup, K_1 takes e_q as input and yields u_1 as output. Hence we may find Q as $Q = \tilde{\mathcal{X}}(1) \star K_1$, where $\tilde{\mathcal{X}}(\alpha)$ is chosen such that $\mathcal{K} \star \tilde{\mathcal{K}}(1)$ is an identity system. Fairly straightforward calculations yield

$$\tilde{\mathcal{K}}(\alpha) = \begin{bmatrix} A & 0 & L_0 & B_u \\ F_{I0}C_y - rF_0 & (1-r)I & -F_{I0} & rI \\ \hline -\alpha F_0 & -\alpha I & 0 & \alpha I \\ C_y & 0 & -I & 0 \end{bmatrix}$$
(9)

where $\tilde{\mathcal{K}}(\alpha)$ takes u_1 and the prediction error from K_0 as inputs and yields u_q and e_q as outputs.

This particular implementation of the YJBK parameterization has the following surprising properties.

Theorem 2: Assume that the system given by (1) is controlled by the controller $K(\alpha) = \mathcal{K} \star \tilde{\mathcal{K}}(\alpha) \star K_1$ where $\mathcal{K}, \tilde{\mathcal{K}}$, and K_1 are given by (6), (9), and (8), respectively. Then the poles of the resulting closed loop system are given as the eigenvalues of the matrices

$$\begin{bmatrix} A + B_u F_0 & B_u F_{l0} \\ C_y & I \end{bmatrix},$$
$$\begin{bmatrix} A + B_u F_1 & B_u F_{l1} \\ C_y & I \end{bmatrix},$$
$$A + L_0 C_y, \quad A + L_1 C_y, \quad \text{and} \quad -r_l$$

independently of the value of α .

Theorem 2 holds due to a separation property which can be verified by tedious calculations by writing out the state space formulae for the closed loop system and changing coordinates from observer states to state estimation error signals. The proof for this separation property will not be given here, but in the actual bumpless transfer algorithm, we shall use the separation property explicitly in terms of the following state properties:

Theorem 3: Let $x_{\mathcal{K}}$, $x_{\bar{\mathcal{K}}(\alpha)}$, and x_{K_1} denote the state vectors of the three systems given by (6), (9), and (8), respectively. Then, at all times, the control signal *u* generated by the controller $K(\alpha) = \mathcal{K} + \tilde{\mathcal{K}}(\alpha) \star K_1$ is given by:

$$u = \begin{bmatrix} F_0 & I \end{bmatrix} x_{\mathcal{K}} - \alpha \begin{bmatrix} F_0 & I \end{bmatrix} x_{\bar{\mathcal{K}}(\alpha)} + \alpha \begin{bmatrix} F_1 & I \end{bmatrix} x_{K_1}$$

Moreover, if for some time interval, $\alpha\equiv 1,$ then the state difference

$$x_e(t) = x_{\mathcal{K}}(t) - x_{\bar{\mathcal{K}}(\alpha)}(t) \to 0 \quad \text{as} \quad t \to \infty$$
 (10)

at a rate governed by the eigenvalues of the matrices

$$\begin{bmatrix} A+B_{u}F_{0} & B_{u}F_{I0} \\ C_{y} & I \end{bmatrix}, \quad A+L_{0}C_{y}, \quad \text{and} \quad -rI$$

Conversely, if $x_e = 0$ at some time instance, then

$$u = (1 - \alpha) \begin{bmatrix} F_0 & I \end{bmatrix} x_{\mathcal{K}} + \alpha \begin{bmatrix} F_1 & I \end{bmatrix} x_{K_1}.$$

The property (10) follows from the separation principle mentioned above (which can be verified by elementary algebra), whereas the two other properties are trivial consequences of the state space forms.

C. A Bumpless Transfer Procedure

In Subsection II-B a global linear model was intrinsically assumed in order to establish the theoretical results. The practical use of this is based on robustness properties of the results, i.e. that stability etc. is preserved in an open neighborhood of the system parameters. In this subsection, we will present a practical procedure which specifies how to update parameters from one compensator to the next for a system with linear models which depend on the operating point.

In particular, we shall use the controller structure from Subsection II-B with the modification that the system parameters (A, B_u, C_y) are replaced by $(A_0, B_{u,0}, C_{y,0})$ (the original system parameters) in (6) and in (9), whereas the next compensator will be based on the new system parameters, such that (A, B_u, C_y) are replaced by $(A_1, B_{u,1}, C_{y,1})$ in (8).

Procedure 1: Assume that the transfer has to take place between time T_0 and time T_1 , that the system parameters have changed from $(A_0, B_{u,0}, C_{y,0})$ to $(A_1, B_{u,1}, C_{y,1})$ during that time interval, and that the next compensator in line is also an integral observer based compensator with feedback gains F_2 and F_{I2} and observer gain L_2 . Then $\alpha(\cdot)$ should be chosen as a function of time with the following properties:

- 1) α is monotonously non-decreasing, $T_0 < t < T_1$
- 2) $\alpha(T_0) = 0$ and $\alpha(T_1) = 1$
- 3) $\alpha(t) \approx 1$ for $T_1 t_{\varepsilon} < t < T_1$, where t_{ε} is 'sufficiently large' compared to the eigenvalues of

$$\begin{bmatrix} A + B_u F_0 & B_u F_{I0} \\ C_y & I \end{bmatrix}, A + L_0 C_y, \text{ and } -rI$$

At time T_1 the transfer is performed by the following substitutions of parameters and states:

$$\begin{array}{rcl} A_{0}, B_{u,0}, C_{y,0} & \longrightarrow & (A_{1}, B_{u,1}, C_{y,1}) \\ A_{1}, B_{u,1}, C_{y,1} & \longrightarrow & (A_{2}, B_{u,2}, C_{y,2}) \\ (F_{0}, F_{I0}, L_{0}) & \longrightarrow & (F_{1}, F_{I1}, L_{1}) \\ (F_{1}, F_{I1}, L_{1}) & \longrightarrow & (F_{2}, F_{I2}, L_{2}) \\ & x_{\chi} & \longrightarrow & x_{K_{I}} \\ & x_{\tilde{\chi}}(\alpha) & \longrightarrow & x_{K_{I}} \\ & x_{K_{1}} & \longrightarrow & x_{K_{1}} & (\text{unchanged}) \end{array}$$

and $\alpha(T_{1+})$ is reset to 0. $(A_2, B_{n,2}, C_{y,2})$ are the system parameters for the next operating point in line.

According to Theorem 3, under the system assumptions above, Procedure 1 will guarantee

1) stability in the entire time interval $T_0 \leq t \leq T_1$

2) bumpless transfer at $t = T_1$

The intuition behind the procedure above, is that the state convergence property (10) is exploited to guarantee

$$u = F_1 x_{K_1} \tag{11}$$



Fig. 3. Coal-fired power plant.



Fig. 4. Simplified model of boiler.

at $t = T_{1-}$. Now, replacing $x_{\mathcal{K}}$ by x_{K_1} , F_0 by F_1 and resetting α , ensures that (11) is also satisfied at $t = T_{1+}$.

Finally, we note that it is advantageous to add the steadystate control signal corresponding to the operating point in which the controller is designed, to the output from the controller. This control signal is scaled according to the scheduling parameters before being fed to the plant.

III. POWER PLANT CONTROL SIMULATION

In this section we will demonstrate the practical usefulness of the proposed scheduling method on a simulation model of a power plant.

Figure 3 illustrates how the considered power plant works. Water is pumped from a feed water tank through a preheater and into the boiler. In the boiler, the water evaporates in the evaporator and the temperature is further increased in the superheaters. The superheated steam is then expanded through the turbines, which drive a number of generators producing electricity. After the turbines the water is led back to the feed water tank.

Figure 4 shows the simplified model of the boiler used here. The gas in the boiler room and the steam in the evaporator are lumped together into a single average state. Assuming that the mass flow of the smoke (and ashes) equals the mass flow of coal and air, just three state variables are left: the temperature and density of the steam, T_s and ρ_v , along with the temperature of the smoke, T_g . The controlled inputs are the mass flow of coal, \dot{m}_c , and the mass flow of the feed water, \dot{m}_f .

The heat flux from the coal and air is modeled as

$$Q_c = \dot{m}_c h_c + \dot{m}_a h_a,$$

where h_c and h_a are the specific enthalpies of the coal and air, and \dot{m}_a is the mass flow of air. The heat flux of the smoke is modeled as

$$Q_g = (\dot{m}_c + \dot{m}_a)c_g T_g,$$



Fig. 5. Simulation in entire range with no gain scheduling. The top figure shows the steam temperature. The bottom figure shows the steam pressure.

where c_g is the specific heat capacity of the smoke. This gives the following time derivative of T_g :

$$\frac{dT_g}{dt} = \frac{1}{c_g m_g} (Q_c - Q_g - Q_w),$$
 (12)

where m_g is the mass of the smoke (and ashes) and Q_w is the heat flux through the evaporator wall modeled as

$$Q_w = \alpha_w (T_g - T_s) + \varepsilon_w (T_g^4 - T_s^4)$$

where α_w and ε_w are heat transfer coefficients of the wall. The time derivative of T_s is modeled as

$$\frac{dT_s}{dt} = \frac{\rho_s \frac{\partial h_s}{\partial \rho_s} (\dot{m}_s - \dot{m}_f) + \dot{m}_f (h_f - h_s) + Q_w}{C_w + V \rho_s \frac{\partial h_s}{\partial T_s}},$$
 (13)

where $h_s(T_s, \rho_s)$ is the enthalpy of the steam, h_f is the enthalpy of the feed water, C_w is the heat capacity of the wall, V is the volume of the evaporator, and \dot{m}_s the mass flow of steam out of the evaporator modeled as (see [9])

$$\dot{m}_s = \beta_v \sqrt{(P^2 - P_0^2)/T_s},$$

where $P(T_s, \rho_s)$ is the pressure of the steam, P_0 is the pressure in the tank, and β_v is a flow coefficient. The final time derivative needed is that of ρ_s which is simply given by

$$\frac{d\rho_s}{dt} = \frac{m_f - m_s}{V}.$$
(14)

By assuming

and $\beta_v = 0.00031 \ kg K^{1/2}/(sPa)$ to be constants we have a third order dynamical model given by Equations (12), (13), and (14). With \dot{m}_a calculated as a function of \dot{m}_c the model has two control inputs \dot{m}_c and \dot{m}_f .

The values of the constants were found by fitting the model to measurement data from an actual 400 MW power plant. The fitted model showed good agreement with the actual data, considering how simple it is.

The method presented in Section II is applied to the simulation model of the power plant. The control objective is to maintain the steam temperature, T_s , at 700 K while keeping the steam pressure at a desired reference value using the control inputs \dot{m}_f and \dot{m}_c . The operating point is determined by the desired steam pressure, $P_{ref} \in [225;400]$ bar. Three operating points are chosen: $w_1 : P_{ref} = 400$ bar, $w_2 : P_{ref} = 300$ bar, and $w_3 : P_{ref} = 225$ bar. In each of the three points a linearized model of the plant is obtained with a sampling period of 5 s and a discrete time LQR/LQE controller with integral action is designed for this model with emphasis on disturbance rejection.

If we simply use the controller designed for w_2 in the entire operating range we will not obtain an acceptable behavior as shown in Figure 5. At high pressures the temperature control is poor and at low pressures the closed loop is only marginally stable.

Now the three controllers, K_1 , K_2 , and K_3 , are scheduled according to P_{ref} using the method presented in Section II. This is done by finding the Q that schedules between each two controllers, i.e., finding Q_{ij} and K_{ij} such that $K_{ij}(0) = K_i$ and $K_{ij}(Q_{ij}) = K_j$.

Figure 6 shows the simulation going through the three operating points. At the dotted lines the controllers are switched. Initially K_{12} is used. As P_{ref} ramps to w_2 , α is ramped from 0 to 1 making $K_{12}(\alpha Q_{12})$ go from K_1 to K_2 . At the first dotted line a bumpless transition to K_{23} is performed and α is set to 0. At the next dotted line we switch to K_{32} and at the last line we switch to K_{21} . Before each transition α has been 1 for a while to ensure the bumpless transfer. As seen, the transfer is indeed completely bumpless and the performance during the relatively fast ramping is good.

IV. DISCUSSION

A procedure for bumpless transfer has been proposed, which, under assumptions of mild nonlinearities, is able to guarantee stability and to ensure that the entire state of the new controller is aligned with the former state. The stability is established by virtue of the Youla-Jabr-Bongiorno-Kucera parameterization of all stabilizing controllers, which in the particular implementation in the present paper provides a novel and interesting separation principle.

An interesting application of the bumpless transfer scheme is for smooth phasing in of a new control system to supplement and/or replace an existing control system at a largescale plant, where downtime is expensive and safety is important. That is, the gain scheduling scheme could be implemented at the medium-to-high level of the control hierarchy, where the computational demands can be met easily, and ensure a smooth transition to a new and (hopefully) better performing closed-loop system.

It should be noted that in a similar manner as the classical methods for bumpless transfer, it is straight-forward to incorporate an anti-windup scheme. Since the control action is



Fig. 6. Simulation in entire range. At the dotted lines the controllers are switched. The figures show from top to bottom: Scheduling weight, steam temperature, steam pressure, steam pressure error, mass flow of coal, and mass flow of feed water.

composed by observer based action and integral action, both . parts just have to be fed with the real (saturated) input.

Finally, even if a gain-scheduling control design method with bumpless transfer is guaranteed to stabilize a large model class, there is never any guarantee for stability of the real plant. However, at least such a design method should guarantee stability while scheduling between controllers for a *fixed* linear model. This is satisfied for the proposed method in contrast to several of the classical methods. In addition, the method updates the whole state vector, which the authors consider to be a sound approach. Future work will investigate the nature of parameter variations for which stability guarantees can be given for gain scheduling in between operating points, i.e., a rigorous examination of what constitutes a "sufficiently well-behaved" system, as referred to in Section II.

V. REFERENCES

- J. Bendtsen, J. Stoustrup, "Transformation of Neural State Space Models into LFT Models for Robust Control Design," in Proc. of the Fourth IFAC International Symposium on Robust Control Design, June 2003
- [2] S. Crisafulli, R. D. Pierce, "Surge Tank Control in a Cane Raw Sugar Factory," *Journal of Process Control*, Vol. 9, 33-39, 1999
- [3] R. Garduno-Ramirez, K.Y. Lee, "Overall Control of Fossil-Fuel Power Plants," in Proc. of the 2001 Winter Meeting of the IEEE Power Engineering Society, 2001
- [4] S.F. Graebe, A.L.B. Ahlén, "Dynamic Transfer Among Alternative Controllers and Its Relation to Antiwindup Controller Design", *IEEE Trans. Control Systems Tech*nology, Vol. 4, No. 1, 1996
- [5] M.E. Hangstrup, J. Stoustrup, P. Andersen, T.S. Pedersen, "Gain-Scheduled Control of a Fossil-Fired Power Plant Boiler," in Proc. of the IEEE Conference on Control Applications, August 1999
- [6] D. Hrovat, M. Tran, "Application of Gain Scheduling to Design of Active Suspension," in *Proc. of the IEEE Conference on Decision and Control*, Dec. 1993
- [7] R. A. Hyde, K. Glover, "The Application of Scheduled H_∞ Controllers to a VSTOL Aircraft," *IEEE Trans. Aut.* Control Vol. 38, 1021–1039, 1993
- [8] P. Kallappa, A. Ray, "Fuzzy Wide-range Control of Fossil Power Plants for Life Extension and Robust Performance," *Automatica* Vol. 36, 69–82, 2000
- [9] S. Lu, B. W. Hogg, "Dynamic nonlinear modelling of power plant by physical principles and neural networks," *International Journal of Electrical Power and Energy* Systems Vol. 22, 1:67-78, 2000
- [10] R. A. Nichols, R. T. Reichert, W. Rugh, "Gain Scheduling for H_∞ Controllers: a Flight Control Example," *IEEE Trans. Control Systems Technology*, Vol. 1, 69–75, 1993
- [11] T. Mølbak, "Advanced Control of Superheater Steam Temperatures—an evaluation based on practical applications," *Control Engineering Practice*, Vol. 7, 1–10, 1999
- [12] H. Niemann, J. Stoustrup, "An Architecture for Implementation of Multivariable Controllers", Proc. of the American Control Conference, June 1999
- [13] A. G. Parlos, G. Alexander, O. T. Rais. T. Omar, "Nonlinear Control of U-tube Steam Generators via H_{∞} control," *Control Engineering Practice*, Vol. 8, 921–936, 2000
- [14] J. S. Shamma, M. Athans, "Analysis of Gain Scheduled Control for Nonlinear Plants," *IEEE Trans. Aut. Control*, Vol. 35, 898–907, 1990
- [15] W. Rugh, J. S. Shamma, "Research on Gain Scheduling," Automatica Vol. 36, 1401–1425, 2000
- [16] K. Zhou, J. Doyle, K. Glover, "Robust and Optimal Control," Prentice Hall, Inc., 1996, ISBN 0-13-456567-3