

A detailed map of the Demer river system in Belgium, showing the river's course through various towns and regions. The river is highlighted in blue, and the surrounding area is colored in shades of green and yellow. Major roads and towns are labeled, including Herk-de-Stad, Kermt, and Hasselt. The map is used as a background for the presentation slide.

# Flood control of river systems with Model Predictive Control

The river Demer as case study

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# Why is this research necessary?

- Number of heavy floodings ↑↑

	1970- 1979	1980- 1989	1990- 1999	2000- 2009
worldwide	263	526	780	1729
Europe	23	38	94	239
Belgium	1	2	4	6

- The Rhine: 400 – 500 million euro (1993)
- > 100 big floods: 25 billion euro (1998-2004),  
700 people †, half million homeless
- Example in Belgium: **the Demer**

# The Demer: a history of normalization and floodings

Measures taken in the past:

- Normalization
- Dikes

+ increasing urbanization in flood sensitive areas

New vision on flood control/management

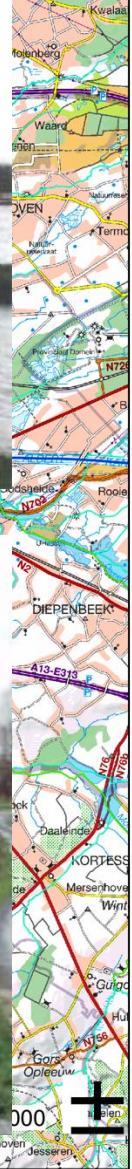
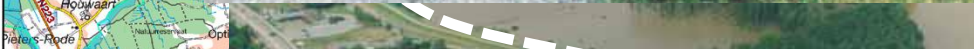
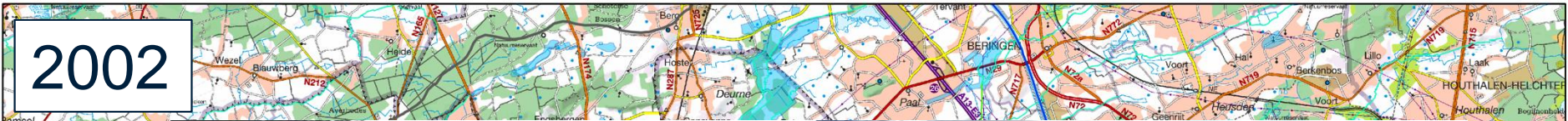
- Preservation/restoration of natural flood areas
- Reservoirs
- Computer controlled management:  
advanced three-position controller

**Not effective**

**Not effective**



2002



© De Digitale Demer



# The Demer: a history of normalization and floodings

## Objective:

Can Model Predictive Control be used for set-point control and flood control of river systems?



## Approach:

1. General modelling framework
2. Find accurate approximate model
3. Design controller

advanced three-position controller

# Not effective

More intelligent flood regulation required!

# Model Predictive Control?

BETEKOM

WERCHTER

# What is Model Predictive Control?

$$\min_{\mathbf{u}, \mathbf{x}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x(j)\|_{\mathbf{Q}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{d}(j), \quad j = 0, \dots, N_P-1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

$$\underline{\mathbf{x}} \leq \mathbf{x}(j) \leq \bar{\mathbf{x}}, \quad j = 1, \dots, N_P$$

$$j = 1, \dots, N_P$$

$$\underline{\mathbf{u}} \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}, \quad j = 0, \dots, N_P-1$$

$$j = 0, \dots, N_P-1$$

$$|\mathbf{u}(j) - \mathbf{u}(j-1)| \leq \Delta_u, \quad j = 0, \dots, N_P-1$$

$$j = 0, \dots, N_P-1$$

# Why Model Predictive Control?

- Constraints incorporation
  - Use of (approximate) process model: optimal solution for entire river system
  - Prediction window + process model: rain predictions
  - Objective function + constraints: set-point control together with flood control
  - River systems have relatively slow dynamics
- MPC is suitable for flood control of river systems

# Outline

- Social relevance
- Modelling framework
- Model Predictive Control
- Conclusions



# White box modelling

## 1. What do we need?

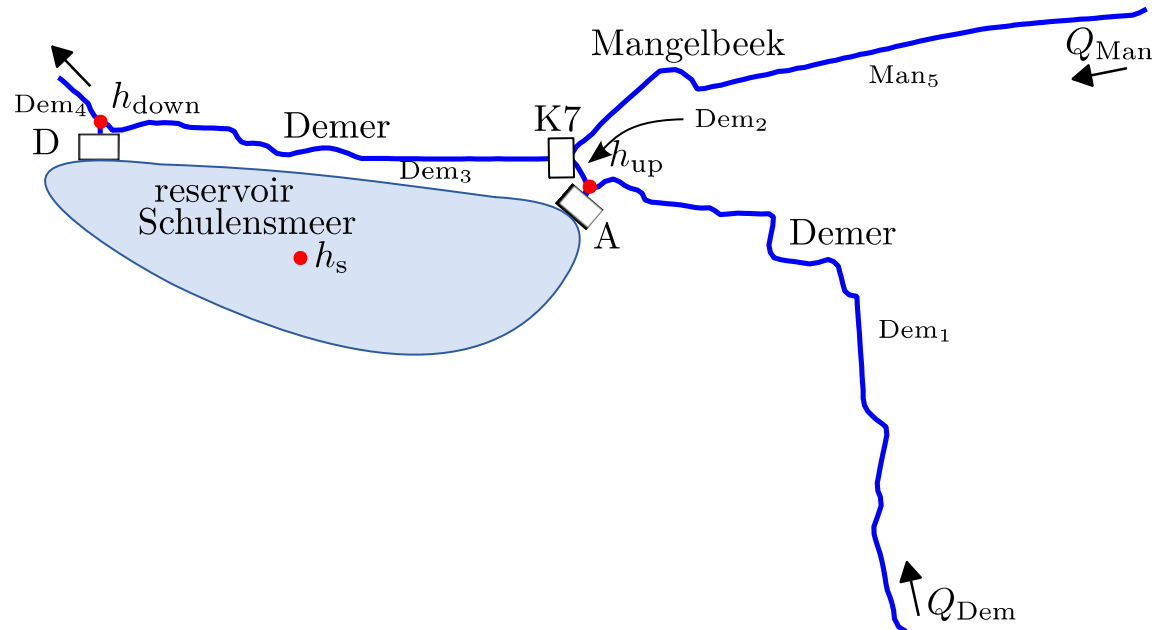
- Dynamics of a single reach
- Boundary conditions for connecting reaches
- Reservoirs



## 2. Numerical simulator



## 3. Approximate model



# Dynamics of a single reach: The Saint-Venant equations

conservation  
of mass

$$\frac{\partial A}{\partial h} \frac{\partial h}{\partial t} + \frac{\partial Q}{\partial z} = 0$$

conservation  
of momentum

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial z} \frac{Q^2}{A} + gA \frac{\partial h}{\partial z} + gA(S_f - S_0) = 0$$

with

$A$  the cross-sectional flow area (m<sup>2</sup>)

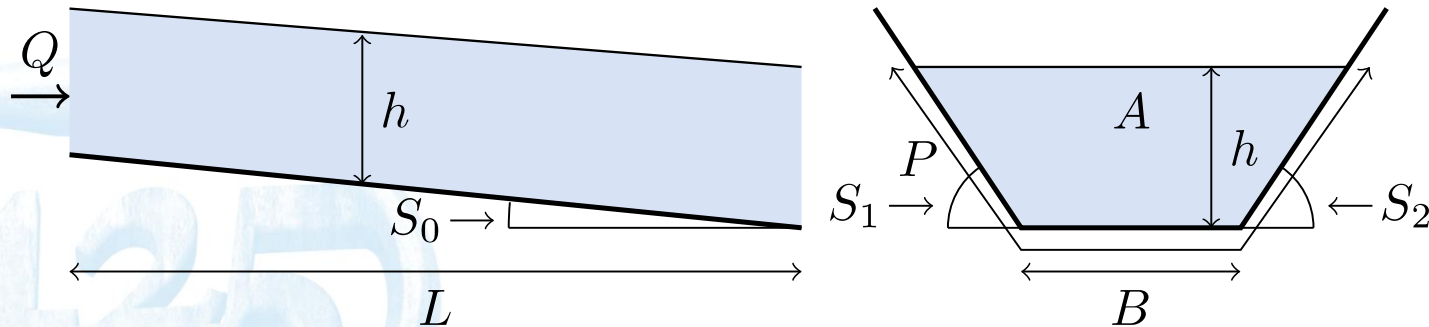
$Q$  water discharge (m<sup>3</sup>/s)     $h$  water depth (m)

$S_0$  bed slope     $S_f$  friction slope

# Dynamics of a single reach: The resistance law

The resistance law of Manning:

$$S_f = n_{\text{mann}}^2 \frac{Q|Q|}{A^2 R^{1/3}}$$

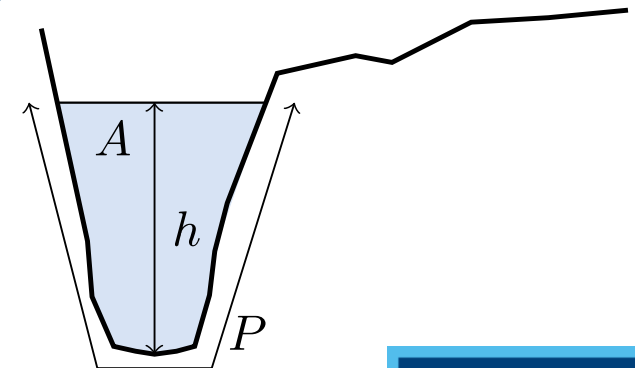
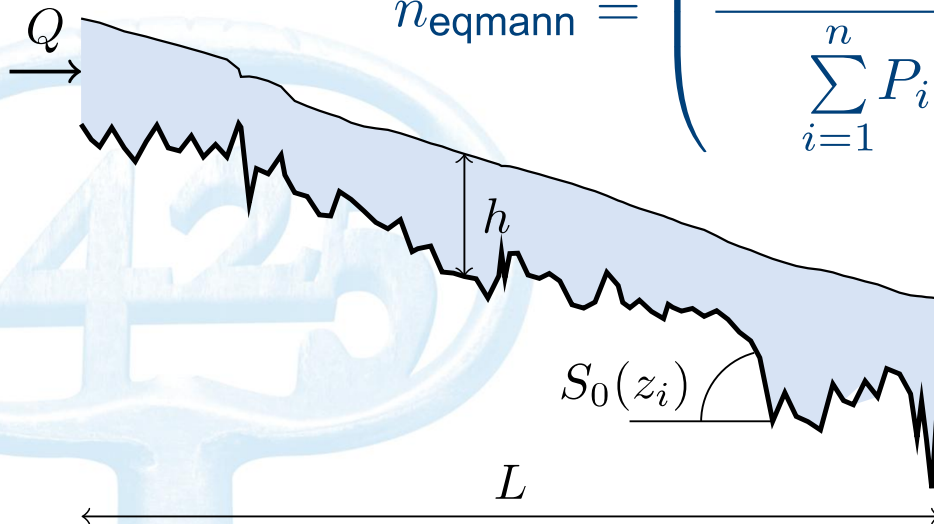


# Dynamics of a single reach: The resistance law

The resistance law of Manning:

$$S_f = n_{\text{eqmann}}^2 \frac{Q|Q|}{A^2 R^{1/3}}$$

$$n_{\text{eqmann}} = \left( \frac{\sum_{i=1}^n P_i n_{\text{mann},i}^{3/2}}{\sum_{i=1}^n P_i} \right)^{2/3}$$



# Boundary conditions for a single reach

- Given upstream/downstream discharge

$$Q^{(i)}(0, t) = Q_{\text{up}}(t)$$

$$Q^{(i)}(L^{(i)}, t) = Q_{\text{down}}(t)$$

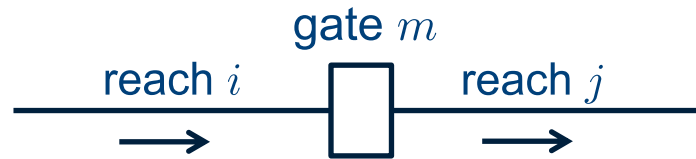
- Rating curve

$$f\left(h^{(i)}(L^{(i)}, t), Q^{(i)}(L^{(i)}, t)\right) = 0$$

# Boundary conditions connecting reaches

- Hydraulic structures:

$$Q_{\text{gate}}(t) = \tilde{f}(c(t), h_{\text{up}}(t), h_{\text{down}}(t))$$



$$Q^{(i)}(L^{(i)}, t) = Q_{\text{gate}}^{(m)}(t),$$

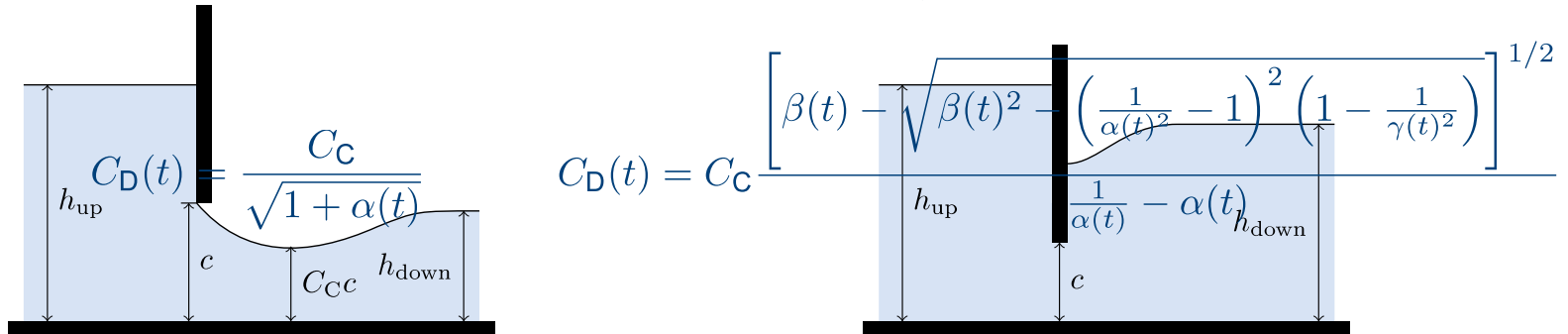
$$Q^{(j)}(0, t) = Q_{\text{gate}}^{(m)}(t),$$

$$Q_{\text{gate}}^{(m)}(t) = \tilde{f}(c^{(m)}(t), h^{(i)}(L^{(i)}, t), h^{(j)}(0, t))$$

- Vertical sluice
- Gated weir

# Boundary conditions connecting reaches

- Vertical sluice:  $Q_{\text{gate}} = C_D(t)wc(t)\sqrt{2gh_{\text{up}}(t)}$

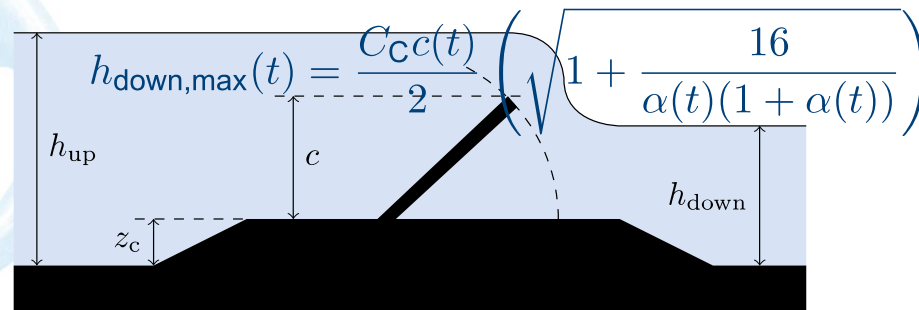


$$\beta(t) = (1/\alpha(t) - 1)^2 + 2(\gamma(t) - 1),$$

$$\alpha(t) = C_C c(t) / h_{\text{up}}(t),$$

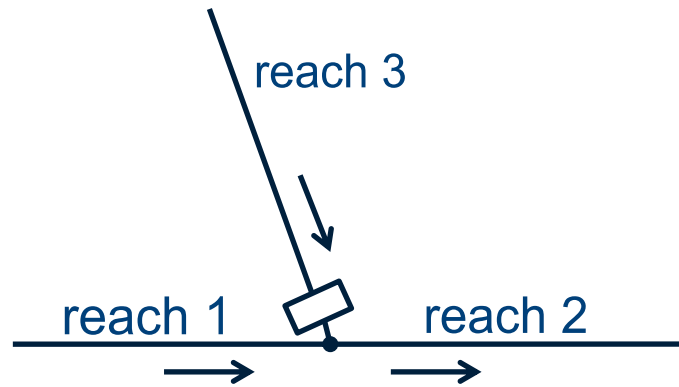
$$\gamma(t) = h_{\text{up}}(t) / h_{\text{down}}(t),$$

- Gated weir:



# Boundary conditions connecting reaches

- Junctions



$$h^{(1)}(L^{(1)}, t) = h^{(2)}(0, t),$$

$$Q^{(1)}(L^{(1)}, t) + Q_{\text{gate}}(t) = Q^{(2)}(0, t),$$

$$Q^{(3)}(L^{(3)}, t) = Q_{\text{gate}}(t),$$

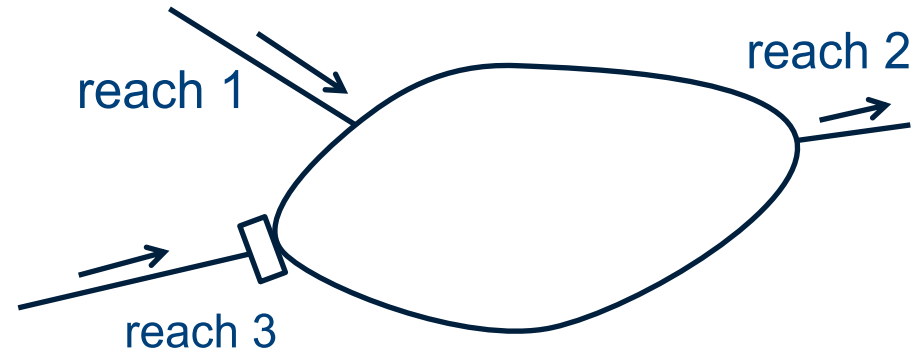
$$Q_{\text{gate}}(t) = \tilde{f} \left( c^{(\text{gate})}(t), h^{(3)}(L^{(3)}, t), h^{(2)}(0, t) \right)$$



# Reservoirs

Two options

- Saint-Venant equations

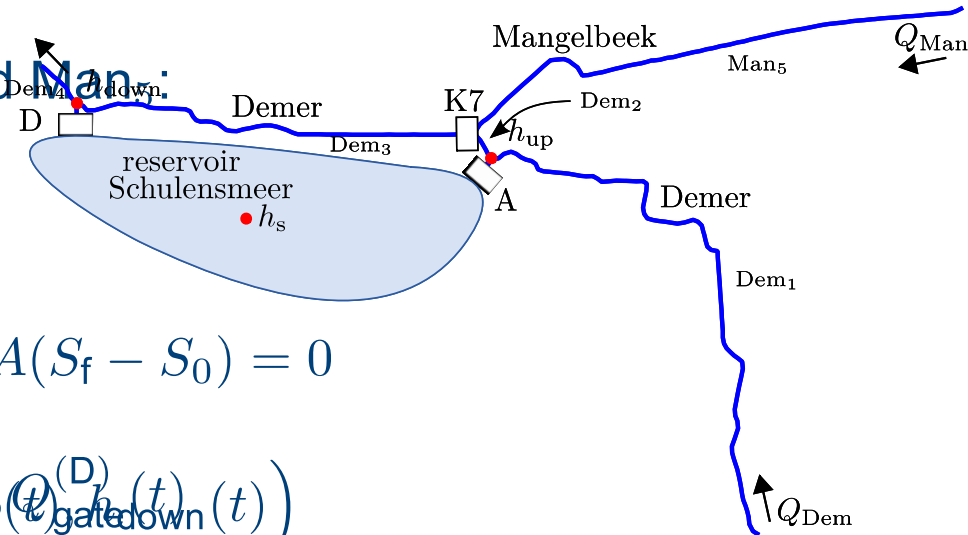


- Model as a tank

$$dV_{\text{res}}/dt = Q^{(1)}(L^{(1)}, t) + Q_{\text{gate}}(t) - Q^{(2)}(0, t)$$

# The hydrodynamic model of the Demer

For Dem<sub>1</sub>, Dem<sub>2</sub>, Dem<sub>3</sub>, Dem<sub>4</sub> and Man:



$$\frac{\partial A}{\partial h} \frac{\partial h}{\partial t} + \frac{\partial Q}{\partial z} = 0$$

For junction at gate A:

$$\frac{\partial Q}{\partial t} + \frac{\partial Q^2}{\partial z} + gA \frac{\partial h}{\partial z} + gA(S_f - S_0) = 0$$

with

$$Q_{\text{gate}}^{(D)}(0, t) = Q_{\text{gate}}^{(A)}(0, t) + Q_{\text{gate}}^{(D)}(0, t)$$

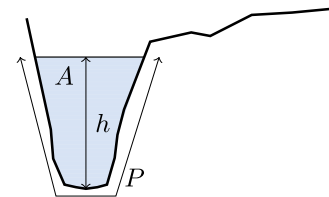
with

$$S_f = \frac{n_{\text{eqmann}}^2 Q^2}{A^2 R^{4/3}}$$

For junction at gate D:

$$V_s = \begin{cases} (h_s - 20.38) / 0.000771 & h_s < 20.38, \\ ((h_s - 20.38) / 0.000771)^{0.838549} & h_s \geq 20.38. \end{cases}$$

$$Q^{(4)}(0, t) = \sum_{i=1}^n Q(L_i^{(3)}, t) + Q_{\text{gate}}^{(D)}(t).$$



# White box modelling

## 1. What do we need?

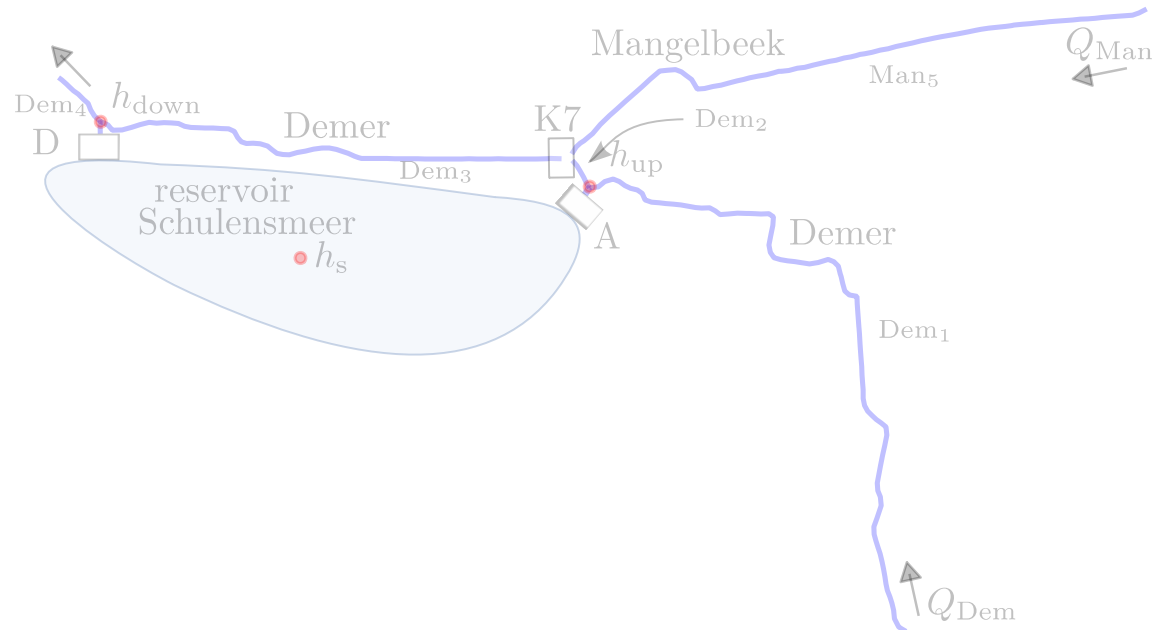
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## 2. Numerical simulator



## 3. Approximate model



# Numerical simulator

- For every reach:

$$h_1^{(i)} \quad h_2^{(i)} \quad h_3^{(i)}$$

$$h_{n_h^{(i)}-1}^{(i)} \quad h_{n_h^{(i)}}^{(i)}$$

- Approximate partial derivatives with finite differences

For PDE  $\Delta z$

$$\frac{\partial A}{\partial h} \frac{\partial h}{\partial t} + \frac{\partial Q}{\partial z} = 0$$

$$\left( h^{(i)}(z_j, t_k) = h_{j,k}^{(i)} \right)$$

$$\frac{\partial h}{\partial t} \approx \frac{h_{j,k+1}^{(i)} - h_{j,k}^{(i)}}{\Delta t}$$

$$\frac{\partial Q}{\partial z} \approx \theta \frac{Q_{j+1,k+1}^{(i)} - Q_{j,k+1}^{(i)}}{\Delta z} + (1 - \theta) \frac{Q_{j+1,k}^{(i)} - Q_{j,k}^{(i)}}{\Delta z}$$


$$\frac{\partial A}{\partial h} \approx \theta \left( \frac{\partial A}{\partial h} \right)_{j,k+1}^{(i)} + (1 - \theta) \left( \frac{\partial A}{\partial h} \right)_{j,k}^{(i)}$$

# Numerical simulator

- For PDE 2:

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial z} \left( \frac{Q^2}{A} \right) + g \underline{A} \frac{\partial h}{\partial z} + g \underline{A} (\underline{S}_f - S_0) = 0$$

$$\frac{\partial}{\partial z} \left( \frac{Q^{(i)2}}{A^{(i)}} \right)_{j,k} \simeq \begin{cases} \frac{1}{\Delta z} \left( \left( \frac{Q^{(i)2}}{A^{(i)}} \right)_{j+1,k+\theta} - \left( \frac{Q^{(i)2}}{A^{(i)}} \right)_{j,k+\theta} \right) & Q_{j,k}^{(i)} < 0, \\ \frac{1}{\Delta z} \left( \left( \frac{Q^{(i)2}}{A^{(i)}} \right)_{j,k+\theta} - \left( \frac{Q^{(i)2}}{A^{(i)}} \right)_{j-1,k+\theta} \right) & Q_{j,k}^{(i)} \geq 0. \end{cases}$$


$$\mathbf{f} \left( \mathbf{h}^{(i)}(t_{k+1}), \mathbf{h}^{(i)}(t_k), \mathbf{q}^{(i)}(t_{k+1}), \mathbf{q}^{(i)}(t_k) \right) = \mathbf{0}_{n_h^{(i)} + n_Q^{(i)} - 2}$$

Use similar procedure for boundary conditions...

# White box modelling

## 1. What do we need?

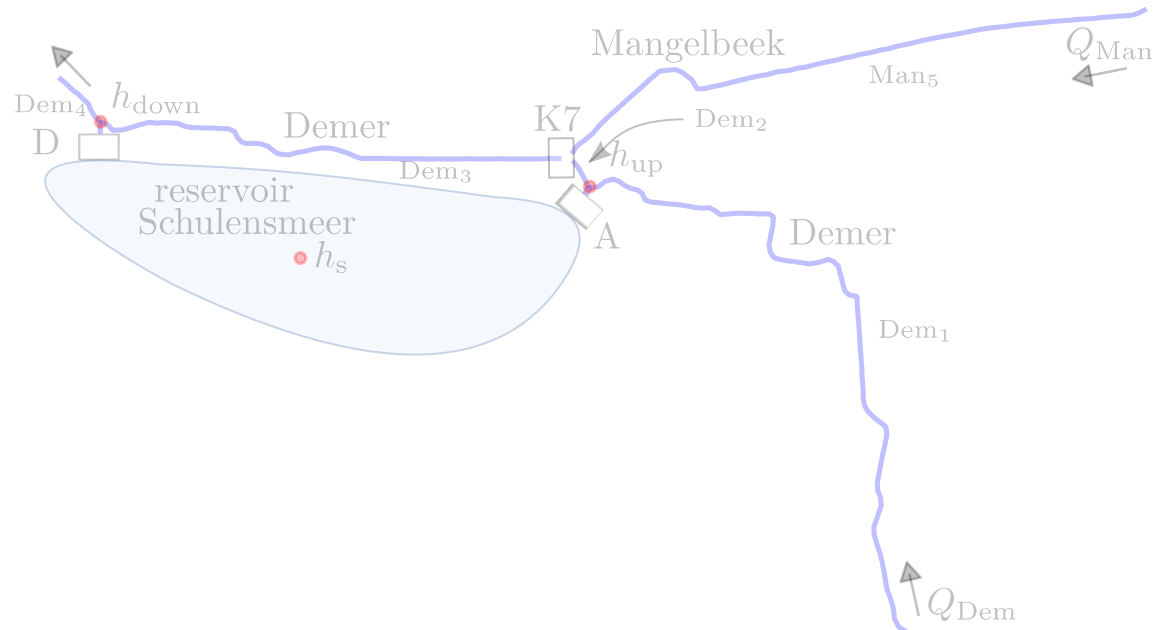
- Dynamics of a single reach
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## 2. Numerical simulator



## 3. Approximate model



# Approximate model

- Goal: find an approximate model that is accurate enough but with a low complexity
- Linear state space model:

$$\mathbf{x}(k+1) = \tilde{\mathbf{A}}\mathbf{x}(k) + \tilde{\mathbf{B}}\mathbf{u}(k) + \tilde{\mathbf{E}}\mathbf{d}(k) + \tilde{\boldsymbol{\beta}}$$

with

$$\mathbf{x}(k) = [\mathbf{h}(k); \mathbf{q}(k)],$$

$$\mathbf{u}(k) = [c^{(A)}(k); c^{(D)}(k); c^{(K7)}(k)],$$

$$\mathbf{d}(k) = [Q_{\text{Dem}}(k); Q_{\text{Man}}(k)]$$

**Not accurate**

# Approximate model

- Linear-Nonlinear model:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{F}\mathbf{d}(k) + \beta$$

$$Q_{\text{gate}}^{(m)}(k) = \tilde{f} \left( c^{(m)}(k), h_{\text{up}}^{(m)}(k), h_{\text{down}}^{(m)}(k) \right), \text{ for } m = A, D, K7$$

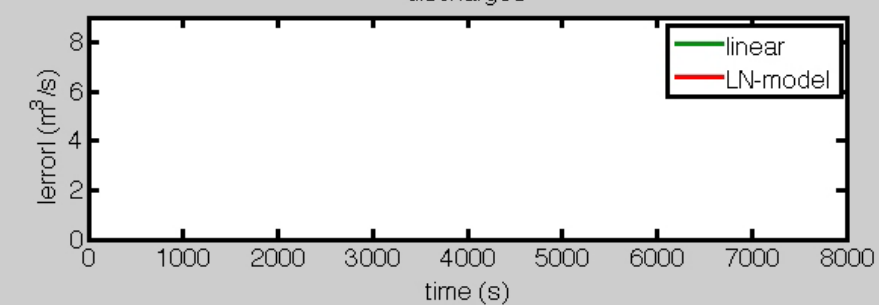
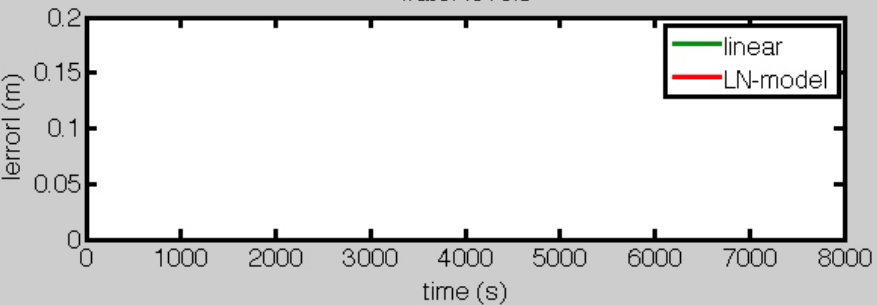
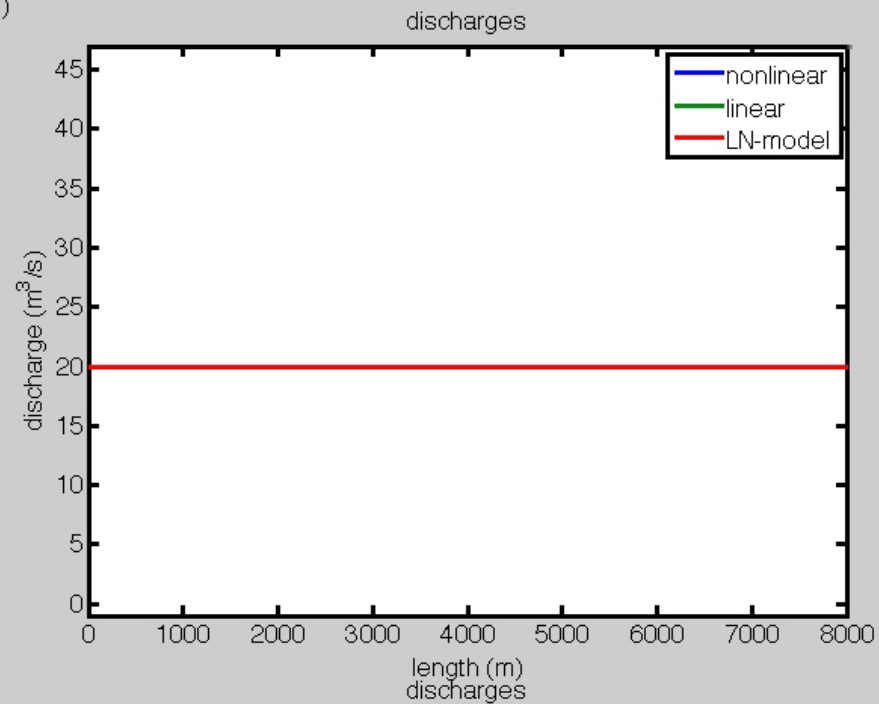
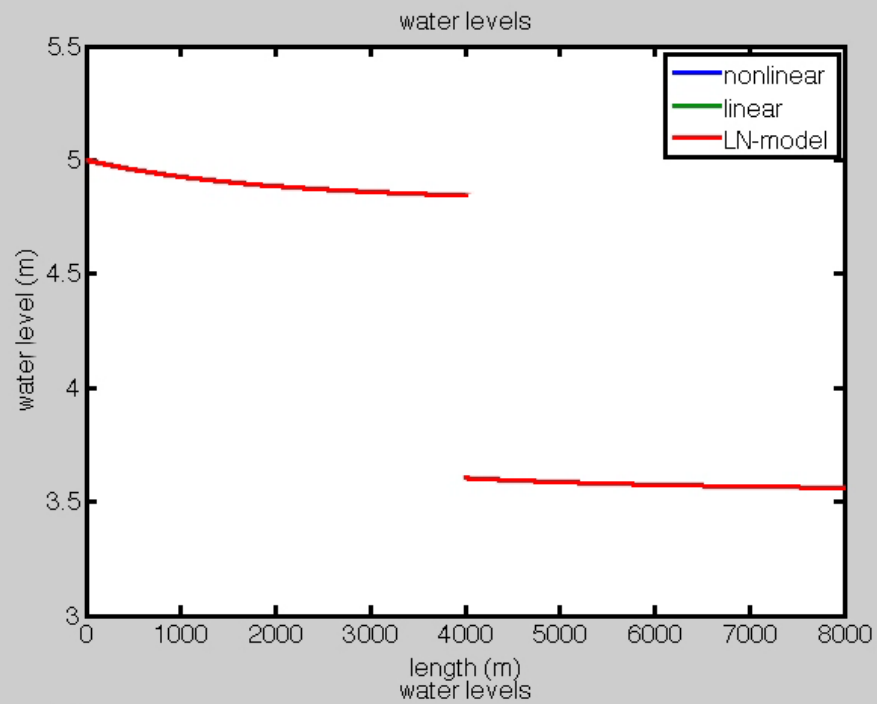
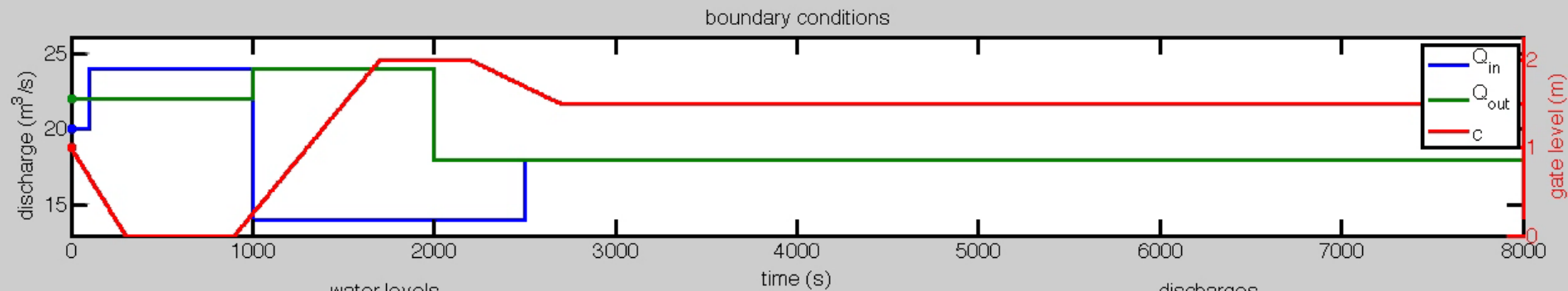
with

$$\mathbf{x}(k) = [\mathbf{h}(k); \mathbf{q}(k)],$$

$$\mathbf{u}(k) = \left[ Q_{\text{gate}}^{(A)}(k); Q_{\text{gate}}^{(D)}(k); Q_{\text{gate}}^{(K7)}(k) \right],$$

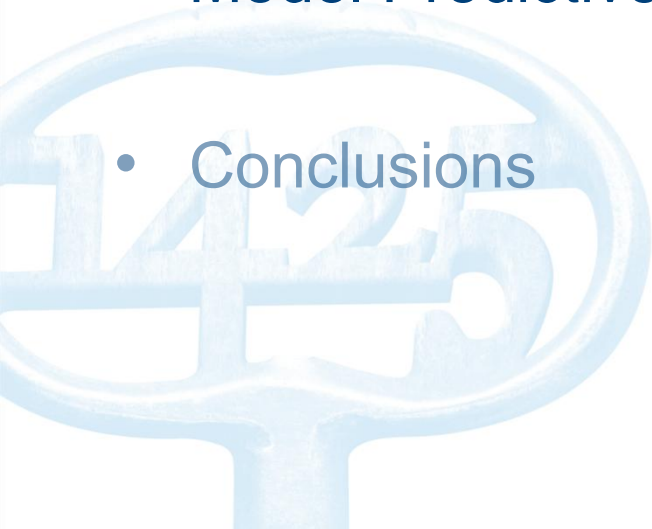
$$\mathbf{d}(k) = [Q_{\text{Dem}}(k); Q_{\text{Man}}(k)]$$



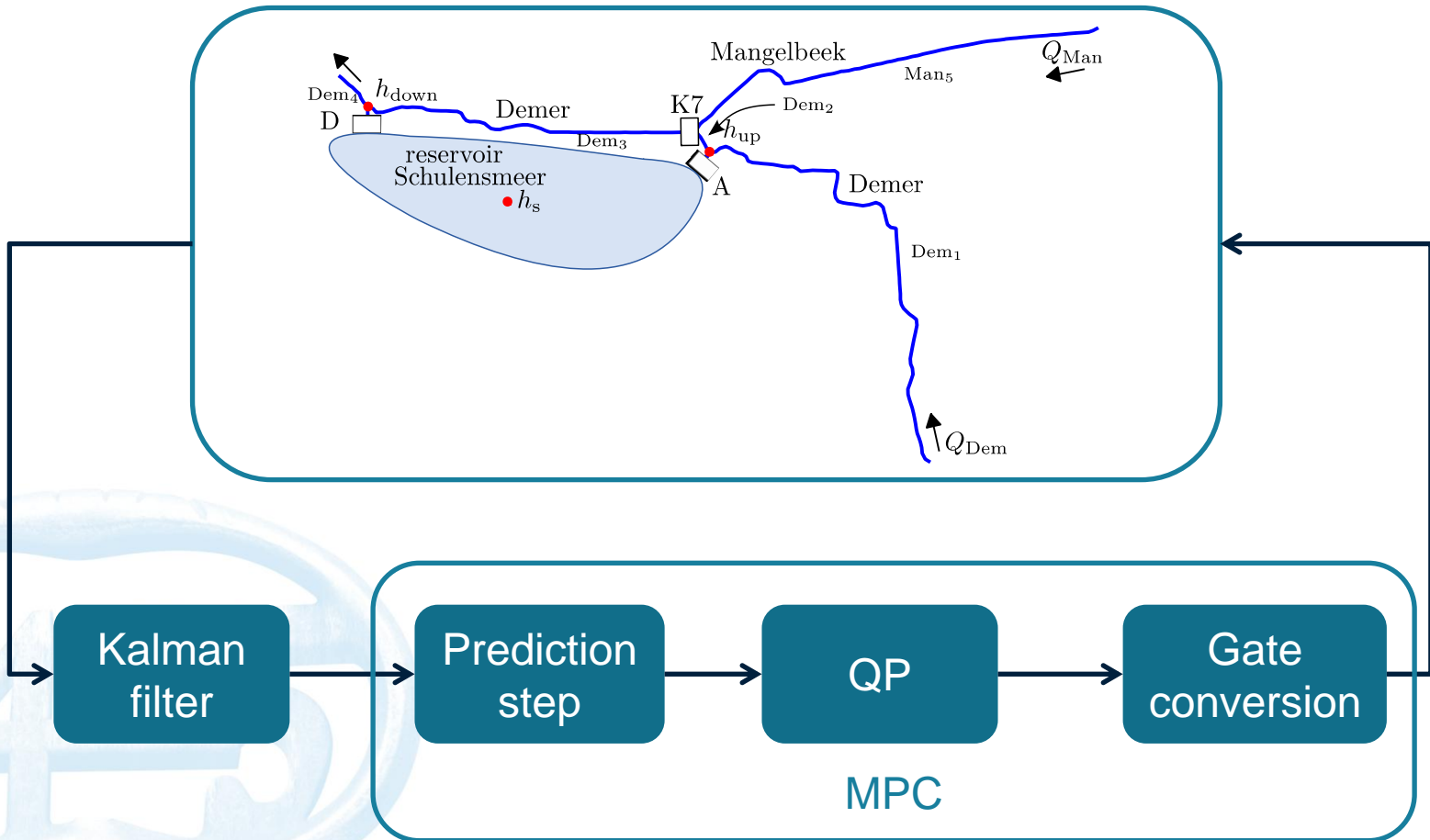


# Outline

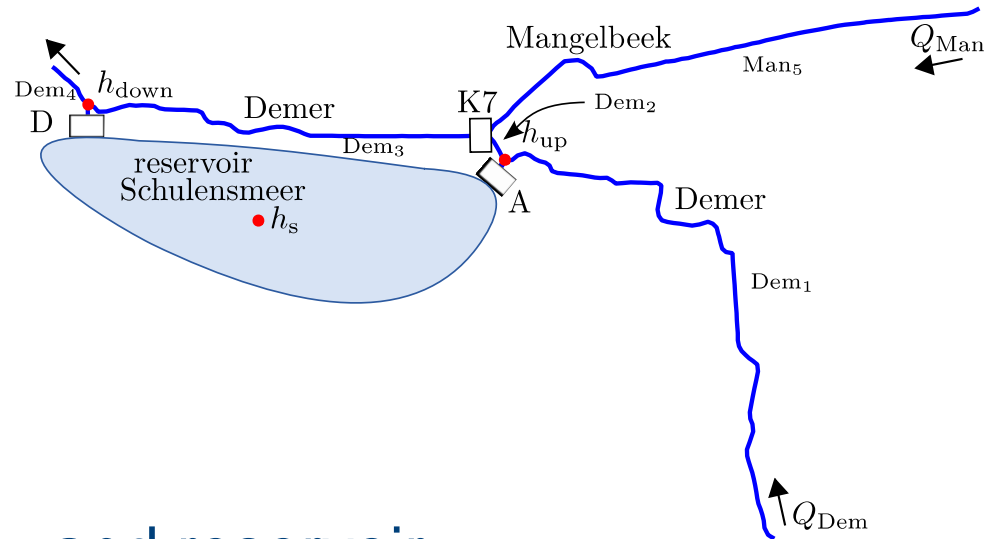
- Social relevance
- Modelling framework
- Model Predictive Control
- Conclusions



# Model Predictive Control

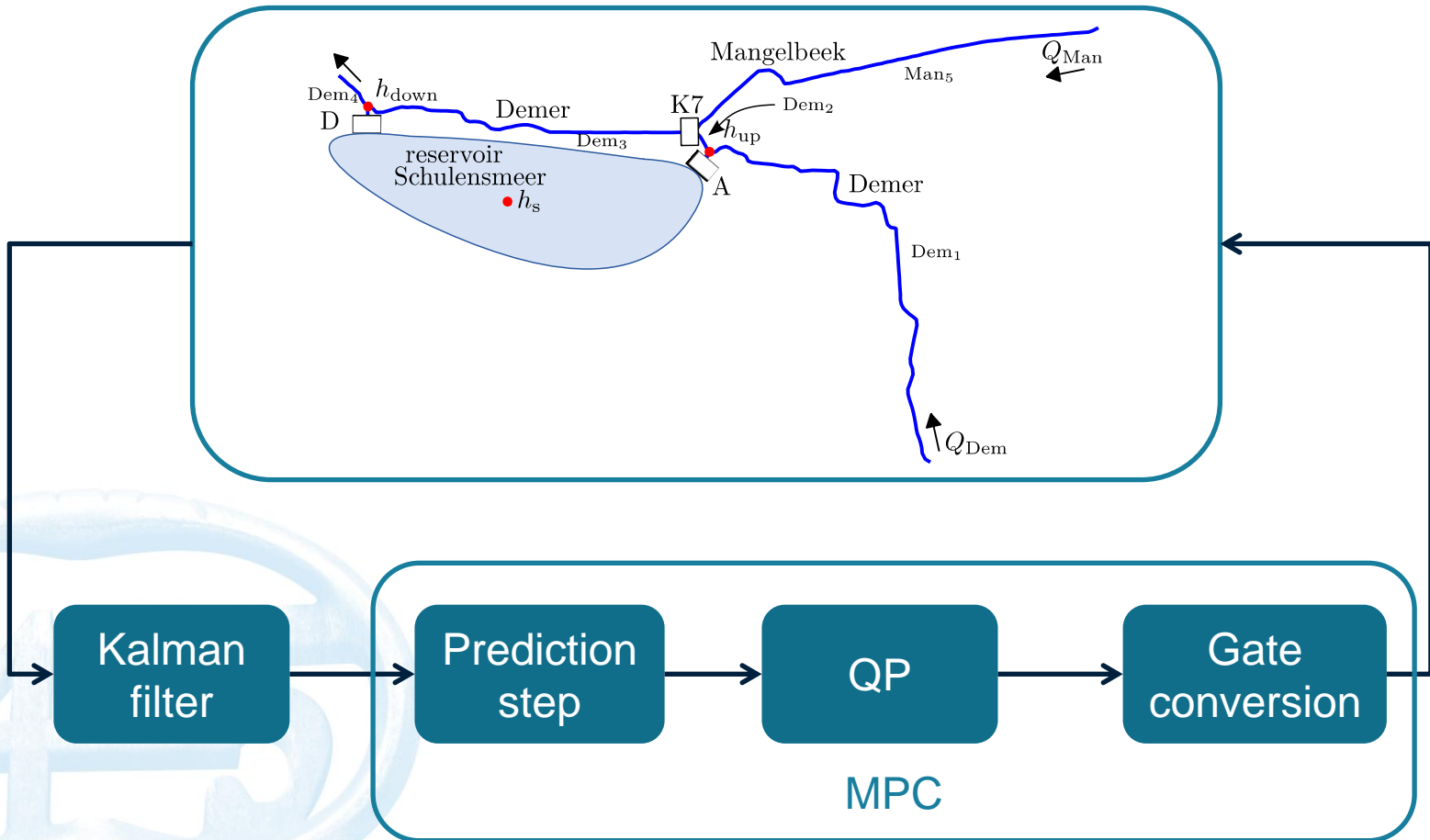


# The requirements



- Control objectives:
  - Set-point control for  $h_{up}$  and reservoir
  - Flood control + respect safety limits and flood limits
  - Recovery of used buffer capacity
- Limitations:
  - Physical limits for gate positions:  $\underline{c}$ ,  $\bar{c}$ ,  $\Delta_c$
  - Only  $h_{up}$ ,  $h_s$  and  $h_{down}$  are measured

# Model Predictive Control



# Model Predictive Control: Approximate model

Use LN-model

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B} \begin{pmatrix} Q_{\text{gate}}^{(A)}(k) \\ Q_{\text{gate}}^{(D)}(k) \\ Q_{\text{gate}}^{(K7)}(k) \end{pmatrix} + \mathbf{D}\mathbf{d}(k) + \boldsymbol{\beta}$$

$$\left\{ \begin{array}{l} Q_{\text{gate}}^{(A)}(k) = \tilde{f}(c^{(A)}(k), h^{(1)}(L^{(1)}, t_k), h_s(t_k)) \\ Q_{\text{gate}}^{(D)}(k) = \tilde{f}(c^{(D)}(k), h_s(t_k), h^{(4)}(0, t_k)) \\ Q_{\text{gate}}^{(K7)}(k) = \tilde{f}(c^{(K7)}(k), h^{(2)}(L^{(2)}, t_k), h^{(3)}(0, t_k)) \end{array} \right.$$

but work only with linear part inside the optimization problem!  
→ optimize over gate discharges

# Model Predictive Control: The optimization problem

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \zeta} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\zeta\|_{\mathbf{V}}^2 + \mathbf{v}^T \zeta$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

for  $i = 1, \dots, 5$  :

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,1}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \xi_i, \quad j = 1, \dots, N_P$$

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,1}^{(\text{schulen})} + \eta(j) \xi_6, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\zeta \geq 0$$

# Model Predictive Control: Flood control and set-point control

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \boldsymbol{\zeta}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\boldsymbol{\zeta}\|_{\mathbf{V}}^2 + \mathbf{v}^T \boldsymbol{\zeta}$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

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$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

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$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\boldsymbol{\zeta} \geq 0$$



# Model Predictive Control: Ensure feasibility of QP

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \boldsymbol{\zeta}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\boldsymbol{\zeta}\|_{\mathbf{V}}^2 + \mathbf{v}^T \boldsymbol{\zeta}$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

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$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\boldsymbol{\zeta} \geq 0$$

# Model Predictive Control:

## Control objectives → weighting matrices

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \boldsymbol{\zeta}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\boldsymbol{\zeta}\|_{\mathbf{V}}^2 + \mathbf{v}^T \boldsymbol{\zeta}$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

for  $i = 1, \dots, 5$  :

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,1}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \xi_i, \quad j = 1, \dots, N_P$$

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,1}^{(\text{schulen})} + \eta(j) \xi_6, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\boldsymbol{\zeta} \geq 0$$

# Model Predictive Control: Limits on gate discharges & model update

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \zeta} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\zeta\|_{\mathbf{V}}^2 + \mathbf{v}^T \zeta$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}d(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

for  $i = 1, \dots, 5$  :

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,1}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \xi_i, \quad j = 1, \dots, N_P$$

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,1}^{(\text{schulen})} + \eta(j) \xi_6, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\zeta \geq 0$$

# Model Predictive Control:

$$\underline{\mathbf{c}}, \bar{\mathbf{c}}, \Delta_c \Rightarrow \underline{\mathbf{u}}(j), \bar{\mathbf{u}}(j)$$

At time  $t_k$ :  $\mathbf{c}(t_{k-1})$ ,  $\mathbf{h}(t_k)$  and  $\mathbf{q}(t_k)$  are known.

For gate  $m$ :

$$\underline{u}^{(m)}(k) = \tilde{f} \left( c^{(m)}(k-1) + \Delta_c, h_{\text{up}}(k), h_{\text{down}}(k) \right),$$

$$\bar{u}^{(m)}(k) = \tilde{f} \left( c^{(m)}(k-1) - \Delta_c, h_{\text{up}}(k), h_{\text{down}}(k) \right).$$

For  $\underline{u}^{(m)}(k+1)$ ,  $\bar{u}^{(m)}(k+1)$ ?

- $\mathbf{h}(t_{k+1})$ ? use (non)linear model to predict  $\mathbf{x}(k+1)$  based on  $\mathbf{x}(k)$ ,  $\mathbf{d}(k)$  and  $\mathbf{u}_{\text{opt}}(k)$
- $\mathbf{c}(t_k)$ ? use  $\mathbf{u}_{\text{opt}}(k)$  but prevent **uncontrollability of gates!**

# Model Predictive Control:

## Model update

- Update linear model to match predictions with nonlinear model:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{D}\mathbf{d}(k) + \tilde{\boldsymbol{\beta}}(k)$$

with

$$\tilde{\boldsymbol{\beta}}(k) = \boldsymbol{\beta} + (\mathbf{x}_{\text{nonlin}}(k+1) - \mathbf{x}_{\text{lin}}(k+1))$$

# Model Predictive Control: Buffer capacity recovery

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \boldsymbol{\zeta}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\boldsymbol{\zeta}\|_{\mathbf{V}}^2 + \mathbf{v}^T \boldsymbol{\zeta}$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}}$ ,

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

for  $i = 1, \dots, 5$  :

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,1}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \xi_i, \quad j = 1, \dots, N_P$$

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,1}^{(\text{schulen})} + \eta(j) \xi_6, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\boldsymbol{\zeta} \geq 0$$

# Model Predictive Control: Constraint selection

$$\min_{\mathbf{u}, \mathbf{x}, \boldsymbol{\xi}, \boldsymbol{\zeta}} \sum_{j=1}^{N_P} \|\mathbf{x}(j) - \mathbf{r}_x\|_{\mathbf{W}}^2 + \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{u}(j-1)\|_{\mathbf{R}}^2 +$$

$$+ \sum_{j=0}^{N_P-1} \|\mathbf{u}(j) - \mathbf{r}_u\|_{\mathbf{U}}^2 + \|\boldsymbol{\xi}\|_{\mathbf{S}}^2 + \mathbf{s}^T \boldsymbol{\xi} + \|\boldsymbol{\zeta}\|_{\mathbf{V}}^2 + \mathbf{v}^T \boldsymbol{\zeta}$$

s.t.  $\mathbf{x}(0) = \hat{\mathbf{x}},$

$$\mathbf{x}(j+1) = \mathbf{A}\mathbf{x}(j) + \mathbf{B}\mathbf{u}(j) + \mathbf{F}\mathbf{d}(j) + \tilde{\boldsymbol{\beta}}(j), \quad j = 0, \dots, N_P - 1$$

$$\underline{\mathbf{u}}(j) \leq \mathbf{u}(j) \leq \bar{\mathbf{u}}(j), \quad j = 0, \dots, N_P - 1$$

$$\mathbf{u}(-1) = \mathbf{u}_{\text{prev}},$$

for  $i = 1, \dots, 5$  :

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,1}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \xi_i, \quad j = 1, \dots, N_P$$

$$\mathbf{M}^{(i)} \mathbf{h}^{(i)}(j) \leq \mathbf{M}^{(i)} \mathbf{h}_{\max,2}^{(i)} + \mathbf{1}_{n_{\text{con}}^{(i)}} \cdot \eta(j) \zeta_i, \quad j = 1, \dots, N_P$$

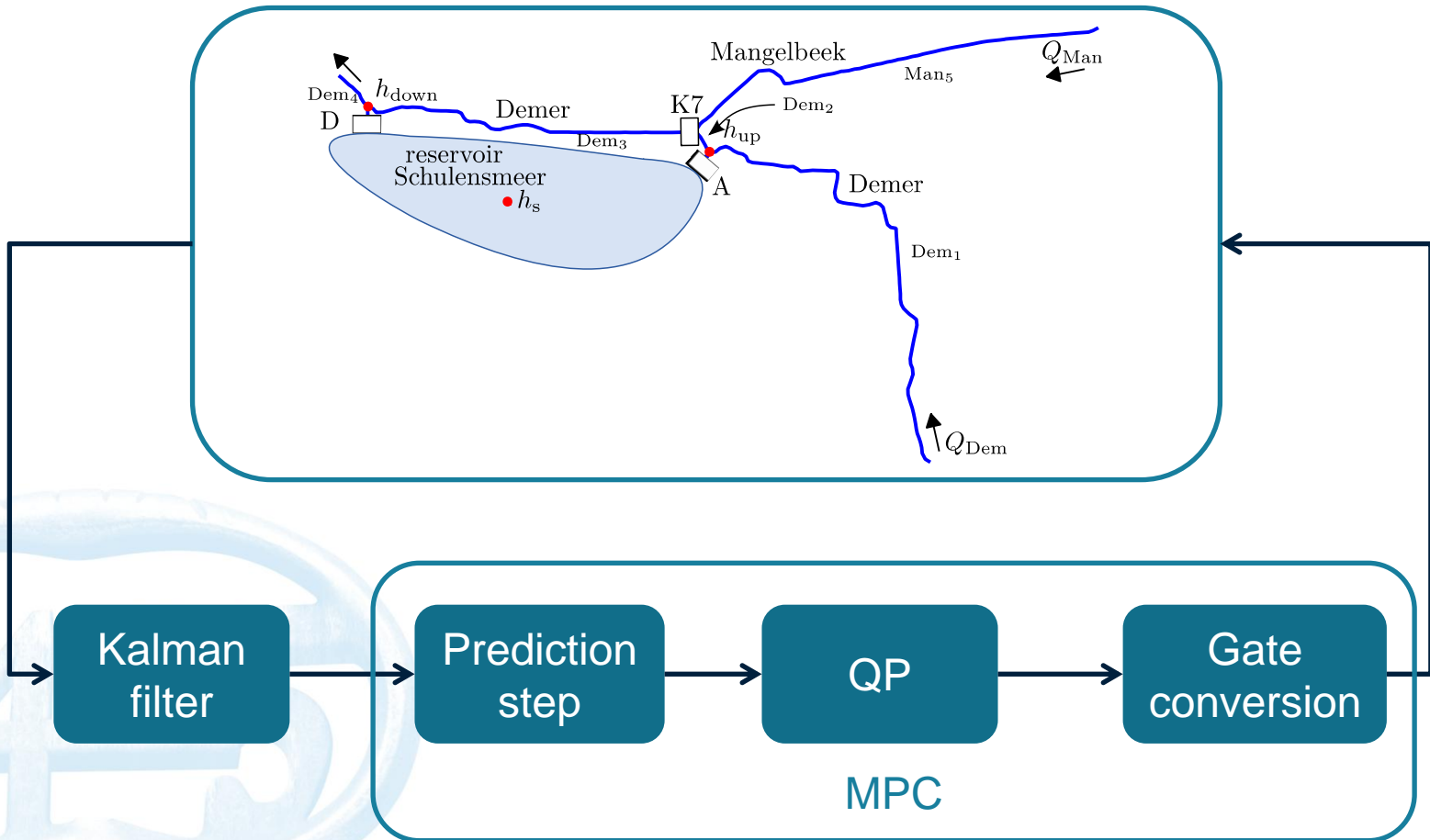
$$h^{(\text{schulen})}(j) \leq h_{\max,1}^{(\text{schulen})} + \eta(j) \xi_6, \quad j = 1, \dots, N_P$$

$$h^{(\text{schulen})}(j) \leq h_{\max,2}^{(\text{schulen})} + \eta(j) \zeta_6, \quad j = 1, \dots, N_P$$

$$\boldsymbol{\xi} \geq 0,$$

$$\boldsymbol{\zeta} \geq 0$$

# Model Predictive Control





# Kalman Filter

Estimate the entire state of the river system based on the three measured water levels together with the control actions:

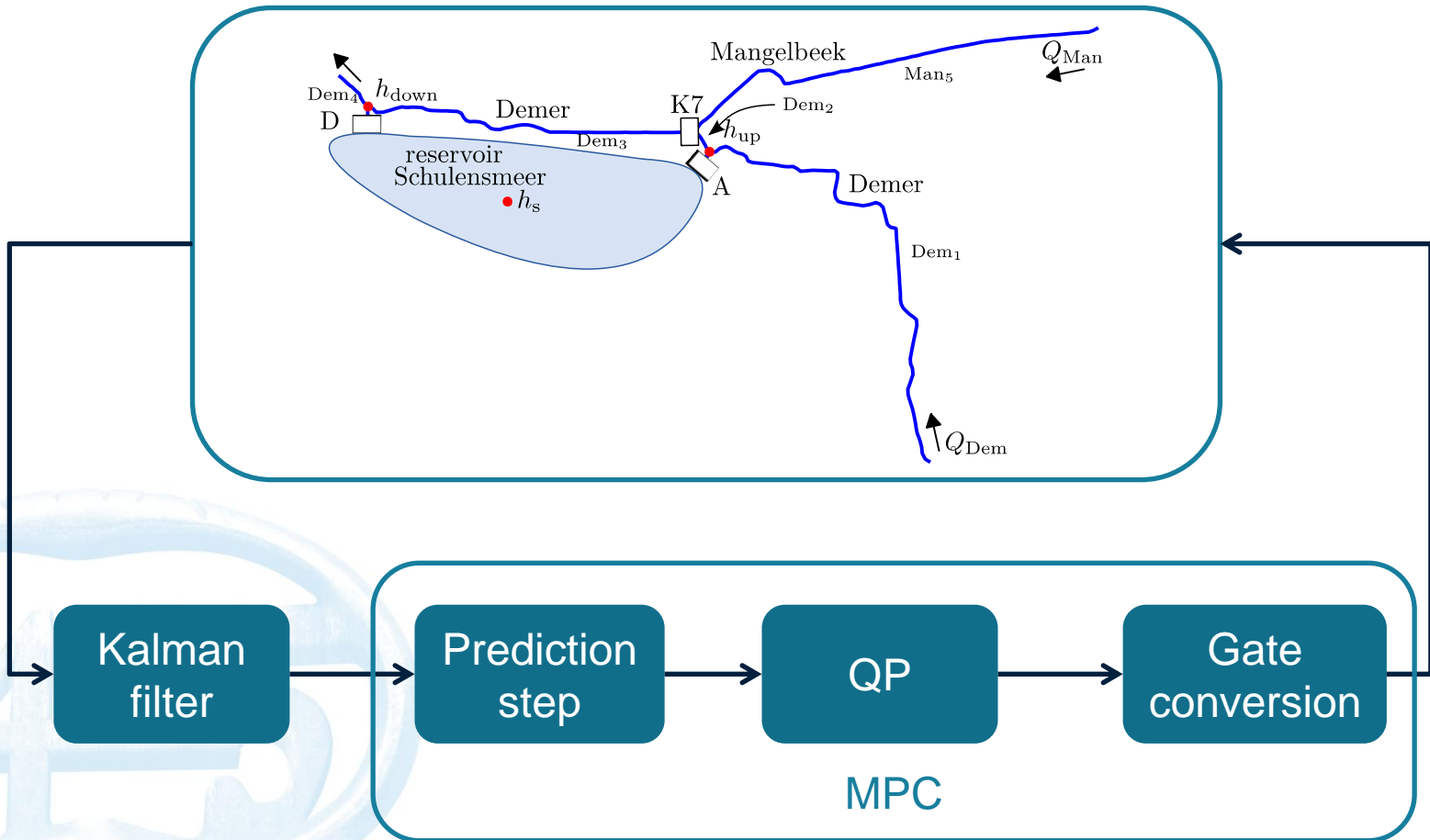
$$\hat{\mathbf{x}}(k+1) = \mathbf{L} (\Delta \mathbf{y}(k) - \Delta \hat{\mathbf{y}}(k)) + \mathbf{x}_{\text{nonlin}}(k+1)$$

$$\Delta \hat{\mathbf{x}}(k+1) = \mathbf{L} (\Delta \mathbf{y}(k) - \Delta \hat{\mathbf{y}}(k)) + \mathbf{A} \Delta \hat{\mathbf{x}}(k) + \mathbf{B} \Delta \mathbf{u}(k) + \mathbf{D} \Delta \mathbf{d}(k),$$

$$\Delta \hat{\mathbf{y}}(k) = \mathbf{C} \Delta \hat{\mathbf{x}}(k)$$

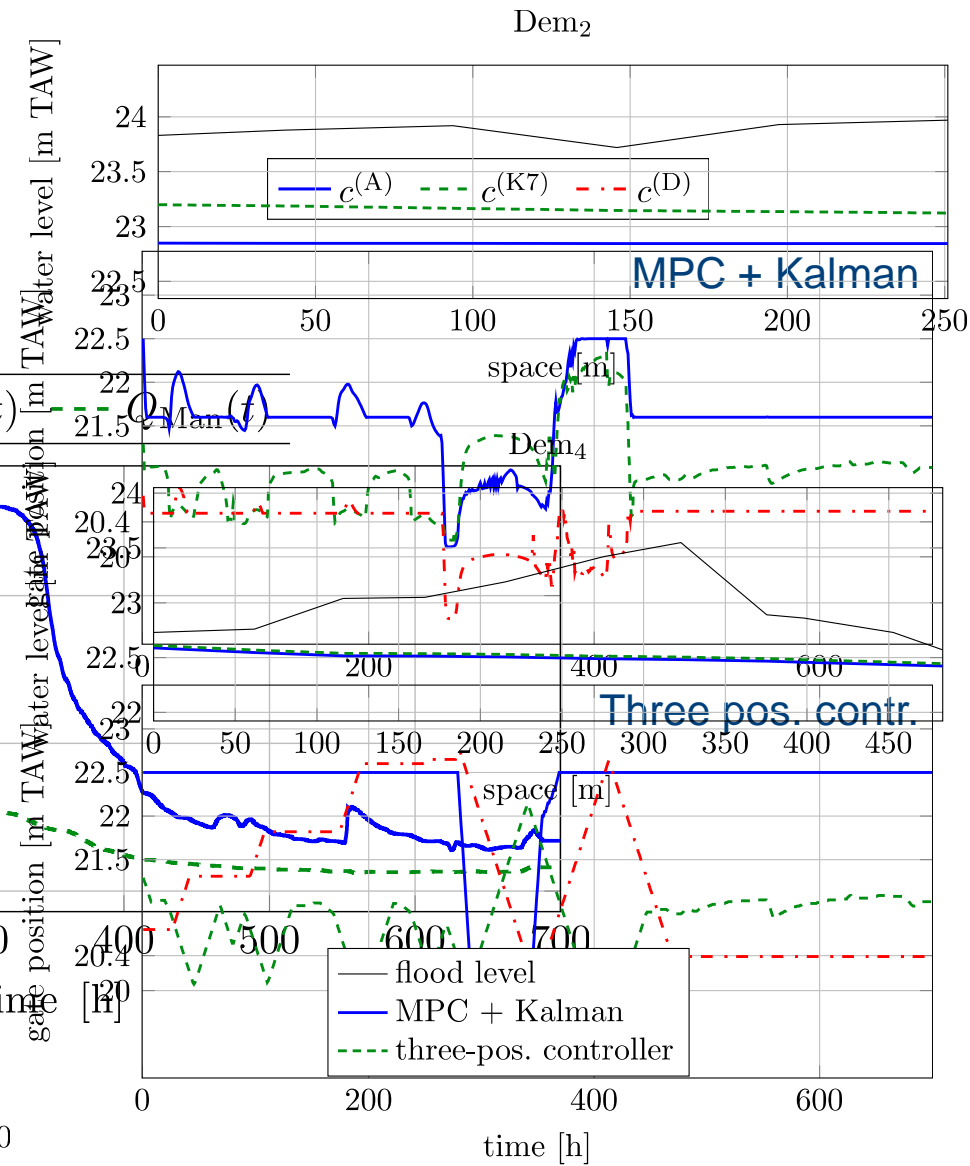
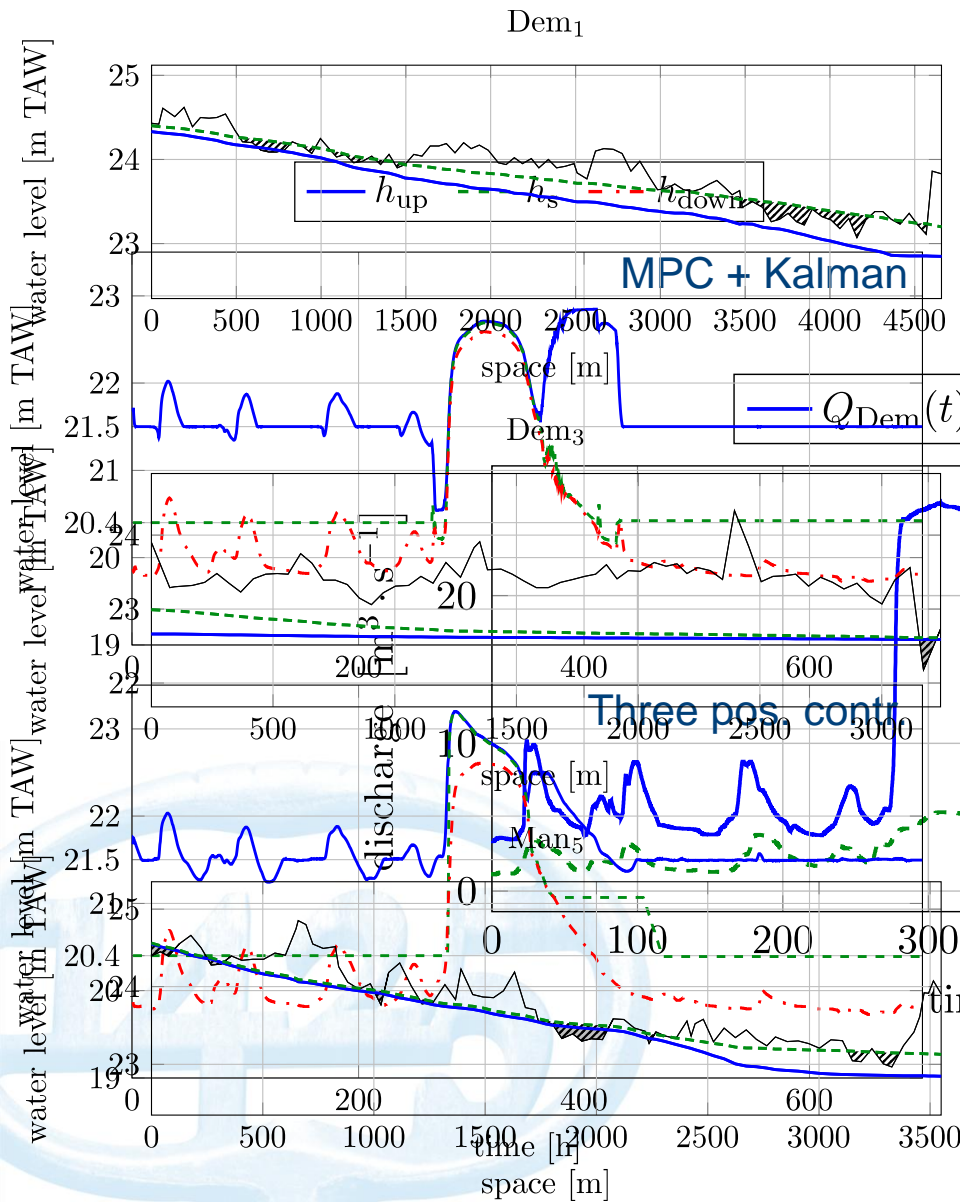


# Model Predictive Control: The proof of the pudding



# Simulation results

	Dem <sub>1</sub>	Dem <sub>2</sub>	Dem <sub>3</sub>	Dem <sub>4</sub>	Man <sub>5</sub>	Schulensmeer
<b>W</b> ∈ ℝ <sup>534×534</sup>						
water levels	[10 <sup>-3</sup> · <b>1</b> <sub>94</sub> ; 10]	10 <sup>-3</sup> · <b>1</b> <sub>6</sub>	10 <sup>-3</sup> · <b>1</b> <sub>66</sub>	10 <sup>-3</sup> · <b>1</b> <sub>11</sub>	10 <sup>-3</sup> · <b>1</b> <sub>86</sub>	50
discharges	[10 <sup>-3</sup> · <b>1</b> <sub>94</sub> ; 0.01] <sup>(*)</sup> 10 <sup>-3</sup> · <b>1</b> <sub>96</sub>	10 <sup>-3</sup> · <b>1</b> <sub>7</sub>	0.01 · <b>1</b> <sub>66</sub> <sup>(*)</sup> 10 <sup>-3</sup> · <b>1</b> <sub>67</sub>	0.01 · <b>1</b> <sub>11</sub> <sup>(*)</sup> 10 <sup>-3</sup> · <b>1</b> <sub>12</sub>	10 <sup>-3</sup> · <b>1</b> <sub>87</sub>	
<b>S</b> ∈ ℝ <sup>6×6</sup>						
safety levels	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>4</sup>
<b>s</b> ∈ ℝ <sup>6×1</sup>						
safety levels	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>3</sup>	10 <sup>4</sup>
<b>V</b> ∈ ℝ <sup>6×6</sup>						
flood levels	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>
<b>v</b> ∈ ℝ <sup>6×1</sup>						
flood levels	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>	10 <sup>5</sup>
			Q <sup>(A)</sup>	Q <sup>(K7)</sup>	Q <sup>(D)</sup>	
<b>R</b> ∈ ℝ <sup>3×3</sup>						
control actions			0.01	0.01	0.01	
<b>U</b> ∈ ℝ <sup>3×3</sup>						
control actions			1000 0.001 <sup>(*)</sup>	0.001	1000 0.001 <sup>(*)</sup>	

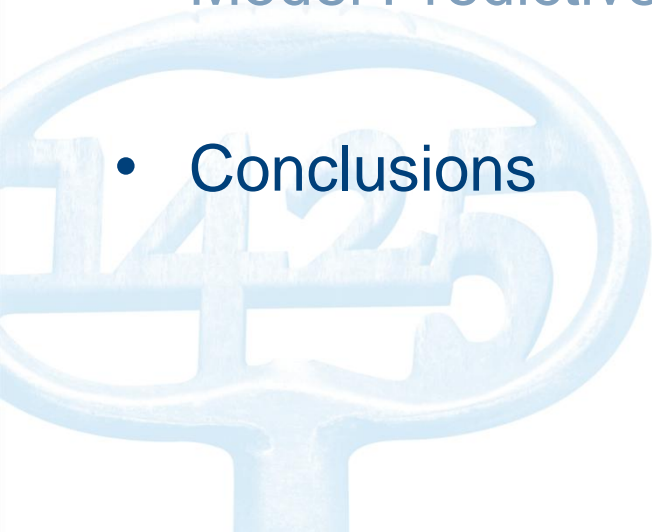


# Simulation results

	Dem <sub>1</sub>	Dem <sub>2</sub>	Dem <sub>3</sub>	Dem <sub>4</sub>	Man <sub>5</sub>	Schulensmeer
<b>maximal flooding [m]</b>						
three-pos. controller	0.275	-0.573	0.432	-0.119	0.216	-0.006
MPC+Kalman	0.036	-0.875	0.409	-0.142	0.168	-0.509
<b>total flooding [m]</b>						
three-pos. controller	2877	0	1243	0	4096	0
MPC+Kalman	69	0	1138	0	2032	0
<b>flood duration [h]</b>						
three-pos. controller	49.1	0	63.1	0	60.5	0
MPC+Kalman	27.3	0	62.9	0	46.6	0

# Outline

- Social relevance
- Modelling framework
- Model Predictive Control
- Conclusions



# Conclusions

## Objective:

Can Model Predictive Control be used for set-point control and flood control of river systems?

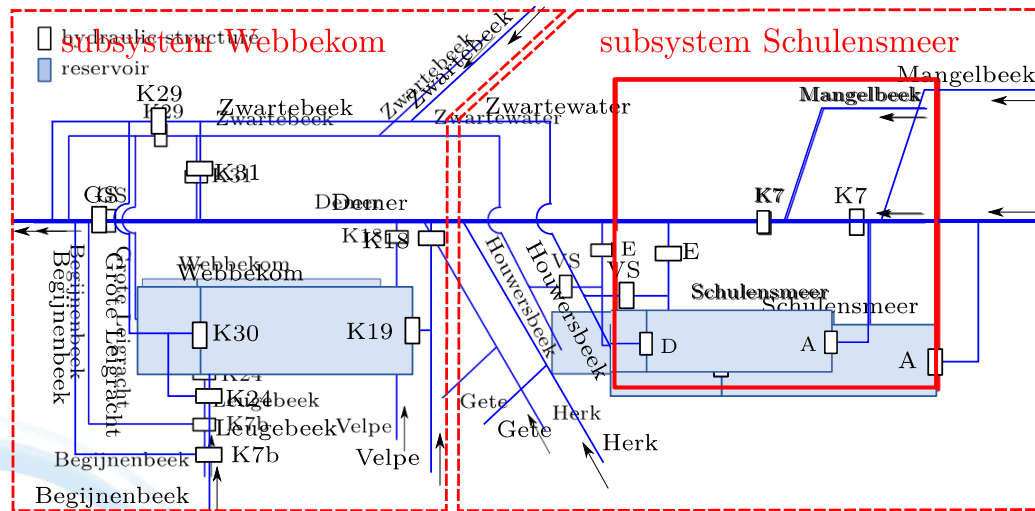
Good control performance due to

- incorporation of flood levels as (soft) constraints
- minimization of the set-point deviations
- incorporation of rain predictions via process model and prediction window
- fast buffer capacity recovery

Important: smart choice of control variables → linear MPC  
Kalman filter as state estimator

# Future research opportunities

- Apply to larger part of the Demer



Distributed MPC – Hierarchical MPC ?

- Plant-model mismatch
- Uncertainty on weather predictions





**Thank you for  
your attention!**

# Flood control of river systems with Model Predictive Control

The river Demer as case study

**Maarten Breckpot**

Jury:

Y. Willems, chair

B. De Moor, promotor

P. Willems

M. Diehl

B. De Schutter

(TU Delft)

B. Pluymers

(IPCOS NV)

**KU LEUVEN**

# Dynamics of a single reach: The Saint-Venant equations

## Assumptions:

- The **vertical pressure distribution** is **hydrostatic**.
- The **channel bottom slope** is **small**: the flow depth measured normal to the channel bottom or measured vertically are approximately the same.
- The **bedding** of the channel is **stable**: the bed elevation does not change with time.
- The **flow** is assumed to be **one-dimensional** (flow velocity over the entire channel is uniform + water level across the section is horizontal).
- The **frictional bed resistance** is the same in unsteady flow as in steady flow meaning that steady state **resistance laws** can be used to evaluate the average boundary shear stress.

# Numerical simulator: $\Delta z$ , $\Delta t$ , $\theta$

- Numerical scheme is unconditional stable if

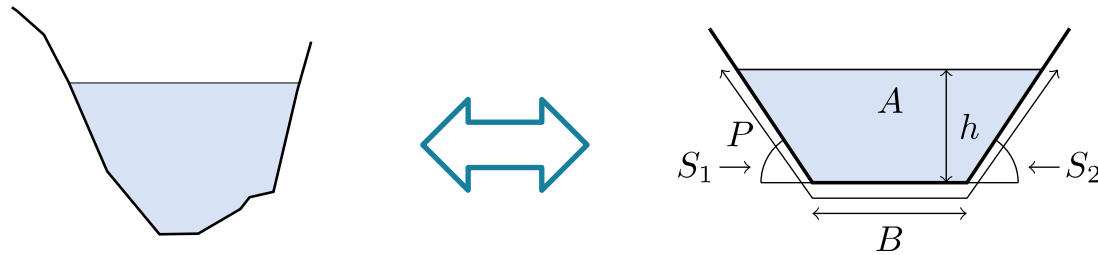
$$\theta \in \left[\frac{1}{2}, 1\right]$$

- Accuracy affected by Courant number

$$C_n = \frac{|v| \pm \sigma}{\Delta z / \Delta t}$$

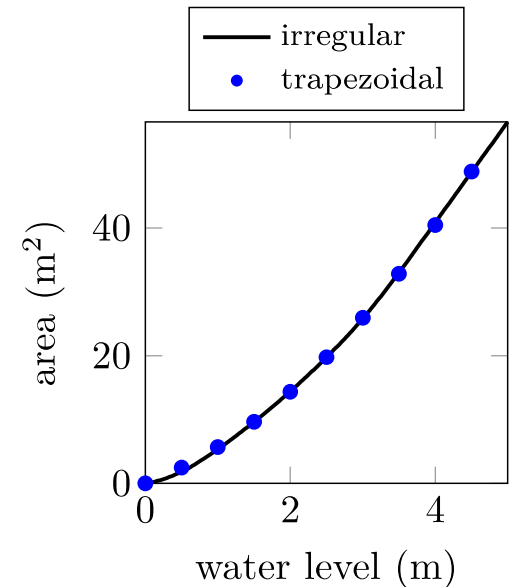
# Adaptations to MPC scheme: Approximate model

- Use (linear part of) LN-model ...  
but first approximate the irregular profiles with trapezoidal cross sections

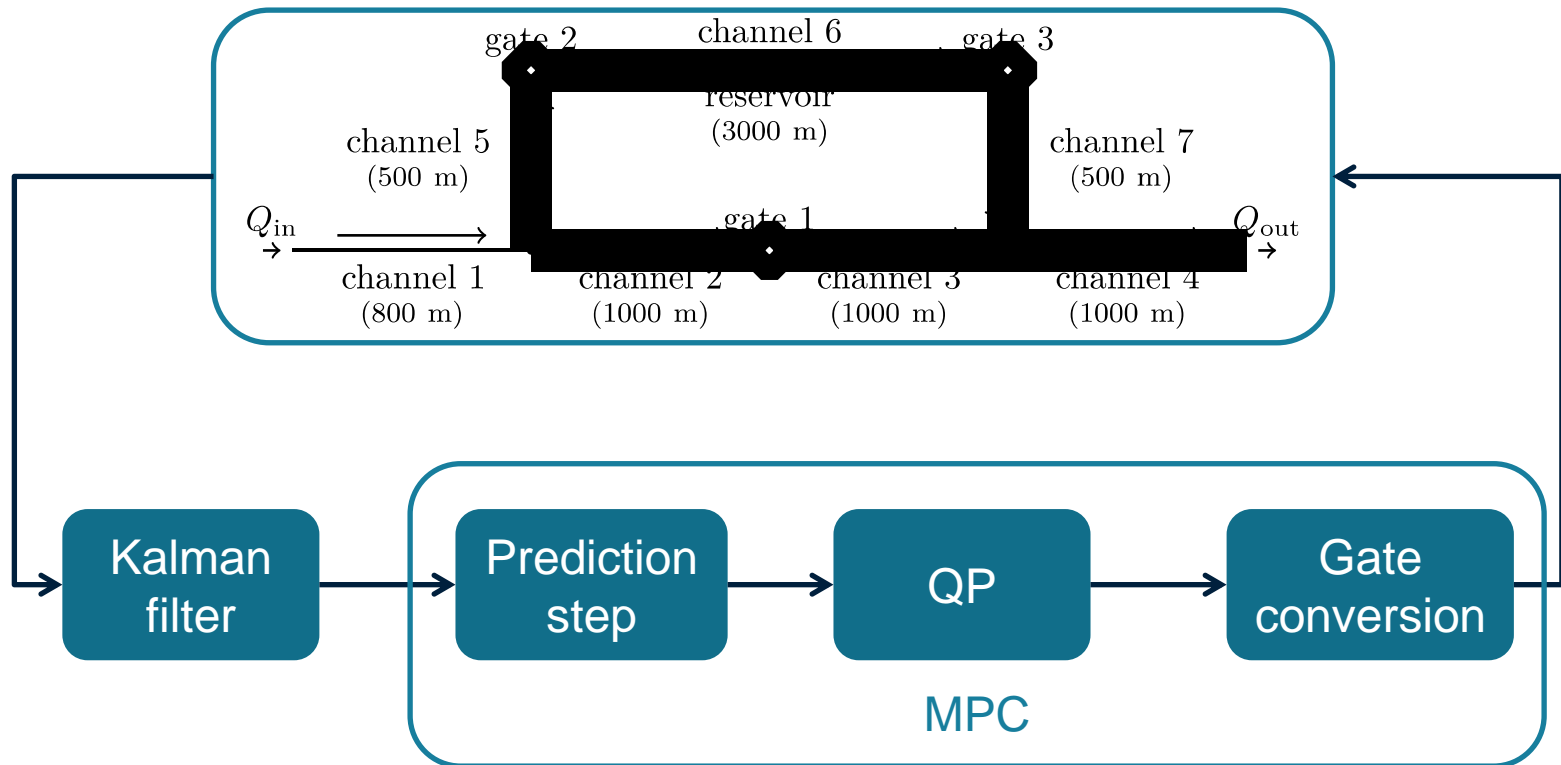


$$\min_{B,S} \sum_{i=1}^m (A_i - (h_i B + h_i^2 S))^2$$

s.t.  $B \geq 0, S \geq 0.$



# Model Predictive Control & artificial test example

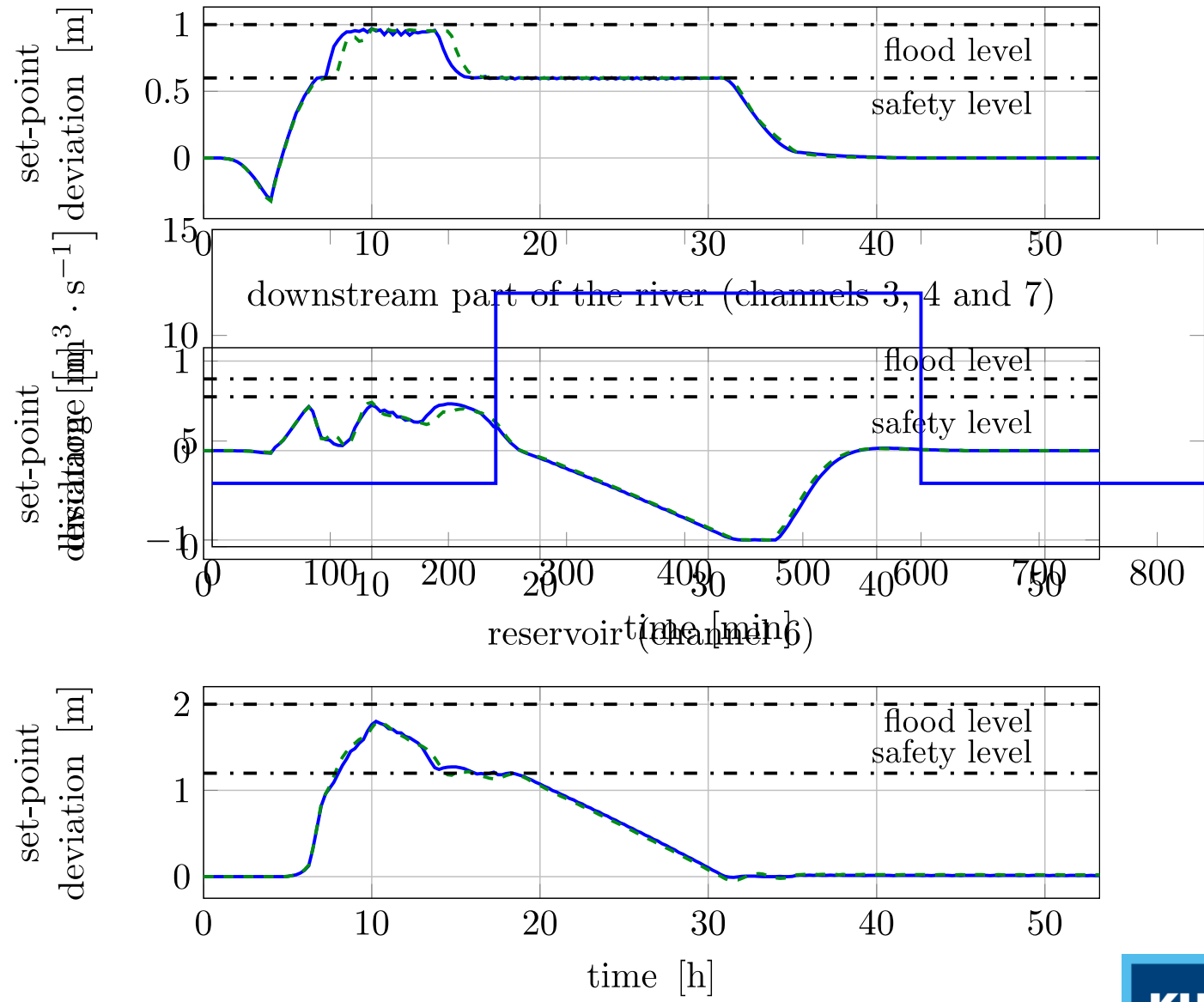


# Simulation results

	channel 1	channel 2	channel 3	channel 4	channel 5	reservoir	channel 7
$\mathbf{W} \in \mathbb{R}^{333 \times 333}$							
water levels	$10 \cdot \mathbf{1}_{17}$	$0.001 \cdot \mathbf{1}_{21}$	$0.001 \cdot \mathbf{1}_{21}$	$1 \cdot \mathbf{1}_{21}$ $800 \cdot \mathbf{1}_{21}^{(*)}$	$0.001 \cdot \mathbf{1}_{11}$	$1000 \cdot \mathbf{1}_{61}$	$0.001 \cdot \mathbf{1}_{11}$
discharges	$0.001 \cdot \mathbf{1}_{18}$	$0.001 \cdot \mathbf{1}_{22}$	$0.001 \cdot \mathbf{1}_{22}$	$0.001 \cdot \mathbf{1}_{22}$	$0.001 \cdot \mathbf{1}_{12}$	$0.001 \cdot \mathbf{1}_{62}$	$0.001 \cdot \mathbf{1}_{12}$
$\mathbf{S} \in \mathbb{R}^{7 \times 7}$							
safety levels	$10^5$	$10^5$	$10^5$	$10^5$	$10^5$	$10^6$	$10^5$
$\mathbf{s} \in \mathbb{R}^{7 \times 1}$							
safety levels	$10^5$	$10^5$	$10^5$	$10^5$	$10^5$	$10^6$	$10^5$
$\mathbf{V} \in \mathbb{R}^{7 \times 7}$							
flood levels	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$
$\mathbf{v} \in \mathbb{R}^{7 \times 1}$							
flood levels	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$	$10^8$

	$Q_{\text{gate}}^{(1)}$	$Q_{\text{gate}}^{(2)}$	$Q_{\text{gate}}^{(3)}$	$Q_{\text{out}}$
$\mathbf{R} \in \mathbb{R}^{4 \times 4}$				
control actions	175	175	175	10

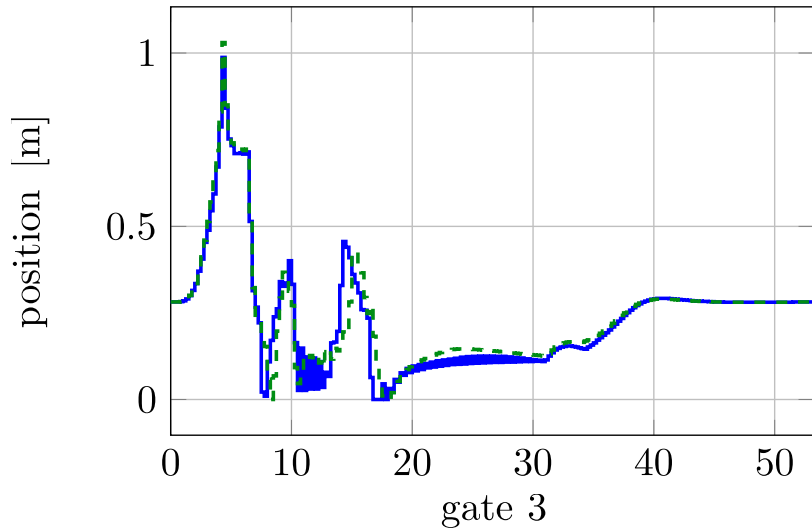
LN-MPC    LN-MPC + Kalman  
 upstream part of the river (channels 1, 2, 5)



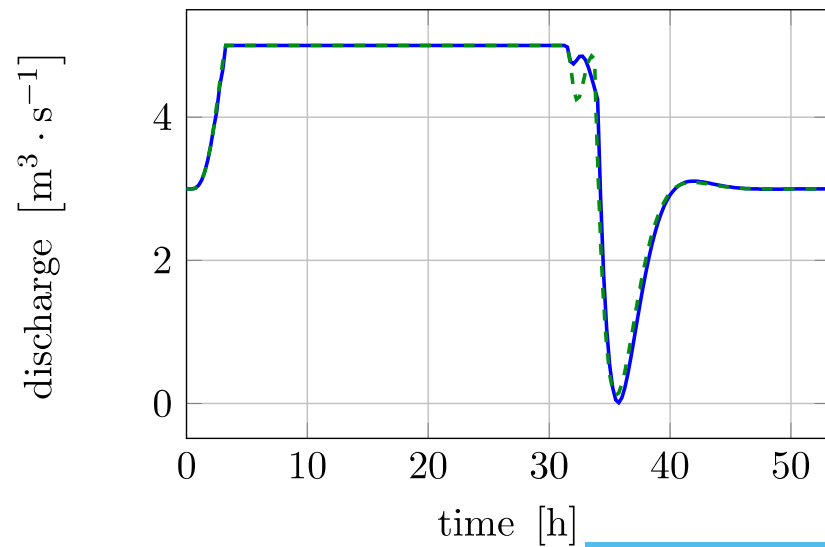
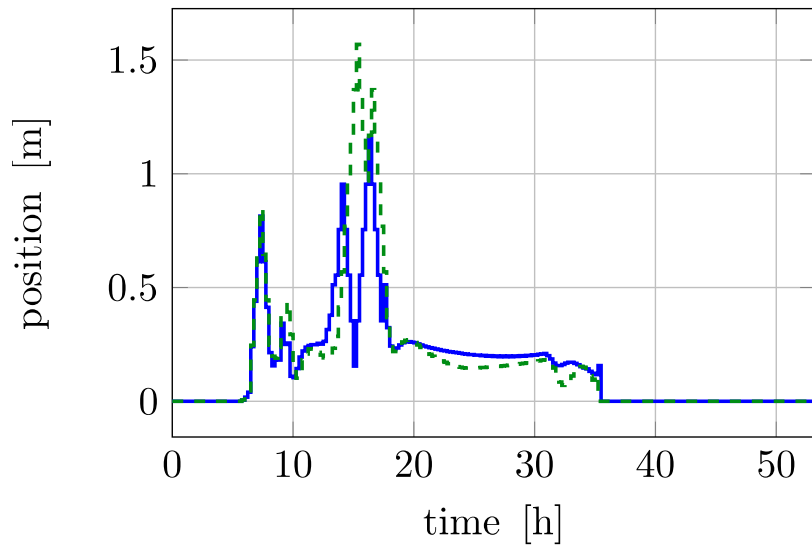
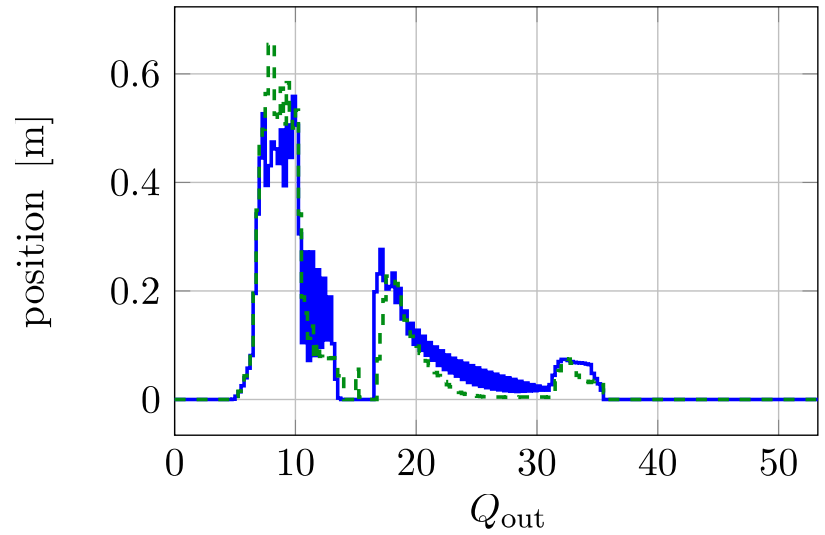


— LN-MPC    - - - LN-MPC + Kalman

gate 1



gate 2



# Simulation results

	maximal flooding (m)		average set-point deviation (m)	
	LN-MPC	LN-MPC + Kalman	LN-MPC	LN-MPC
channel 1	0.0081	0.0090	$1.51 \cdot 10^{-5}$	$1.10 \cdot 10^{-5}$
channel 2	0.0018	0.0030	$1.54 \cdot 10^{-5}$	$1.10 \cdot 10^{-5}$
channel 3	-0.2735	-0.2591	$2.31 \cdot 10^{-5}$	$7.09 \cdot 10^{-6}$
channel 4	-0.2738	-0.2583	$2.27 \cdot 10^{-5}$	$6.88 \cdot 10^{-6}$
channel 5	-0.0080	-0.0126	$1.56 \cdot 10^{-5}$	$1.14 \cdot 10^{-5}$
channel 6 (reservoir)	-0.1992	-0.2057	0.01	0.02
channel 7	-0.2742	-0.2582	$2.24 \cdot 10^{-5}$	$6.48 \cdot 10^{-6}$