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Application of Model Predictive Control to a Cascade of River Power Plants

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Abstract: River power plants are important contributors to the over 19% of world electricity produced by hydro-electric plants. Built in the natural course of a river, they produce energy by manipulating the water discharge through their facilities. They therefore introduce fluctuations in the river's natural water level and flow, which might conflict with various constraints imposed for environmental and operational purposes. Motivated by these issues, we present in this paper the application of Model Predictive Control for regulating the turbine discharge of river power plants, taking into account environmental, navigational and economical constraints and limitations. Large disturbances caused by the operation of locks are particularly investigated, as well as the issue of reducing abrasion by keeping the frequency of turbine discharge adjustments modest.

Keywords: Modeling, Optimal control, Predictive control, Hydroelectric systems.

1. INTRODUCTION

Hydroelectric power plants are constructions built into the natural course of a river to generate electrical energy. By manipulating the water flow through their facilities (turbines and weirs), the power plants affect the river's natural water level and flow. Unless the power plants are controlled properly, excessive variations in flow and level can result, which may have an adverse impact on the flora and fauna within the river and at the riverbank. Additionally, water discharge variations are unfavorable for navigation. The authorities thus require the turbines to be manipulated such that a specified water level upstream each power plant – the so-called concession level – is kept close to a predefined reference value and within specified bounds while keeping the changes in the discharge modest.

If a river is used for navigation, it is usually equipped with locks for the ships to by-pass the power plants. When the locks are in operation, up to 50% of the water by-passes the turbines and flows through the lock branches. Lock operations thus induce significant discharge variations and water level deviations that have to be compensated for by adjusting the water flow through the turbines of the power plants appropriately. However, frequent altering of the turbine discharges leads to turbine wear out and increases the risk of damaging the turbine blades.

Currently, the most common control scheme employed in practise to cope with these challenges comprises a PI controller with disturbance feed-forward installed on each individual power plant. Often, a dead band is added at the output of each controller to reduce the amount of control moves executed by the power plant equipment. The parameter tuning of the PI controllers is demanding due to the contradictory control objectives, and furthermore, since there is little or even no coordination and exchange of information between the power plants, natural discharge fluctuations are often amplified considerably as they propagate through the cascade.

In the literature, a number of different approaches have been investigated, see v. Siebenthal et al. (2005) for a thorough overview of similar control problems and the solutions considered. In the latter work, Model Predictive Control (MPC) was applied to a cascade of five hydroelectric power plants situated in the river Aare, Switzerland. The supervisory MPC controller achieved significantly better damping of discharge variations than the local PI controllers used in practice and demonstrated the benefits of coordination between the control actions of the different power plants.

In the paper at hand, we extend this method and apply MPC to a cascade of power plants situated along a river that is heavily used for navigation. The latter fact implies that additional (and frequent) disturbances are introduced in the control problem due to the significant amount of water that is drawn out of or into the river every time the locks are in operation. The problem is further complicated by the scarcity of available measurements and the slow dynamics of the river flow. Here, we analyze the effects of these disturbances on the control performance and demonstrate potential benefits that could be achieved if information regarding *anticipated* lock operations were made available to such a supervisory control scheme.

Furthermore, the restriction of the amount of applied control moves is also considered explicitly as a control ob-

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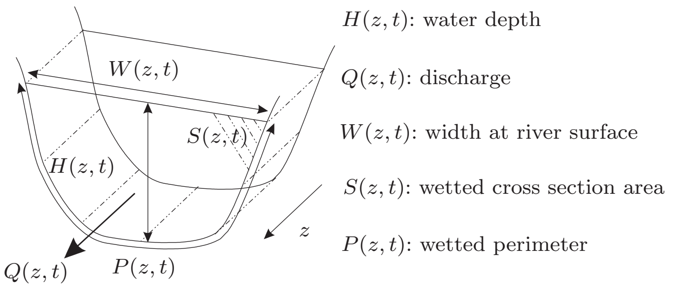

Fig. 1. River cross section parameters

jective in the controller design. This constraint requires the inclusion of logic statements in the control model. Binary variables are introduced in the model equations, rendering the resulting control problem even more challenging. In the sequel, we investigate the complexity introduced by such an extension and present solution heuristics that can provide the desired performance while maintaining an affordable computational complexity.

2. MODELING

2.1 Physical Model

The nonlinear, first-order system of partial differential equations of de Saint-Venant (1871) represent the state of the art for modeling one-dimensional river hydraulics with constant fluid density, see Hervouet (2007). The hydraulic state of the river is described by two variables: the water depth $H(z,t)$ and the discharge $Q(z,t)$, both varying as a function of space z and time t. The river dynamics are expressed by

$$\frac{\partial Q}{\partial z} + \frac{\partial S}{\partial t} = 0. \tag{1a}$$

$$\frac{1}{g}\frac{\partial}{\partial t}\left(\frac{Q}{S}\right) + \frac{1}{2g}\frac{\partial}{\partial z}\left(\frac{Q^2}{S^2}\right) + \frac{\partial H}{\partial z} + I_f - I_0 = 0. \tag{1b}$$

The first Saint Venant equation (1a) originates from the conservation of mass principle while the second equation (1b) results from the conservation of momentum. The gravitational constant is denoted by g, I_0 is the slope of the river bottom along z and I_f refers to the so-called friction slope. All other parameters are derived from the river geometry as shown in Figure 1.

2.2 Model of a Single River Reach

The complete system to be modeled is a river containing five river power plants which divide the river into four reaches. The connections between the reaches are the discharges through the turbines and the locks. Apart from these connections, the hydraulic state of each river reach is independent from the state of the others and each river reach can therefore be modeled separately. For modeling, the inputs of the system are the discharges through up and downstream turbines and locks while its output is the concession level. The Saint Venant equations are simplified to obtain a linear discrete-time state space model for each single river reach. We mainly follow Chapuis (1998). A detailed description of the modeling approach can also be found in v. Siebenthal and Glanzmann (2004).

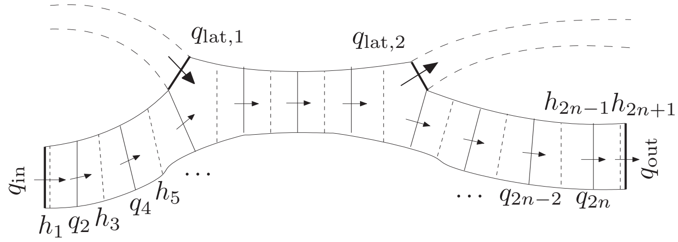

Fig. 2. Division of the river into level and discharge cross sections, lock disturbances modeled as lateral flows

Linearization and Discretization: The system (1a) and (1b) is linearized around an operating point $H_0(z)$ and $Q_0(z)$ and discretized in time and space. The result is a discrete-time model for each river reach i (with lock disturbances still disregarded) of the form

$$\begin{aligned} x^{[i]}(k+1) &= A^{[i]}x^{[i]}(k) + B^{[i]}u^{[i]}(k) + B_{\text{d}}^{[i]}d^{[i]}(k) \\ y^{[i]}(k) &= Cx^{[i]}(k) = h_{\text{c}}^{[i]}(k) \end{aligned} \tag{2}$$

with the state vector $x^{[i]}$, the input vector $u^{[i]}$ and the disturbance vector $d^{[i]}$ according to

$$x^{[i]}(k) = \begin{bmatrix} h_1(k) \\ q_2(k) \\ h_3(k) \\ \vdots \\ q_{2n}(k) \\ h_{2n+1}(k) \end{bmatrix}, \quad \begin{aligned} u^{[i]}(k) &= [q_{\text{out}}(k)]\,, \\ d^{[i]}(k) &= [q_{\text{in}}(k)]\,, \\ & \\ \text{for } i &= 1 \ldots 4. \end{aligned} \tag{3}$$

The matrices $A^{[i]}$, $B^{[i]}$ and $B_{\text{d}}^{[i]}$ are obtained from topographic river data as well as from the considered operating point. The state vector $x^{[i]}$ consists of alternating water levels and discharges (h_j and q_{j+1} respectively) at different cross sections j, shown in Figure 2. For each river reach, $C^{[i]}$ selects the water level at the cross section closest to the measured level, i.e. the concession level $h_{\text{c}}^{[i]}$.

Incorporating Lateral Flows: In this work, not only disturbances coming from power plants further upstream need to be considered, but also additional disturbances due to lock operations. Since the time delay until a disturbance caused by a lock operation reaches the natural river is short, the lock disturbances are incorporated as instantaneous lateral in- and outflows $q_{\text{lat},1}$ and $q_{\text{lat},2}$, as depicted in Figure 2. To add lateral in- and outflows, the model (2) is augmented by changing the state update equation for the cross sections in the neighbourhood of a junction of a lock branch and the natural river accordingly (see v. Siebenthal and Glanzmann (2004)) and by adding the lateral in- and outflows $q_{\text{lat},1}$ and $q_{\text{lat},2}$ to the disturbance vector $d^{[i]}$.

2.3 Model of the Entire Cascade

Figure 3 shows the segmentation of the power plant cascade into four reaches. For each reach, an affine discrete-time state space model (2) is derived as described above. Since one of the control objectives consists in minimizing the changes in the turbine discharges, we rewrite the state space representation into a Δu-formulation. The concatenation of the four models leads to a model for the entire power plant cascade

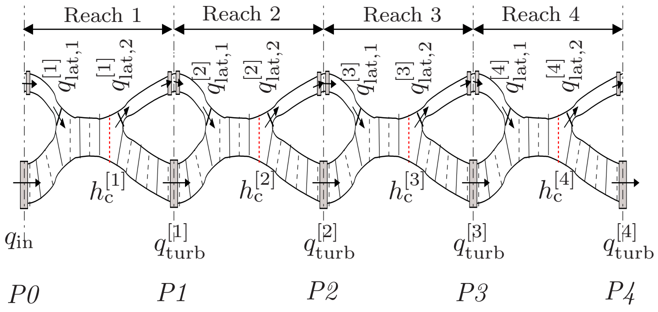

Fig. 3. States and inputs for the power plant cascade

$$\begin{aligned} x(k+1) &= Ax(k) + B\Delta u(k) + B_d d(k), \\ &= Ax(k) + B\Delta u(k) + f(k), \qquad (4) \\ y(k) &= Cx(k) = \left[\, h_c^{[1]}(k)\ h_c^{[2]}(k)\ h_c^{[3]}(k)\ h_c^{[4]}(k) \,\right]^T, \end{aligned}$$

with $h_c^{[i]}$ denoting the deviations of the concession levels from their reference values and f being the affine part of the system. The vector Δu contains the changes in the turbine discharges of the four controlled power plants. The disturbance vector d consists of the lateral in- and outflows caused by lock operations $q_{\text{lat},1}^{[1]}, \ldots, q_{\text{lat},2}^{[4]}$ as well as of the uncontrolled turbine discharge q_{in} of the upstream power plant *P0*. The state vector of the entire cascade is defined as

$$x(k) = \left[\, x^{[1]}(k),\ q_{\text{turb}}^{[1]}(k-1),\ x^{[2]}(k),\ \ldots,\ x^{[4]}(k),\ q_{\text{turb}}^{[4]}(k-1) \,\right]^T$$

with $x^{[i]}$ being the state vector of the river reach i containing water levels and discharges, as denoted in 3. The turbine discharges of the controlled power plants are denoted by $q_{\text{turb}}^{[i]}$.

3. CONTROL

3.1 Control Problem

The inflow and lock disturbances affect the water levels and the discharges of the river. By changing the turbine discharges at the end of each of the four reaches, the water levels are regulated. Hence, the manipulated variables comprise the turbine discharge changes of the four power plants *P1 - P4*. As indicated in (4), the controlled variables are the four concession level deviations.

The control objectives for the controller design problem are threefold. We aim at minimizing a) the deviations of the concession levels from their reference values, b) the turbine discharge variations and c) the amount of control moves, i.e. the number of applied turbine discharge changes. Due to the contradictory nature of the control objectives - e.g. a certain deviation of the concession levels has to be accepted so that the fluctuation in the discharges is kept modest and the amount of control moves small - the plant behavior will result from a compromise between the performance of the concession levels and the turbine discharge variations. Furthermore, constraints on the concession level deviations and the turbine discharges must be respected. These are time-invariant environmental and navigational constraints on the concession level deviations, economical restrictions on the lower boundary and physical constraints on the upper boundary of the turbine discharges. Additionally, the rate of change in the turbine discharges is limited.

3.2 Model Predictive Control

The control approach employed in this work is Model Predictive Control (MPC) (see Maciejowski (2001)). An internal model of the plant is used to predict the evolution of the system's state over a prediction horizon. For the chosen horizon, the optimal sequence of future control moves is computed by minimizing a cost function subject to the constraints. Thereof, only the first control move of the optimal control sequence is applied. At the next time step, the optimization process is repeated from the new initial state by taking actual measurement data into account. A new input sequence is thus determined over the shifted prediction horizon. This process, referred to as the *Receding Horizon Policy*, is repeatedly applied and introduces feedback in the MPC scheme.

3.3 Control of the Power Plant Cascade

We start with a discussion on realizing a control scheme considering only the first two objectives of minimizing the concession level deviations and the turbine discharge variations. This can be achieved using optimization techniques which only involve continuous variables. The third control objective is of a different nature and requires binary variables rendering the control problem more complex as shown in Section 3.4.

The internal model used in this work is an affine discrete-time model given by (4). The control objectives are to minimize the manipulated variables Δu and to keep the concession level deviations close to their reference.

The constraints on the states and the inputs are defined by linear inequalities where the constraints on the concession level deviations, the turbine discharges and the turbine discharge changes per minute are given by

$$\begin{aligned} h_{c,\min} \leq\ & h_c^{[i]} \leq h_{c,\max} \quad \text{for } i = 1, \ldots, 4 \\ q_{\text{turb,min}} \leq\ & q_{\text{turb}}^{[i]} \leq q_{\text{turb,max}} \\ \Delta u_{\min} \leq\ & \Delta q_{\text{turb}}^{[i]} \leq \Delta u_{\max}. \qquad (5) \end{aligned}$$

Due to the presence of constraints, the optimization problem may become infeasible. Although physical constraints cannot be relaxed, operational constraints such as the constraints on the concession level deviations, can be softened. As long as the concession level deviations are within a particular *preferred zone*, higher priority is given to damping the - high frequent - discharge variations. Beyond the preferred zone, the deviation is further categorized into the *emergency zone* which shall be avoided as much as possible. By introducing slack variables for the preferred zone, the constraints on the concession level deviations $h_c^{[i]}, i = 1, \ldots, 4$ are relaxed in the form of *soft* constraints, see Heinrich and Setz (2006) for the formulation details.

The objectives of the control problem and the soft constraints are mathematically formulated in a quadratic cost function calculated over the horizon N,

$$J_N(x(0|t), \Delta U_N) = \qquad (6)$$
$$\sum_{k=1}^{N} x^T(k|t)\mathcal{Q}x(k|t) + \sum_{k=0}^{N-1} \Delta u^T(k|t)\mathcal{R}\Delta u(k|t).$$

Heuristic	# binary variables per plant	$\mathcal{H}_t$	p_t
Int. dead band	$2N$	$\{0,\dots,N-1\}$	N
A	$\sim \log_2 N$	$\emptyset$	1
B	2	$\{0\}$	N
C	$\sim \log_2 N$	$\{0\}$	1

Table 1. Overview of the employed heuristics and their characteristics.

The cost J_N is a function of the initial state $x(0|t)$ at time t and the sequence of control inputs $\Delta U_N = [\Delta u^T(0|t),\dots,\Delta u^T(N-1|t)]^T$. The weight matrices $\mathcal{Q}$ and $\mathcal{R}$ penalize the deviations of the states and inputs from the origin. The cost function (6) is augmented appropriately for the incorporation of slack variables and their weight matrices chosen such that the cost is substantially increased when a violation of the soft constraints occurs.

The optimal input sequence is retrieved by solving the optimization problem

$$J_N^*(x(0|t)) = \min_{\Delta U_N} J_N(x(0|t), \Delta U_N) \tag{7}$$

subject to (4) and (5). This optimal control problem is formulated as a standard QP (Quadratic Program) for which efficient solvers exist. Online optimization is used where the optimal control sequence is computed and the first control move applied according to the receding horizon policy.

3.4 Control of the Cascade with Reduced Number of Control Moves

The minimization of the amount of control moves per day and per turbine is harder to achieve without significantly deteriorating the performance. In order to lessen the amount of controller actions, a heuristic in the form of a dead band is employed in practice where only a discharge variation with an absolute value above Δq_{dband} is allowed to be applied to the system. By making use of the predictive feature of MPC, the dead band can be considered within the controller and is included in the optimization process. For the present time step $\Delta q_{\text{turb}}(0|t)$ as well as for the predicted system inputs $\Delta q_{\text{turb}}(k|t), k = 1,\dots,N-1$, the restrictions $|\Delta q_{\text{turb}}| \geq \Delta q_{\text{dband}}$ or $\Delta q_{\text{turb}} = 0$ are taken into account for each river reach.

The internal dead band of each powerplant is modeled by the following constraint inequalities using two binary variables δ_1 and δ_2 such that

$$\begin{aligned} \Delta q_{\text{turb}} &\geq \Delta q_{\text{dband}} \cdot \delta_1 + \Delta u_{\min} \cdot \delta_2 \\ \Delta q_{\text{turb}} &\leq -\Delta q_{\text{dband}} \cdot \delta_2 + \Delta u_{\max} \cdot \delta_1 \\ 1 &\geq \delta_1 + \delta_2. \end{aligned} \tag{8}$$

The optimal control problem is thus augmented and described by (7) s.t. (4), (5) and (8) using the so-called MLD formulation, Bemporad and Morari (1999).

Integrating the internal dead band into the controller for each control move within the prediction horizon may amount to an excessive computation time and memory requirements for the optimization problem. This is due to the introduction of new binary variables for each power plant and control move within the horizon. In order to obtain a relaxation of the original problem, other heuristics are applied. Mixed-integer inequalities are implemented with less complex logical conditions still forcing the number of control moves to decrease.
In the following, three heuristics are introduced. Let us denote with

$$\mathcal{H}_t = \Big\{ k \in \Big\{0,\dots,N-1\Big\} \,\Big|\, |\Delta q_{\text{turb}}(k|t)| \overset{!}{\geq} \Delta q_{\text{dband}} \text{ or } \Delta q_{\text{turb}}(k|t) \overset{!}{=} 0 \Big\}. \tag{9}$$

the set of indices of all the control moves within the horizon N for each power plant on which the dead band constraint is taken into account at time t. Additionally, the variable p_t is defined, denoting the number of allowed control moves during the prediction horizon for each plant. The characteristics of the employed heuristics are summarized in Table 1.

In the first *Heuristic A*, only one control move per turbine during the prediction horizon is permitted in order to reduce the amount of control moves but at the same time allowing a good performance by not restricting the input values (thus $\mathcal{H}_t = \emptyset$ and $p_t = 1$). This requires the use of a single integer variable for each power plant.
However, applying the constraint $p_t = 1$ does not guarantee only one move every N time steps due to the receding horizon policy. The computed optimal input sequence $\Delta q_{\text{turb}}(k|t), k = 0,\dots,N-1$, at each time step t is likely to render the first control move $\Delta q_{\text{turb}}(0|t)$ unequal to zero. As a consequence, a rather high number of control moves have been observed using *Heuristic A*.

In *Heuristic B*, the internal dead band (8) is implemented only for the first control move of the optimal input sequence in order to reduce the computational complexity. By these means, the first move is selected only when necessary. The control move restrictions are expressed as $\mathcal{H}_t = \{0\}$ and $p_t = N$. The first control move is expected to be often set to zero since there is no value restriction on the following control moves and no constraint on the amount of control moves within the prediction horizon. This effect drastically reduces the number of control moves, however at the cost of a large decrease in performance.

Based on the benefits and the drawbacks of the above heuristics, *Heuristic C* is derived which is a combination of *Heuristic A* and *Heuristic B* profiting from the assets of both. One control move is permitted during the prediction horizon and the dead band is only applied if the first control move within the horizon is selected. In order to produce a lower cost when setting the first control move $\Delta q_{\text{turb}}(0|t)$ to zero, the dead band restrictions on $\Delta q_{\text{turb}}(k|t), k = 1,\dots,N-1$ are lifted. The controller setting is characterized by $\mathcal{H}_t = \{0\}$ and $p_t = 1$.

For details regarding the comparison of the above heuristics, see Heinrich and Setz (2006).

4. SIMULATION RESULTS

4.1 Simulation Setup

All investigated scenarios are performed at low water flow where the mean discharge in the river is around

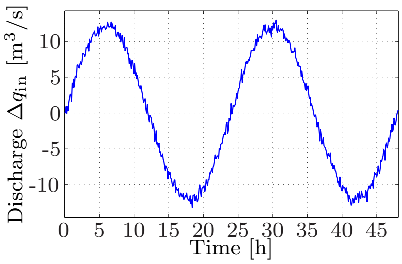

Fig. 4. Inflow disturbance

40 m^3/s, since the control task is most difficult in this situation. In order to run closed-loop simulations for different MPC controllers, the real power plant cascade is replaced by a FLORIS[1] hydraulics software model, also used to obtain the parameters of the internal model of the MPC controller, as described in Section 2.3. Local PI controllers with feed-forward and a dead band of 2.5 m^3/s are employed for comparison with MPC. The parameters for the PI controllers are set according to the parameters used in practice for the real power plant cascade.

An MPC sampling time of 6 minutes is chosen, and the horizon N amounts to 25 time steps (2.5 hours). This corresponds approximately to the propagation delay of a disturbance traveling from the inflow of the cascade to the last controlled power plant. A realistic scenario of 48 hours was investigated. As disturbance entering at the uncontrolled power plant, a sine wave with a period of 24 hours and an amplitude of 12 m^3/s, overlaid with gaussian noise, was chosen as depicted in Figure 4. At every controlled power plant as well as at the uncontrolled power plant at the beginning of the cascade, locks operate 20 times a day between 5.00 a.m. and 10.00 p.m. with a constant frequency. The discharge at a particular lock gate during lock operation depends on the size of the lock. It ranges from 12.8 to 23.12 m^3/s.

4.2 Control of the Power Plant Cascade

Figures 5 and 6 show a comparison between the PI controller and three MPC controllers. Figure 5 presents the concession levels in the reaches three and four of the four controlled power plants while Figure 6 shows the corresponding turbine discharges. See Heinrich and Setz (2006) for the results of the reaches one and two. All signals are depicted as deviation from the operating point. The two solid lines in Figure 5 represent the boundaries of the preferred zone for the concession levels. The solid lines in Figure 6 indicate the lower constraint on the turbine discharges.

The MPC controller in the second row of Figure 5 and 6 represents an ideal case. There are no restrictions on the amount of control moves and all information regarding future disturbances is assumed to be available within the prediction horizon. Since in reality there is only limited information about the lock operations, we show in the third row the performance of an MPC controller not using any inflow or lock disturbance information.

The deviations of the concession levels, Figure 5, for both MPC controllers are smaller than for the PI controller.

[1] SCIETEC, developer and distributor of the river simulation software FLORIS, http://www.scietec.at

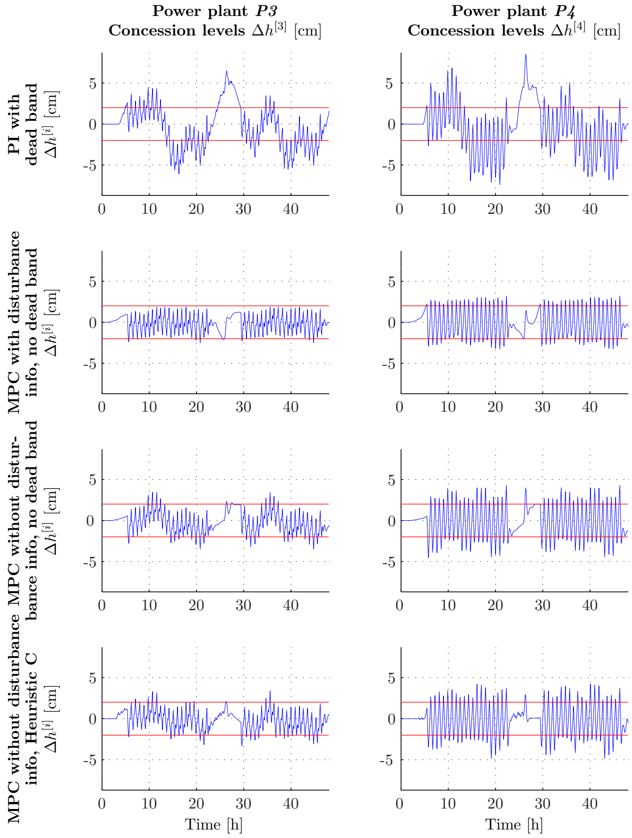

Fig. 5. Comparison of PI and MPC, concession levels

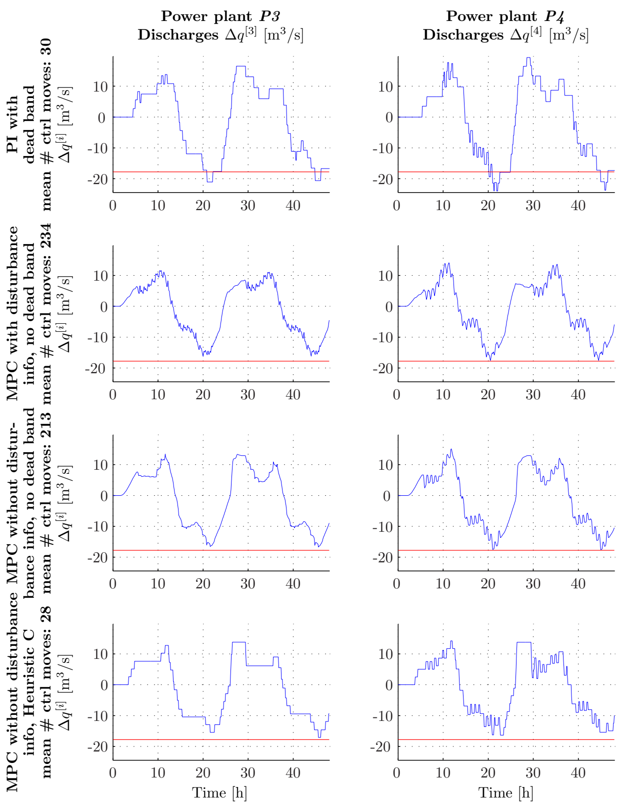

Fig. 6. Comparison of PI and MPC, turbine discharges

However, for the controller not using any disturbance anticipation, the concession levels are not kept inside the preferred zone of ± 2 cm. One reason is the lack of lock information. Incorporating lock disturbance information significantly improves the performance of the MPC controller. The concession levels are now kept within the preferred zone for reach three while in the fourth reach, the violations of the ± 2 cm bounds are reduced. The latter is a result of the small storage capacity of the fourth river reach (the fourth reach is the shortest reach within the considered cascade) and the proximity of the concession level to the lateral outflow.

Regarding the discharges in Figure 6, both MPC controllers achieve a better damping of the low-frequent variations induced by the inflow disturbance than the PI controller. The damping of the high-frequent, lock induced variations is comparable for MPC and PI control. Furthermore, the PI controller violates the lower constraint on the turbine discharges while the MPC controllers respect it. The high-frequent discharge variations for the MPC controller incorporating disturbance anticipation are slightly larger than for the MPC controller without disturbance information in order to keep the concession levels within the preferred zone.

4.3 Control of the Cascade with Reduced Number of Control Moves

In the following, we comment on the simulation results for the control of the power plant cascade with the aim to reduce the number of applied control moves. The MPC controller is based on *Heuristic C* derived in Section 3.4 and is compared with the PI controller to which an external dead band is added.

Rows one and four of Figures 5 and 6 compare the PI controller with the MPC controller based on *Heuristic C*. For reasons of computation time, the horizon is chosen as $N = 15$. In addition, the dead band of the MPC controller has been incorporated adaptively in order to achieve smaller limit cycles. The PI controller has slightly more control moves and performs worse, especially regarding the violation of the preferred zone boundaries. Contrary to the PI controller, the economical lower constraint on the turbine discharges is always obeyed by the MPC controller.

5. CONCLUSIONS

This paper presents a supervisory MPC scheme for a cascade of five hydroelectric power plants. The main aim is to keep the water level deviations small by manipulating the turbine discharges in a coordinated fashion. Locks facilitating navigation in the river introduce additional disturbances that need to be coped with.

The control objective of minimizing the changes in the water discharges through the turbines, while keeping the water levels of the river within certain prespecified tolerance bounds is formulated mathematically. Based on this formulation together with a first principles model of the river an MPC controller is derived.

Subsequently, the problem is augmented by an additional control objective, namely that of achieving the above mentioned performance while keeping the number of the applied changes in the turbine discharges modest in order to avoid the excessive use of the equipment and therefore their wearing out. The mathematical expression of the latter objective requires the introduction of binary variables in the control problem, which significantly increases its complexity. Three heuristics using different move blocking strategies are developed and evaluated in terms of the trade off between the computational complexity and the achieved performance. As the simulation results show, the introduced MPC controller can achieve a significantly better performance than the PI controller.

Moreover, the potential benefits of utilizing additional information of anticipated future lock disturbances are investigated and the achieved performance compared to the one of the currently employed control scheme.

Ongoing work comprising the actual implementation of the controller on the river will test the behavior of the designed MPC controller in practice. Furthermore it will be investigated how the control scheme scales up for longer cascades comprising a larger number of power plants. Distributed MPC implementations and robustness issues will be considered as well.

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