Flood control of rivers with nonlinear model predictive control and moving horizon estimation

Maarten Breckpot, Toni Barjas Blanco and Bart De Moor.

***Abstract*— This paper shows that model predictive control (MPC) in combination with moving horizon estimation (MHE) can more effectively be used for flood prevention in comparison with an advanced three-position controller. Because MPC takes rain predictions into account, it uses the buffer capacity of the available flood basins in a more optimal way. Simulation results for historical data for the Demer, a river in Belgium with a history of large floodings, show a significant reduction of the number and the impact of floodings when MPC is used. Because of the strong nonlinear river dynamics it is necessary to use nonlinear MPC. The use of a state estimator like MHE is necessary because only some of the states are measured.**

I. INTRODUCTION

Flooding of rivers is a worldwide problem with severe consequences. The Demer, a river in Belgium, has in this context a bad reputation. The Demer often floods during periods of heavy rainfall. As counter measure the local water administration expanded the storage capacity of the river with flood reservoirs to store the excessive amount of water during periods of heavy rainfall. They also installed hydraulic gates to control the discharges in the river and the flow of water from and into these reservoirs. Nowadays, the hydraulic structures are controlled with an advanced three-position controller which determines the control actions based on some simple rules. However, these constructions could not prevent the Demer from flooding again in 1998 and 2002. The main reason is that the controller does not take the rain forecasts into account. Therefore the control actions are often suboptimal. This paper shows that this is not the case when a model predictive controller is used.

A. *Model Predictive Control*

Model predictive control (MPC) is an optimal control strategy originating from the process industry to operate power stations and petroleum refineries more efficiently in combination with the tightened environmental, quality and safety regulations. Nowadays it has gained widespread acceptance in industry due to its unique advantages compared to classic control methods and it is used in many diverse industries like the food industry and aviation [9]. MPC distinguishes itself by the ability to efficiently control large-scale interconnected systems and the inherent ability to handle physical and other constraints of the controlled system. MPC works with a dynamical model of the system and applies mathematical optimization techniques to obtain the optimal inputs to be applied to the system [13].

Several studies can be found in literature where MPC is used to control water systems [15], [16] and [5]. However, these studies are focussed on steering the water levels to their set-points and not on flood prevention. This simplifies the use of MPC as the nonlinear river dynamics can be approximated sufficiently accurate by a linear model. A simple linear model is not sufficient for flood control because heavy rainfall excites the entire nonlinear dynamics. In previous work [2], [3] and [4] a MPC strategy was presented for flood control of the Demer. In this work all the constraints were imposed as hard constraints and a constraint strategy had to be developed. In the work presented in this paper the flood levels are imposed as soft constraints. The previous work also assumes that all the states of the system are known at every time step. This is however not realistic as only the water levels are measured and e.g. the discharges not. In this paper this assumption is dropped and a moving horizon estimator is used as state estimator.

B. *Moving Horizon Estimation*

For the estimation of the current state of the system, moving horizon estimation (MHE) is used [10], [11] and [8]. MHE can be regarded as the dual of MPC. Also MHE makes use of a dynamical model of the system which is used in an optimization problem that minimizes the deviations between the measurements and the estimated states over a finite horizon.

II. CURRENT CONTROL

There exist many different control strategies for the control of rivers. An overview can be found in [12] and [7]. Nowadays the hydraulic structures in the Demer are controlled by an advanced three-position controller. The control actions of a standard three-position controller are based on the deviation of the water levels from their set-point:

1) move the gate to decrease the water level if it is above its set-point,
2) move the gate to increase the water level if it is below its set-point
3) and do not move the gate if the water level is close enough to the set-point.

In practice this type of controller is often used to steer the corresponding water level to a desired reference level. The three-position controller used to control the Demer is more advanced. It contains extra logical rules that are based on the experience of operators which are used to avoid

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flooding instead of optimal set-point regulation. However this controller still has two important drawbacks: the control actions are only based on the current state of the system and do not take rain predictions into account. Therefore it will not react preventive on periods of heavy rainfall. A better alternative is to use a control strategy that takes the rain forecasts into account like model predictive control.

III. MODEL PREDICTIVE CONTROL

A. Why MPC?

The use of MPC for flood control can be justified by the following properties:

- Because MPC solves an optimization problem, it can cope with all the constraints that are present in a river system like physical upper and lower bounds of the gates and maximal gate movement. Also upper constraints on the water levels can be taken into account which is necessary for flood prevention. There is no strict limit on the time allowed for solving the optimization problem because river systems have relatively slow dynamics.
- MPC can use the mathematical model of the river to predict the influence of the rainfall predictions on the future water level. This information can be used to make better decisions to prevent flooding.
- River systems are typically highly interactive multi-input-multi-output systems (MIMO). It is known that traditional control design for such kind of systems is very difficult because they make use of relatively little information about the system. MPC, however, can effectively deal with MIMO systems.
- Because during a flood event all the nonlinear dynamics of the river system are excited, it is necessary to have a controller that can work with a nonlinear model of the river system. In literature efficient nonlinear MPC schemes can be found that work with nonlinear models [6].

B. The river models

Because MPC uses a process model, the first task is to find an appropriate model. The models used for the Demer are built, calibrated and validated by the Department of Civil Engineering of the K.U.Leuven. These models are of the reservoir type and are based on the principles described in [14]. Fig. 1 shows the structure of the model for the study scope of the Demer. This model contains two basins: Schulensmeer and Webbekom. Because this work is the first time MPC is used in combination with MHE for flood control, the focus is limited to the upper stream part of the Demer indicated in the figure by the (red) ellipse. See Fig. 2 for a more detailed view. This upper stream part of the river consists of ten states (three water levels, four discharges and three volumes) and three inputs (the gates A, D and K7). The outputs of the system are the three water levels h_{opw} (the upstream water level), h_{afw} (the downstream water level) and h_{s} (the water level of the reservoir Schulensmeer). The

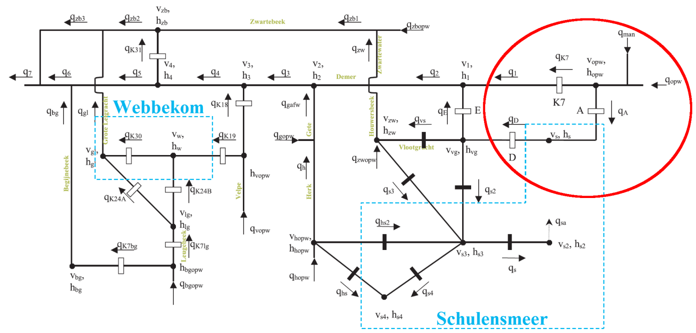

Fig. 1. Model structure of the Demer for the study area with the basins Webbekom and Schulensmeer.

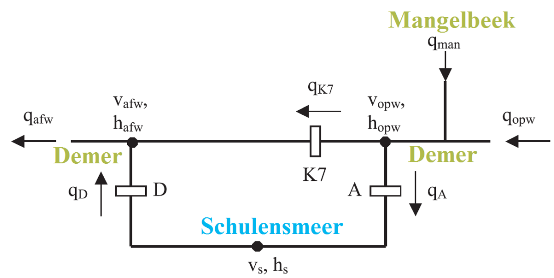

Fig. 2. Model structure of the Demer for the area around Schulensmeer.

disturbance inputs are the upstream discharges q_{opw} and q_{man} which model the rainfall entering the river system.

The river model is a nonlinear state space model:

$$\begin{cases} \boldsymbol{x}_{k+1} &= \boldsymbol{s}(\boldsymbol{x}_k, \boldsymbol{u}_k, \boldsymbol{d}_k) \\ \boldsymbol{y}_k &= \boldsymbol{C}\boldsymbol{x}_k \end{cases} \tag{1}$$

with $\boldsymbol{x}_k$ the state vector at time k, $\boldsymbol{u}_k$ the input vector at time k, $\boldsymbol{d}_k$ the disturbance vector at time k and $\boldsymbol{y}_k$ the output vector at time k. The same model is used as in [2]. One difficulty in using MPC for flood control lies in the nonlinear river dynamics. The relation between the discharge over a gate and the height of the gate and the water surrounding the gate is strongly nonlinear. For flood control it is very important that the controller can deal with these nonlinearities. Therefore nonlinear model predictive control (NMPC) will be used.

C. NMPC algorithm

In [6] efficient nonlinear MPC schemes can be found that work with nonlinear models. The algorithm used in this paper consists of the following steps:

1) Predict at step n the future states in the prediction horizon with the nonlinear model for the optimal inputs found in the previous step $n-1$ and the rain forecasts. Derive at each time instant within the prediction horizon a linear state space model based on the future states and the optimal inputs of the previous step:

$$\boldsymbol{A}_{k+i}(:,m) = \left.\frac{\partial \boldsymbol{s}}{\partial \boldsymbol{x}_{k+i}(m)}\right|_{\boldsymbol{x}^0_{k+i},\boldsymbol{u}^0_{k+i}}, \tag{2}$$

$$\boldsymbol{B}_{k+i}(:,m) = \left.\frac{\partial \boldsymbol{s}}{\partial \boldsymbol{u}_{k+i}(m)}\right|_{\boldsymbol{x}^0_{k+i},\boldsymbol{u}^0_{k+i}} \tag{3}$$

with $\boldsymbol{A}_{k+i}(:,m)$ and $\boldsymbol{B}_{k+i}(:,m)$ the m-th column of $\boldsymbol{A}_{k+i}$ and $\boldsymbol{B}_{k+i}$, $\boldsymbol{u}^0_{k+i}$ the optimal inputs found in the previous step on time instant i in the prediction horizon and $\boldsymbol{x}^0_{k+i}$ the predicted future states at time instant i. The linearization used in this paper is done with central differences. This step gives a sequence of time variant linear models of the form:

$$\begin{cases} \boldsymbol{x}_{k+i+1} = \boldsymbol{A}_{k+i}\boldsymbol{x}_{k+i} + \boldsymbol{B}_{k+i}\boldsymbol{u}_{k+i} + \boldsymbol{f}_{k+i} \\ \boldsymbol{y}_{k+i} = \boldsymbol{C}\boldsymbol{x}_{k+i} \end{cases} \tag{4}$$

with $i \in \{0,\dots,N-1\}$ and $\boldsymbol{f}_{k+i}$ a vector containing the information of the linearization point $(\boldsymbol{x}^0_{k+i}, \boldsymbol{u}^0_{k+i})$:

$$\boldsymbol{f}_{k+i} = \boldsymbol{x}^0_{k+i+1} - \boldsymbol{A}_{k+i}\boldsymbol{x}^0_{k+i} - \boldsymbol{B}_{k+i}\boldsymbol{u}^0_{k+i}. \tag{5}$$

2) Solve an optimization problem based on these linear models to determine a sequence of optimal inputs.
3) Because the linear models are only a valid approximation for the nonlinear system around the linearization point, the solution of the optimization problem does not necessarily lead to an improved point. If the new point lies too far away from the linearization point, the new point could be a worse solution. Therefore a simple line search between the linearization point and the new point is performed. More information can be found in [4].
4) Because of the approximation of the nonlinear model, the previous steps are repeated until convergence or until time runs out. Afterwards the first input is applied to the system and the procedure is repeated.

A schematical representation of this procedure can be found in Fig. 3.

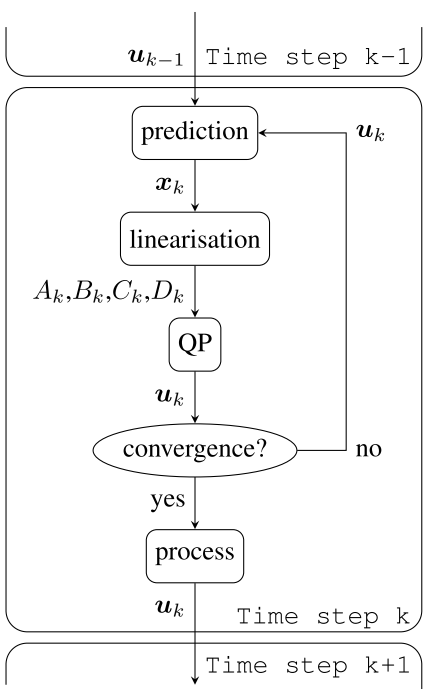

Fig. 3. Schematical representation of the NMPC algorithm.

In [1] it has been shown that this algorithm delivers a local minimum of the nonlinear control problem where the original nonlinear model is used.

D. The optimization problem

When there is no or little rainfall the objective is to steer the most important water levels to their set-point. When there is heavy rainfall the objective is to prevent the water levels from flooding. As it will be shown both tasks can be accomplished with the following quadratic program (QP):

$$\min_{\substack{\boldsymbol{u}_k,\dots,\boldsymbol{u}_{k+N-1}\\ \boldsymbol{x}_{k+1},\dots,\boldsymbol{x}_{k+N}\\ \boldsymbol{y}_{k+1},\dots,\boldsymbol{y}_{k+N}\\ \boldsymbol{\xi}_{k+1,1},\dots,\boldsymbol{\xi}_{k+N,1}\\ \boldsymbol{\xi}_{k+1,2},\dots,\boldsymbol{\xi}_{k+N,2}}} \sum_{i=1}^{N}\left(\left\| \begin{matrix}\boldsymbol{\xi}_{k+i,1}\\ \boldsymbol{\xi}_{k+i,2}\end{matrix} \right\|^2_{\boldsymbol{S}} + \|\boldsymbol{y}_{k+i} - \boldsymbol{y}^{\mathrm{r}}\|^2_{\boldsymbol{Q}} + \|\boldsymbol{u}_{k+i-1} - \boldsymbol{u}^{\mathrm{r}}_{k+i-1}\|^2_{\boldsymbol{R}_{k+j}} \right) \tag{6}$$

subject to

$$\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k, \tag{7}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{x}_{k+j} = \boldsymbol{A}_{k+j-1}\boldsymbol{x}_{k+j-1} + \boldsymbol{B}_{k+j-1}\boldsymbol{u}_{k+j-1} + \boldsymbol{f}_{k+j-1}, \tag{8}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{y}_{k+j} = \boldsymbol{C}\boldsymbol{x}_{k+j}, \tag{9}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{u}_{\min} \le \boldsymbol{u}_{k+j-1} \le \boldsymbol{u}_{\max}, \tag{10}$$

$$j \in \{1,\dots,N-1\}: \quad |\boldsymbol{u}_{k+j} - \boldsymbol{u}_{k+j-1}| \le \Delta_{\max}, \tag{11}$$

$$|\boldsymbol{u}_k - \boldsymbol{u}^0_{k-1}| \le \Delta_{\max}, \tag{12}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{y}_{k+j} - \boldsymbol{\xi}_{k+j,1} \le \boldsymbol{y}_{\max,1}, \tag{13}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{y}_{k+j} - \boldsymbol{\xi}_{k+j,2} \le \boldsymbol{y}_{\max,2}, \tag{14}$$

$$j \in \{1,\dots,N\}: \quad \boldsymbol{\xi}_{k+j,1} \ge 0, \boldsymbol{\xi}_{k+j,2} \ge 0 \tag{15}$$

with N the length of the prediction horizon, $\boldsymbol{Q}$, $\boldsymbol{R}_k$ and $\boldsymbol{S}$ positive definite diagonal matrices, $\boldsymbol{y}^{\mathrm{r}}$ and $\boldsymbol{u}^{\mathrm{r}}_k$ the reference values for the outputs, resp. the inputs. $\hat{\boldsymbol{x}}_k$ is the estimated state with MHE (see section IV) at time step k. Constraint (10) represents the physical limits of the gates and constraints (11) and (12) represent the maximal possible gate movement with $\boldsymbol{u}^0_{k-1}$ the optimal inputs applied in the previous time step. Constraints (8) and (9) make sure that the optimization variables obey the linear model equations. Constraints (13) and (14) bound the water levels to prevent them from flooding. Both are soft constraints with slack variables $\boldsymbol{\xi}_{k,1}$ and $\boldsymbol{\xi}_{k,2}$ for which each component is always greater than or equal to zero (constraint (15)). A value different from zero for $\boldsymbol{\xi}_{k,m}$ corresponds with the amount by which the corresponding water level exceed its upper bound $\boldsymbol{y}_{\max,m}$.

The elements of $\boldsymbol{S}$ are taken much larger than the elements of $\boldsymbol{Q}$ and $\boldsymbol{R}_k$. Therefore an increase in $\boldsymbol{\xi}_{k,1}$ or $\boldsymbol{\xi}_{k,2}$ has the greatest impact on the cost function (6). However, they can only be set equal to zero when the water levels do not exceed their upper bounds. When this is possible the objective of the controller should be to steer the most important water levels to their set-point which is achieved when the elements of $\boldsymbol{Q}$ are larger than the elements of $\boldsymbol{R}_k$. It is important that the controller does not use the reservoirs to improve the set-point regulation of the water levels because this would reduce the available storage capacity for future rainfall. This can be prevented by putting a higher weight on the deviation from the water reservoirs from their set-points than on the deviation of the other water levels. When it is not possible to set $\boldsymbol{\xi}_{k,1}$ and $\boldsymbol{\xi}_{k,2}$ equal to zero, this means that there is a risk of flooding. Because of the heavier weight on $\boldsymbol{\xi}_{k,1}$ and $\boldsymbol{\xi}_{k,2}$ in the cost function, the controller will now focus on flood prevention. Instead of steering the water levels to their set-points, the controller will try to minimize the difference between the water levels and their upper bounds and hence reduce the flood risk.

The use of two sets of upper bounds is justified by the following reasoning. Because most weather predictions longer than two days are unreliable, the prediction horizon is limited to two days. However serious rain events that cause floods typically last longer than two days. If a prediction horizon of two days would be used and the flood levels are the only constraints on the water levels, the optimal solution can be to fill the water reservoirs up to their flood level at the end of the horizon because the controller does not know that it might still rain after the prediction horizon. This leaves no storage capacity for future rainfall and floodings will take place. Therefore, conservativeness must be added to the control strategy. This is achieved by using two sets of upper bounds on the water levels:

- For each water level a guard level ($\boldsymbol{y}_{\max,1}$) is defined by the local water administration. Every guard level has a value smaller than the corresponding flood level ($\boldsymbol{y}_{\max,2}$). As long as the water levels do not violate their guard level, all the slack variables are zero and the reservoirs will not be used.
- When a water level will violate its guard level, its slack variable $\boldsymbol{\xi}_{k,1}$ will be different from zero. Because the controller tries to minimize these variables, its focus shifts towards flood prevention and it will use the water reservoirs to prevent the violation of the guard levels. However, to prevent the usage of the complete storage volume available in the reservoirs, every reservoir can only be filled to a first upper limit ($\boldsymbol{y}_{\max,1}$). Once this limit is reached the reservoirs may not be used anymore and the guard levels might get violated. This is achieved by putting a higher weight on $\boldsymbol{\xi}_{k,1}$ for the water reservoirs than for the water levels.
- If it continues raining and MPC cannot keep the water levels beneath their flood level ($\boldsymbol{y}_{\max,2}$), the controller is allowed to further fill the reservoirs until they reach their corresponding flood level. This is achieved by putting a higher weight on $\boldsymbol{\xi}_{k,2}$ than for $\boldsymbol{\xi}_{k,1}$.

Besides reference values for the water level the optimization problem also uses reference values for the gates. This is to keep the gates within their controllable region. The gate equations contain modes for which the discharge over the gate is independent of the gate itself, e.g. when the gate is completely closed or when the gate is much lower than the water levels up- and downstream of the gate. By moving the gate by a small amount the discharge will not change for these modes. This is reflected in the linearized model where the position of the gate has no influence on the discharge over the gate. After the simulation step every gate at every time step in the prediction horizon is checked to see whether it is controllable or not. Every uncontrollable gate gets a reference value between the up- and downstream water levels of the gate and the corresponding weight in the matrix $\boldsymbol{R}_k$ is increased which forces the controller to steer the uncontrollable gate into the controllable region. More details can be found in [3].

In previous work all the constraints on the water levels were hard constraints and a constraint strategy had to be developed in order to keep the QP feasible. On certain time instants multiple optimization problems had to be solved. This is here not necessary because the slack variables keep the QP always feasible. A disadvantage is the increase in the number of optimization variables which makes the optimization problem more complex to solve. In this study the controller is implemented such that the slack variables are included only when they are needed to keep the problem feasible. After the prediction step the simulated water levels are checked to see if they exceed $\boldsymbol{y}_{\max,1}$ or $\boldsymbol{y}_{\max,2}$. For every violation of these constraints only the corresponding slack variable is included in the optimization problem.

IV. MOVING HORIZON ESTIMATION

A. Why MHE?

In order to find a optimal sequence of inputs, the controller needs to know the current state of the system. In previous work it was assumed that all the states are known at every time step. However, in practice not all the states of the river are measured. In fact only the water levels are measured, the discharges and the water volumes not. Therefore it is necessary to include a state estimator in this application.

MHE estimates the states by solving an optimization problem using a moving and fixed-size window of data. When new measurements become available, the oldest measurements are discarded and a new optimization is solved to estimate the new state of the system. MHE has two important advantages compared to the classical Kalman filter. Because MHE is optimization based, MHE can take constraints on states and disturbances into account. A second advantage is the ability to handle explicitly nonlinear systems. Because the river dynamics are strongly nonlinear, MHE is chosen for this study.

B. The optimization problem

The optimization problem that is solved at every time step is of the form:

$$\min_{\substack{\hat{\boldsymbol{x}}_{k-T},\ldots,\hat{\boldsymbol{x}}_k \\ \hat{\boldsymbol{y}}_{k-T+1},\ldots,\hat{\boldsymbol{y}}_k}} \sum_{i=1}^{T} \|\hat{\boldsymbol{y}}_{k-i+1} - \boldsymbol{y}^{\mathrm{m}}_{k-i+1}\|^2_{\boldsymbol{W}} \tag{16}$$

subject to

$$j \in \{1,\ldots,T\}: \quad \hat{\boldsymbol{y}}_{k-j+1} \geq \boldsymbol{y}_{\min}, \tag{17}$$

$$j \in \{1,\ldots,T\}: \quad \hat{\boldsymbol{x}}_{k-j+1} = \boldsymbol{A}_{k-j}\hat{\boldsymbol{x}}_{k-j} + \boldsymbol{B}_{k-j}\boldsymbol{u}_{k-j} + \boldsymbol{f}_{k-j}, \tag{18}$$

$$j \in \{1,\ldots,T\}: \quad \hat{\boldsymbol{y}}_{k-j+1} = \boldsymbol{C}\hat{\boldsymbol{x}}_{k-j+1} \tag{19}$$

where T is the length of the estimation horizon, $\boldsymbol{W}$ is a positive definite diagonal matrix, $\boldsymbol{y}_k^{\mathrm{m}}$ are the measured outputs and $\boldsymbol{y}_{\min}$ are known lower limits for the outputs. $\hat{\boldsymbol{x}}_k$ and $\hat{\boldsymbol{y}}_k$ are the estimates for the unknown states $\boldsymbol{x}_k$, resp. unknown outputs $\boldsymbol{y}_k$.

Just like for MPC, the MHE estimator has to solve this optimization problem multiple times untill convergence is achieved or time runs out. The linear models can be derived on a same way as for MPC. The estimator gives the estimate $\hat{\boldsymbol{x}}_k$ of the current state to the controller which it uses to find a new sequence of optimal inputs. The first input is applied to the system, new measurements are taken and the entire procedure is repeated.

V. SIMULATION RESULTS

In this section the MHE based MPC controller will be compared with the advanced three-position controller by performing a simulation based on the historical rainfall data of 1998. Some important details of the simulation are (all the mentioned values are above mean sea level, AMSL):

1) During periodes of no or light rainfall, the controller should keep the upstream water level h_{opw} as close as possible to 21.5 m while avoiding an increase of the water level h_{s} of the reservoir Schulensmeer.
2) During periods of heavy rianfall, the objective of the controller is to keep the three water levels below their flood levels ($\boldsymbol{y}_{\max,2}$):
   - $h_{\mathrm{opw}} \leq 23.2$ m,
   - $h_{\mathrm{s}} \leq 23.2$ m
   - and $h_{\mathrm{afw}} \leq 22.75$ m.

   The values for $\boldsymbol{y}_{\max,1}$ are given by:
   - $h_{\mathrm{opw}} \leq 23$ m,
   - $h_{\mathrm{s}} \leq 23$ m
   - and $h_{\mathrm{afw}} \leq 22.75$ m.

   Note that the values of $\boldsymbol{y}_{\max,1}$ and $\boldsymbol{y}_{\max,2}$ are the same for h_{afw}.
3) The physical limits on the gates are:
   - 20 m $\leq k_{\mathrm{A}} \leq$ 23 m,
   - 20.03 m $\leq k_{\mathrm{K7}} \leq$ 23 m
   - and 18.9 m $\leq k_{\mathrm{D}} \leq$ 22.9 m.

   The gates are not allowed to move faster than 0.1 m/hour.
4) It is assumed that the nonlinear model of the Demer is perfectly known (no plant-model mismatch) and that the rain predictions are also perfectly known.

For the simulations the prediction horizon N equals 48 hours while the estimation horizon T equals 10 hours. The simulation results for the advanced three-position controller are visualized in Fig. 4, the results for the MHE based MPC controller in Fig. 5:

1) During the first 250 hours the MHE based MPC controller steers h_{opw} much closer to its set-point of 21.5 m than the advanced three-position controller. The oscillations for the MHE based MPC controller are also much smaller. The advanced three-position controller can also not prevent that the storage capacity of the reservoir is reduced. This is not the case when MPC is used.
2) The advanced-three position controller is not capable to prevent the downstream part of the river from flooding with more than 40 cm during the heavy rainfall during the next 150 hours. There is also almost no margin left for the two other water levels. The results are much better when MPC is used because it uses the basins and the available information in an optimal way: the flooding for the downstream part of the river is reduced to only 2.5 cm and the two other water levels have a margin of almost 20 cm.
3) After the heavy rainfall MPC succeeds in restoring the storage capacity of the reservoir in a much faster way. With MPC a second period of heavy rainfall could more easily be covered than with the advanced three-position controller. MPC also steers h_{opw} much closer to its set-point.

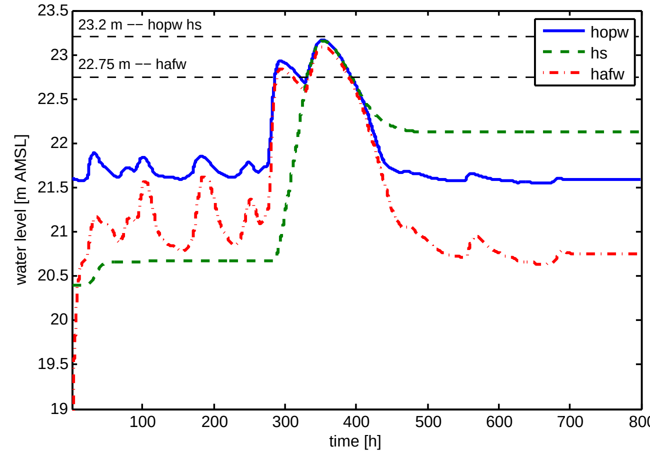

Fig. 4. Simulation results for the water levels for the advanced three-position controller for the small model of the Demer.

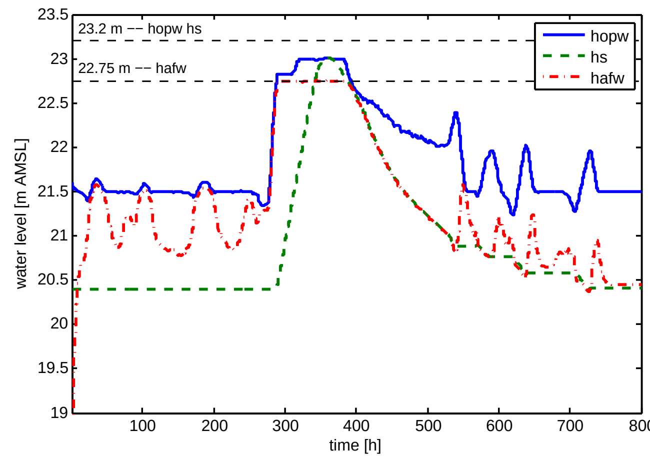

Fig. 5. Simulation results for the water levels for the MHE based MPC controller for the small model of the Demer.

VI. CONCLUSIONS AND FUTURE WORKS

In this work a nonlinear MHE based MPC controller for flood control is discussed and compared with the current controller used for flood prevention of the Demer. The optimization problem solved by the MPC controller is formulated with slack variables. Since only some of the states are measured in practice, a MHE estimator is included to estimate the other states. The MHE based MPC controller is tested on the historical data of the flood event of 1998. The simulations show that the MHE based MPC controller outperforms the current advanced three-position controller.

The MHE based MPC controller is in this study implemented for only a limited part of the Demer. Future research will be the implementation of a MHE based MPC controller for a much larger part of the Demer. Another topic will be to investigate the impact of uncertainties on the weather predictions on the performance of the controller. Finally a last topic is to use a very detailed model of the river to simulate the process and to see what the influence of this plant-model mismatch is on the performance.

VII. ACKNOWLEDGMENTS

Maarten Breckpot and Toni Barjas Blanco are research assistants at the Katholieke Universiteit Leuven, Belgium. Dr. Bart De Moor is a full professor at the Katholieke Universiteit Leuven, Belgium. Research supported by Research Council KUL: GOA AMBioRICS, GOA MaNet, CoE EF/05/006 Optimization in Engineering(OPTEC), IOF-SCORES4CHEM, several PhD/postdoc & fellow grants; Flemish Government: FWO: PhD/postdoc grants, projects G.0452.04, G.0499.04, G.0211.05, G.0226.06, G.0321.06, G.0302.07, G.0320.08, G.0558.08, G.0557.08, G.0588.09 research communities (ICCoS, ANMMM, MLDM); G.0377.09; IWT: PhD Grants, McKnow-E, Eureka-Flite+, SBO LeCoPro, SBO Climaqs, POM; Belgian Federal Science Policy Office: IUAP P6/04 (DYSCO, Dynamical systems, control and optimization, 2007-2011); EU: ERNSI; FP7-HD-MPC (INFSO-ICT-223854), COST intelliCIS, EMBOCOM; Contract Research: AMINAL; Other: Helmholtz: viCERP, ACCM, Bauknecht, Hoerbiger;

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