Real-time control of combined surface water quantity and quality: polder flushing

M. Xu, P. J. van Overloop, N. C. van de Giesen and G. S. Stelling

ABSTRACT

In open water systems, keeping both water depths and water quality at specified values is critical for maintaining a 'healthy' water system. Many systems still require manual operation, at least for water quality management. When applying real-time control, both quantity and quality standards need to be met. In this paper, an artificial polder flushing case is studied. Model Predictive Control (MPC) is developed to control the system. In addition to MPC, a 'forward estimation' procedure is used to acquire water quality predictions for the simplified model used in MPC optimization. In order to illustrate the advantages of MPC, classical control [Proportional-Integral control (PI)] has been developed for comparison in the test case. The results show that both algorithms are able to control the polder flushing process, but MPC is more efficient in functionality and control flexibility.

Key words | model predictive control, open water system, polder flushing, real-time control, water quality, water quantity

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INTRODUCTION

Quantity and quality are the main characteristics to describe a water system. Much research has been devoted to how to optimize the water usage. For example, in irrigation systems, various real-time control methods have been applied to operate water systems efficiently (Malaterre *et al.* 1998; Schuurmans *et al.* 1999; Litrico & Fromion 2006). For water quality, research on real-time control has only been conducted for sewer systems or urban wastewater systems (Breur *et al.* 1997; Petruck *et al.* 1997; Vanrolleghem *et al.* 2005). For water quality issues in rivers and open canals, more attention has been paid to modeling (Cox 2003; Elshorbagy & Ormsbee 2006), to simulate pollution transport and provide measures or strategies for reducing pollution. As will be shown here, real-time control for water quality can also be used to manage given objectives in such systems.

Many rivers and canals have water quality problems caused by pollution. Here, a polder system is considered. Figure 1 shows a schematic view of a typical Dutch polder. It is a terrain of low-lying areas that is surrounded by dikes. Within the low-lying areas, there lie many polder ditches that are inter-connected through hydraulic structures, such as weirs and sluices. Outside the polder, surrounding the low-lying areas, storage canals are situated. Those storage canals have higher elevations and provide space for the extra water from the polder storage during wet periods. The storage canals also supply fresh water to polders during dry periods. The polder system is only connected to the outside through man-operated devices. Water levels in both polder ditches and surrounding storage canals are maintained close to given target levels by operating hydraulic structures in order to maintain certain ground water levels in the polder, and avoid dike breaks in the storage canal (Lobbrecht *et al.* 1999). Water quality is an issue in a polder system, because many nutrients from fertilizers, such as nitrate or phosphate, drain into the ditches. In summer, surface water quality can also deteriorate due to saline seepage and drainage water from greenhouses (Lobbrecht *et al.* 1999).

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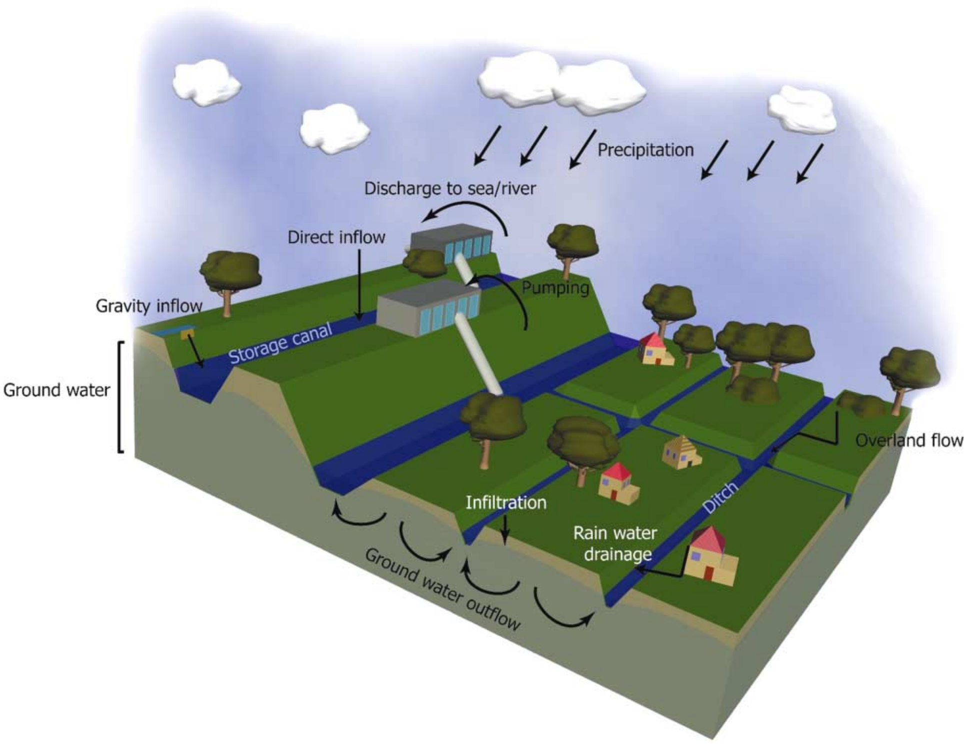

Figure 1 | Schematic view of a Dutch polder.

In polder water management, water quantity and quality control is separated. For water quality control, a certain fixed flushing strategy is used at a specific time interval, for example once every three days depending on the system. This fixed strategy is based on the worst case scenario with respect to pollution that could occur throughout the entire year. This strategy is not only overly conservative, but also inefficient. Any disturbances between two moments of flushing will make the flushing strategy less efficient, sometimes even insufficient. For example, many nutrients from fertilizers quickly drain into the ditches after heavy rainfall and deteriorate the water quality. In this situation, the flushing strategy should be modified to cope with the disturbances. Therefore, real-time control could be used, based on real-time water quality measurements. (Glasgow *et al.* 2004) provides an overview of some techniques of monitoring water quality in real-time, such as measuring salinity, temperature, nutrients, dissolved oxygen, turbidity, pH, etc. Water quality sensors are able to continuously collect the measurements in the order of seconds and they can even work in turbid water conditions, for example the MBARI ISUS nitrate sensor (Johnson & Coletti 2002). Furthermore, real-time control can take water quantity and quality into account at the same time.

Many control methods are available for water quantity control, especially for irrigation systems (Malaterre *et al.* 1998). The present study provides a guideline for extending control theory to water quality as well. In this polder flushing situation, several canal reaches are controlled (multiple variable control) and multiple objectives (water level and quality control) are formulated. Optimization could be subject to certain constraints, such as pump capacities, limitations on changing gate position and limitations on water level and water quality fluctuations. Therefore, an advanced control technique, Model Predictive Control (MPC), is considered (Camacho & Bordons 2004). In order to implement MPC on water quality, a so-called 'forward estimation' is required to predict the control variables for each reach over the prediction horizon. These predictions are part of the inputs of a simplified model used in MPC. The 'forward estimation' is performed outside the MPC optimization. A schematic diagram of the implementation procedure is shown in Figure 2. The innovation of this research is the joint application of this control method on water quantity and quality in an integrated framework.

METHOD

Forward estimation

The 'forward estimation' is regarded as a pre-simulation of flow and pollution transport. It uses two linear approximations of the De Saint-Venant equations and the one-dimensional advection-dispersion transport equation to predict the inflow and outflow concentrations along with the average concentration in the canal reaches. The prediction covers the entire prediction horizon based on the optimized control flows from the previous optimization. These partial differential equations used in the 'forward estimation' are demonstrated in (1), (2) and (3). For the transport equation, instantaneous complete cross-sectional mixing is assumed (Fischer 1979). During the canal flushing processes, the pollution is assumed to be conservative. The schematization of a canal reach is shown in Figure 3 to illustrate the variables.

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=q_1 \tag{1}$$

$$\frac{\partial Q}{\partial t}+\frac{\partial (Qu)}{\partial x}+gA\frac{\partial \zeta}{\partial x}+g\frac{Q|Q|}{C_z^2\cdot R\cdot A}=0 \tag{2}$$

$$\frac{\partial (Ac)}{\partial t}+\frac{\partial (Qc)}{\partial x}=\frac{\partial}{\partial x}\left(KA\frac{\partial c}{\partial x}\right)+q_1c_1 \tag{3}$$

where A is the cross sectional area [m^2], Q is the flow [m^3/s], q_l is the lateral inflow per unit length [$m^3/s/m$], u is the mean velocity [m/s], which equals Q/A, ζ is the water depth above the reference plane [m], C_z is the Chezy coefficient [$m^{1/2}/s$], R is the hydraulic radius [m], which equals A/P_f (P_f is the wetted perimeter [m]) and g is the gravity acceleration [m/s^2], K is the dispersion coefficient [m^2s], c is the average concentration [g/m^3], c_l is the lateral low concentration [g/m^3], t is time and x is horizontal length. Fischer (1979) provides equations to calculate the longitudinal dispersion coefficient K:

$$K=0.011\frac{W^2u^2}{du_s}$$

$$u_s=\sqrt{gRS} \tag{4}$$

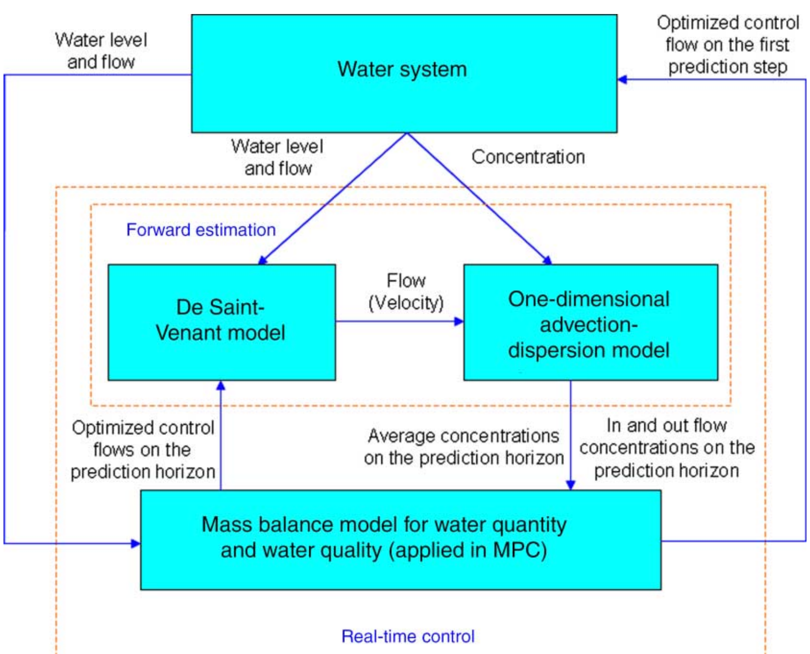

Figure 2 | Schematic diagram of 'forward estimation' and MPC on both water quantity and quality.

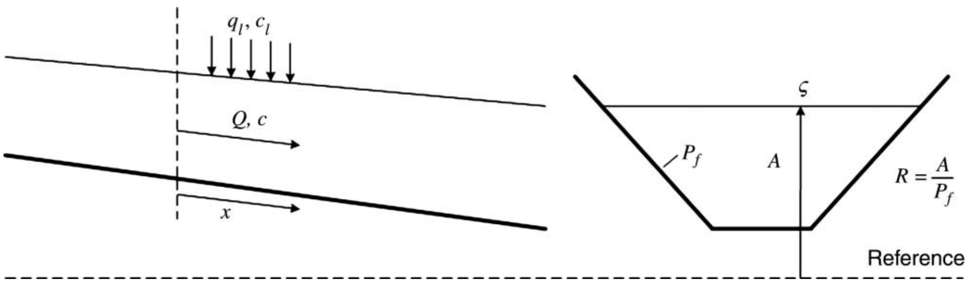

Figure 3 | Canal reach schematization.

where W is the mean width [m], d is the mean water depth [m], u_s is the shear velocity [m/s], and S is the bottom slope of the canal [−].

A spatial discretization of the Equations (1), (2) and (3), has been developed in the form of a staggered conservative scheme in combination with a first order upwind approximation (Versteeg & Malalasekera 1995; Stelling & Duinmeijer 2003). In the staggered grid, the values of ${}^*u_i$ at point i and ${}^*c_{i+1/2}$ at point $(i + 1/2)$ are missing (see Figure 4). An upwind approximation is applied to achieve those values according to the flow direction.

$$\frac{dA_i}{dt} = \frac{Q_{i-1/2} - Q_{i+1/2}}{\Delta x} + q_{l,i} \tag{5}$$

$$\frac{du_{i+1/2}}{dt} + \frac{1}{\bar{A}_{i+1/2}}\left(\frac{\bar{Q}_{i+1}{}^*u_{i+1} - \bar{Q}_i{}^*u_i}{\Delta x} - u_{i+1/2}\frac{\bar{Q}_{i+1} - \bar{Q}_i}{\Delta x}\right) + g\frac{\zeta_{i+1} - \zeta_{i-1}}{\Delta x} + g\frac{u_{i+1/2}|u_{i+1/2}|}{C_z^2 \cdot R} = 0 \tag{6}$$

$$\frac{d(A_i c_i)}{dt} = \frac{Q_{i-1/2}{}^*c_{i-1/2} - Q_{i+1/2}{}^*c_{i+1/2}}{\Delta x} + \frac{1}{\Delta x^2}(K_{i+1/2}\bar{A}_{i+1/2}c_{i+1} - (K_{i+1/2}\bar{A}_{i+1/2} + K_{i-1/2}\bar{A}_{i-1/2})c_i + K_{i-1/2}\bar{A}_{i-1/2}c_{i-1}) + q_{l,i}c_{l,i} \tag{7}$$

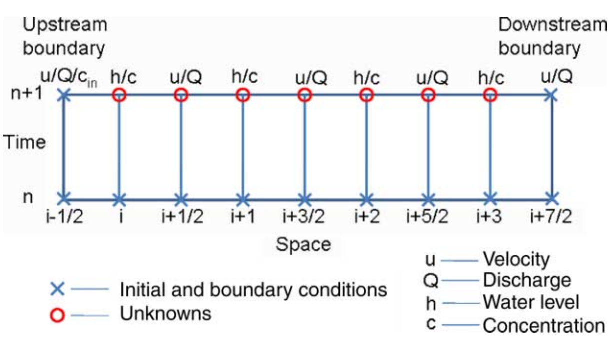

Figure 4 | Schematic view of staggered 1D grid.

where

$$\bar{Q}_i = \frac{Q_{i+1/2} + Q_{i+1/2}}{2} \quad \text{and} \quad \bar{A}_{i+1/2} = \frac{A_i + A_{i+1}}{2}$$

$${}^*u_i = \begin{cases} u_{i-1/2}\,(\text{positive flow}) \\ u_{i+1/2}\,(\text{negative flow}) \end{cases} \quad \text{and}$$

$${}^*c_{i+1/2} = \begin{cases} c_i\,(\text{positive flow}) \\ c_{i+1}\,(\text{negative flow}) \end{cases}$$

The integration scheme in time is based on the 'theta method' (Stelling & Duinmeijer 2003). The equations are connected with each other, giving rise to tri-diagonal matrices. A schematic view of the staggered 1D grid is shown in Figure 4.

Model predictive control

Model Predictive Control (MPC) has been developed in industrial engineering since the 1970s. MPC has recently been introduced in water management, mainly for controlling water levels in the system. For example (Van Overloop 2006) applied MPC on various open channel systems, and (Wahlin & Clemmens 2006) used MPC to control water levels in branching canal networks. A block diagram of MPC describes the process (see Figure 5). Extending this method to combined water quantity and quality control appears promising.

MPC needs a model to predict the future behavior of a system. The commonly used models for describing the dynamics of water quantity and quality in a shallow water system are De Saint-Venant equations and the advection-dispersion transport equation. However, these are non-linear partial differential equations, and make

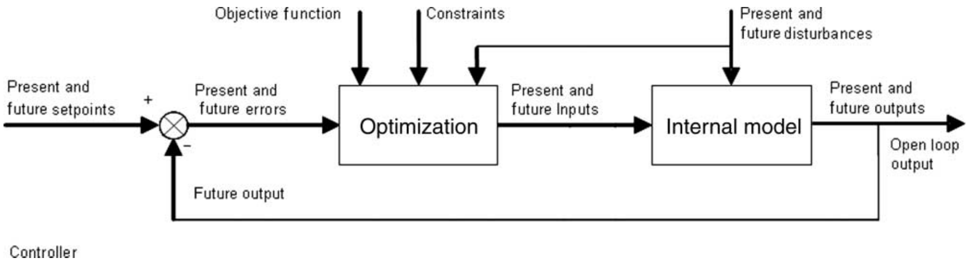

Figure 5 | Block diagram of MPC.

controller design and implementation a difficult task. From a control point of view, it is potentially attractive to design a controller with a linear approximation of the non-linear system model (Leigh 2004). A discrete time-variant state space model from control theory can be expressed as:

$$X(k+1) = A(k) \times X(k) + Bu(k) \times U(k) + Bd(k) \times D(k)$$

$$Y(k) = C \times X(k) \tag{8}$$

where: $X(k)$ is the state vector, $U(k)$ is the input vector, $D(k)$ is the disturbance vector, $A(k)$ is the state matrix, $Bu(k)$ is the control input matrix, $d(k)$ is the disturbance matrix, C is the output matrix and $Y(k)$ is the output. The equations are structured into matrices and can be solved with for example MATLAB.

Many linear approximations have been developed for the De Saint-Venant equations, especially for irrigation canals. A canal reach is divided into several segments and a state 'estimator' or 'observer' is used to estimate the hydraulic information for each segment (Reddy *et al.* 1992; Durdu 2005). However, such approximations are not appropriate for MPC due to the fact that MPC uses on-line (real-time) optimization, and the use of many segments increases the computational power requirements considerably. This problem is compounded if the same linearization procedure for the water quality model is added. Therefore, a simplified model is needed, provided it can preserve the main system characteristics. (Schuurmans *et al.* 1995) developed an Integrator Delay (ID) model, which is a lumped parameter model. The ID model captures the main dynamics of water transport and assumes two elements in a canal reach: uniform flow part, mainly characterized by its delay time, and a backwater part, characterized by its surface area. The equation description is as follows:

$$\frac{de_h}{dt} = \frac{dh}{dt} = \frac{1}{A_s}[Q_{in}(t-\tau) - Q_{out}(t)] \tag{9}$$

where e_h is water level deviation from target level [m], which has the same derivative as the water level h when the target level is constant. Q_{in} and Q_{out} are inflow and outflow [m^3/s], A_s is the backwater surface area [m^2] and τ is the delay time in the uniform flow part [s].

For simplified water quality model, (Thomann & Mueller 1987) provide a lake model as a completely mixed system which maintains the mass balance. This model can be modified to a non-mixed system if the average concentration of the lake and the outflow concentration can be calculated. In this case, the calculation is possible when applying the 'forward estimation'. Then the water quality mass balance can be written as:

$$\frac{d(Vc)}{dt} = Q_{in}(t)c_{in}(t) - Q_{out}(t)c_{out}(t) \tag{10}$$

Substituted with the flow mass balance, Equation (10) becomes:

$$\frac{de_c}{dt} = \frac{dc}{dt} = \frac{1}{V}[Q_{in}(t)(c_{in}(t) - c(t)) - Q_{out}(t)(c_{out}(t) - c(t))] \tag{11}$$

where V is the water volume in the reach [m^3], e_c is the average concentration deviation from the target concentration [g/m^3], which has the same derivative as the average concentration c when the target concentration is constant, c_{in} and c_{out} are inflow and outflow concentrations [g/m^3].

Table 1 | Target values of water level and concentration*

	Reach 1	Reach 2	Reach 3	Reach 4
Target level (m)	−0.4	−0.8	−1.2	−1.8
Target concentration (g/m^3)	0.7	0.7	0.7	0.7

*Target concentration is the average pollutant concentration target.

For MPC, an objective function J is used to describe the goal of controlling combined water quantity and quality:

$$J = \min \sum_{j=1}^{m} \left\{ \sum_{k=1}^{n} \{Q_h e_h^2(k) + Q_c(e_c(k) - e_c^*(k))^2 + R_{\Delta Q}\Delta Q^2(k) + R_c^* e_c^{*2}(k)\} \right\} \quad (12)$$

$$\text{Subject to}: \begin{array}{l} e_c^*(k) \leq 0 \\ \Delta Q_{\min} \leq \Delta Q(k) \leq \Delta Q_{\max} \\ \Delta_{\mathrm{p,min}} \leq Q_p(k) \leq Q_{\mathrm{p,max}} \end{array}$$

where: n is the number of steps in the prediction horizon and m is the total number of canal reaches, ΔQ is the change of flow (both for gate and pump) [m^3/s], Q_h, Q_c and $R_{\Delta Q}$ are the penalties for e_h, e_c and ΔQ separately. e_c^* is a virtual variable as soft constraint [g/m^3] introduced to restrict e_c. The introduction of soft constraint is due to the restriction that water quality control should be deactivated when water is clean (below target concentration). (Van Overloop 2006) points out that soft constraints are implemented as extra penalty when the state or input violates the limitation. R_c^* is the penalty on virtual inputs. Its value is extremely small, which makes the term of $R_c^* e_c^{*2}(k)$ almost equal to zero, no matter what the value of $e_c^*(k)$ is. Q_{p} is the pump flow [m^3/s]. The constraints on ΔQ and Q_{p} are regarded as hard constraints that can never be violated.

TEST CASE

Case setup

To demonstrate the potential of the method, an artificial but realistic polder flushing test case is studied, which consists of four canal reaches, separated by 3 in-line gates. The reaches have different water quality contents at the beginning, but the average concentrations are all below water quality target concentrations. The target values of water quantity and quality are listed in Table 1. The canal characteristics are shown in Figure 6. Each canal reach was divided into 100 segments for spatial discretization, thus 10 metres per segment. The pollution is assumed to be conservative or at least conservative during the flushing period, such as would be the case, for example, in salinity control. At each time step, the dispersion coefficient K at each discretized velocity point is estimated through Equation (4). The canal introduces fresh water from a storage canal through 'Gate 1', and a pump is used to lift water out of the system at the other end. Each reach has several polluted lateral inflows listed in Table 2 with their initial flows and concentrations. These laterals are disturbances to the system.

The total simulation time is 20 hours. During the simulation, the concentration of the second lateral in the second reach was increased from 1.4 g/m to 5.6 g/m (a step change) after 5 hours and kept constant afterwards. Other lateral concentrations and flows remained. This change in disturbance was assumed to be known in advance or could be predicted. The selection of which lateral concentration increased was chosen randomly. Which exact disturbance scenario is used, is assumed to

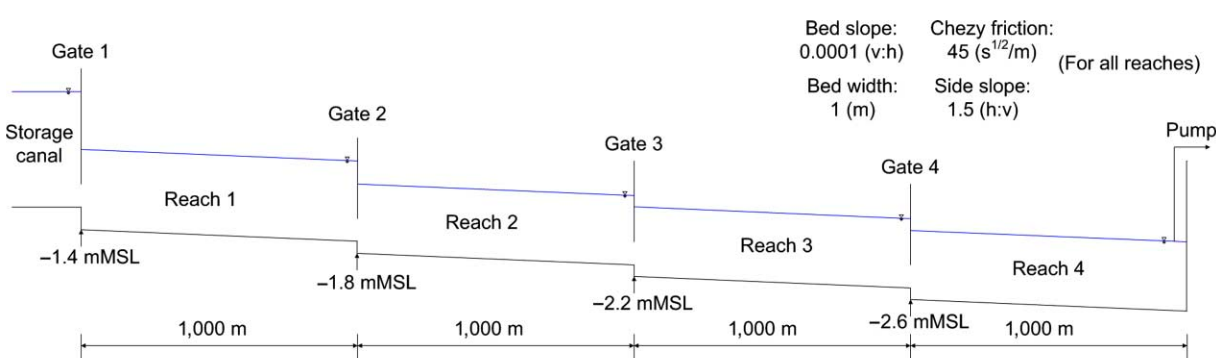

Figure 6 | Longitudinal profile of canal reaches with geometric characteristics.

Table 2 | Lateral flow in each reach

	Lateral 1			Lateral 2			Lateral 3		
Reach	Flow (m^3/s)	Concentration (g/m^3)	Distance to reach head (m)	Flow (m^3/s)	Concen-tration to reach (m^3/s)	Distance to reach head (m)	Flow (m^3/s)	Concentration (g/m^3)	Distance to reach head (m)
1	0.02	1.0	400	0.03	1.2	800			
2	0.02	1.2	300	0.03	$\boxed{1.4}$	700			
3	0.04	0.9	200	0.02	1.5	500	0.03	1.8	900
4	0.02	1.5	500	0.04	1.0	800			

be irrelevant for the evaluation of real-time control. This case demonstrates how real-time control corrects for water quality disturbances while water quantity criteria are still maintained. The total system was modeled and tested in MATLAB.

MPC setup

The internal model and the objective function are in accordance with those in the 'model predictive control' section. In the state space model, $X(k)$ includes the water level deviations and concentration deviations from their setpoints as well as flows on the delayed time steps; $U(k)$ includes the flow changes of each structure and the virtual inputs $e_c^*(k)(\leq 0)$ of each canal reach, which is used to switch on/off the water quality control; $D(k)$ includes all the lateral flows. The discrete delay steps in the model are estimated by the travelling time $(L/(\sqrt{gR}+u))$ (Schuurmans 1997), divided by the control time step and rounded upwards, where L is the canal length [m], R is the hydraulic radius [m], g is the gravity acceleration [m/s^2] and u is the mean velocity [m/s]. The calculation results in 2 delay steps with a 4 min control time step for each reach. The MPC controller uses a 4 hours prediction horizon. When MPC detects the lateral concentration change within the prediction horizon, it should adjust the flow at the present control step.

There are no specific rules for tuning MPC. (Van Overloop 2006) provides a method for obtaining a set of starting penalties for the objective function. Further tuning can be followed through trial-and-error. Table 3 displays the penalties used in this case.

Classical control setup

Proportional-integral control (PI) is a commonly used control method in water management. It is relatively simple and robust with respect to disturbances. Researchers have applied PI controllers on irrigation and river water systems for water level control (Schuurmans 1997; van Overloop *et al.* 2005). The reason for applying PI control in this case is to compare its performance with MPC and to illustrate the advantage of the more advanced control method, MPC. The principle behind PI control is a simple equation:

$$\Delta Q(k) = K_p(e(k) - e(k-1)) + K_i e(k) \tag{13}$$

where k is a discrete time index, ΔQ is the required flow change for a certain structure [m^3/s], K_p and K_i are proportional and integral gain factors, e is water level deviation from a given target level [m].

This method can be extended to water quality control by defining e as the water quality deviation from target value. In this polder flushing case, 'Gate 1' (inflow to the system) is

Table 3 | Penalties in the objective function of MPC

Index	1	2	3	4	5
Q_h	$1/(0.28)^2$	$1/(0.28)^2$	$1/(0.28)^2$	$1/(0.28)^2$	
Q_c	$1/(0.58)^2$	$1/(0.58)^2$	$1/(0.58)^2$	$1/(0.58)^2$	
R_c^*	$1/(1.0\times10^{10})^2$	$1/(1.0\times10^{10})^2$	$1/(1.0\times10^{10})^2$	$1/(1.0\times10^{10})^2$	
$R_{\Delta Q}$	$1/(0.061)^2$	$1/(0.061)^2$	$1/(0.061)^2$	$1/(0.061)^2$	$1/(0.061)^2$

Table 4 | Gain factors of PI control

Gain factor	Gate 1	Gate 2	Gate 3	Gate 4	Pump
K_p	0.65	6.31	6.84	6.31	8.21
K_i	0.06	0.48	0.46	0.48	0.49

linked to the water quality variable in the most polluted reach. The remaining gates and the pump apply local upstream control (Malaterre *et al.* 1998) on water levels in each reach with decouplers. The decoupler is considered to be a feedforward control, which has the function of counteracting the influence of flow interactions between neighboring canal reaches (Schuurmans 1997; Schuurmans *et al.* 1999). In this case, the decoupler sends the upstream gate flow information directly to all structures and avoids flow interactions between neighboring reaches. Thus, it avoids extra water level fluctuations.

Researchers have made important contributions to select proper gain factors for PI control, for example, (Ziegler & Nichols 1993). In simple situations, such as in this test case, a trial-and-error method can even be used. Table 4 displays the selected gain factors of PI control.

RESULTS

The simulation results of using both PI control and MPC are shown in Figures 7 through 11. In these figures, gate and pump flows, water level deviations and average pollutant

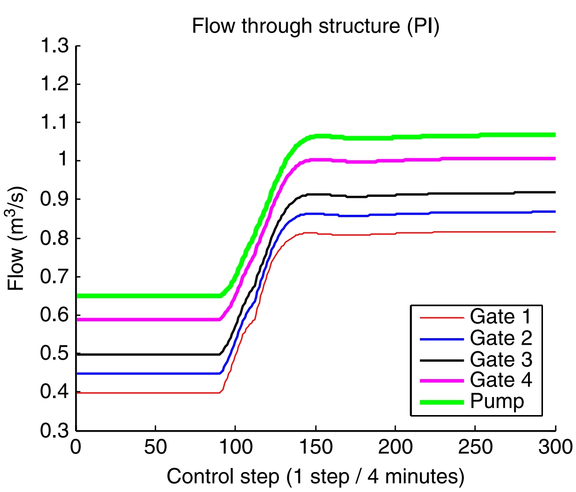

Figure 7 | Structure flow (PI control).

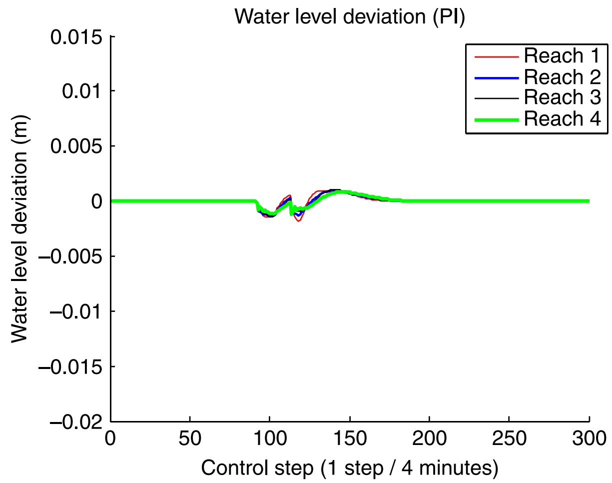

Figure 8 | Water level deviation (MPC).

concentration deviations from their target values are demonstrated. Figures 7 through 9 are the results of PI control and Figures 10 through 11 are for MPC. It is clear that with a step change in water quality, both controls can stabilize water levels and restore water quality back to their target values. They move the system from one steady state to another.

With PI control, 'Gate 1' reacts when the step change happens. This is the moment when the water quality deteriorates. Due to the decoupling, water level controllers take actions at the same time and decrease the water level at the end of each pool. Figures 8 and 9 show that water levels can be efficiently maintained with PI control, but water quality deteriorations in reach 3 and 4 are relatively high.

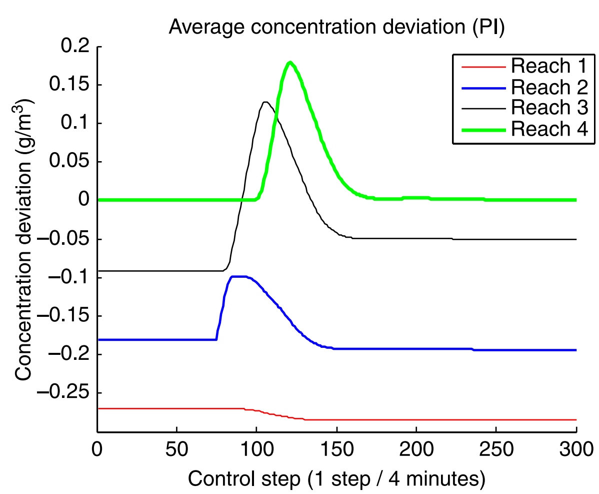

Figure 9 | Average concentration deviation (PI control).

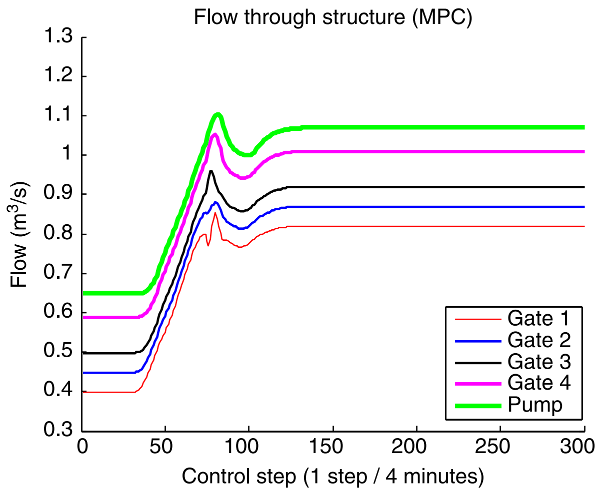

Figure 10 | Structure flow (MPC).

When MPC is applied, it can adjust the system in advance due to the prediction (a 4-hour prediction in this case). When MPC detects lateral concentration increases within the prediction horizon, it increases clean water inflow and thus decreases the concentration first. Figure 10 shows this earlier response when comparing with PI control result in Figure 7. In this case, when the actual lateral change occurs, there is more leeway for concentration increase. This is a significant difference from PI control where the concentration peak is much higher. Figure 9 and 11 demonstrate this difference. Figure 12 show that MPC can also control water levels within a relatively safe margin.

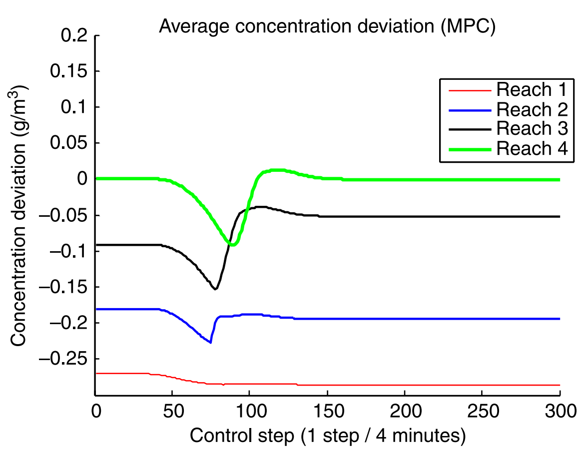

Figure 11 | Average concentration deviation (MPC).

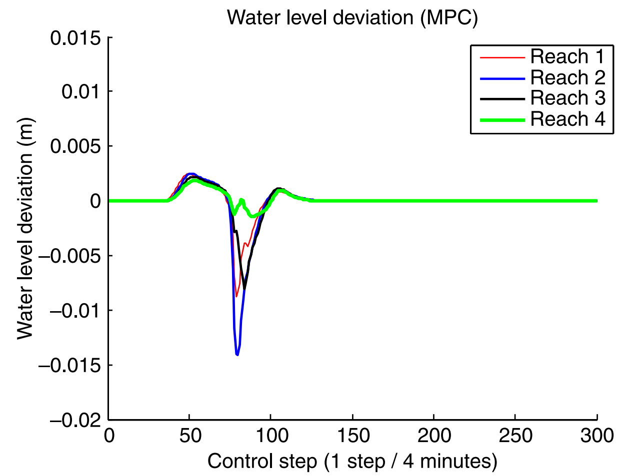

Figure 12 | Water level deviation (MPC).

CONCLUSIONS

This paper explored the innovation of combined surface water quantity and quality control. A polder flushing strategy was studied based on real-time control. Regarding the results of applying PI control and MPC, the following conclusions can be drawn.

1. Both PI control and MPC are able to maintain water levels and restore water quality back to their target values during canal flushing.
2. PI control and MPC performances are different. PI control takes late action, while MPC takes advantage of the prediction, which leads to smaller concentration deviations and a better flushing strategy.
3. The incorporation of a 'forward estimation' process, proposed in Figure 2, is proved to be a feasible procedure when applying simplified water quantity and quality models for MPC.

DISCUSSIONS

Based on the above comparison between MPC and PI control in the canal flushing case, three aspects can be considered for discussion.

1. Functionality: PI control is much simpler than MPC and it uses less computational power. Although it can stabilize the system relatively well, this setup of PI control (the first gate controls water quality and the rest maintains water levels) has limited functionality.

It is specifically designed for canal flushing. If there is water scarcity in the system while water quality is not a problem, this setup is unable to supply water downstream, because the first gate is not programmed to maintain water quantity. In contrast, MPC is a multi-objective control system for both water quantity and quality, and it is designed to optimize flows in any situation. From this viewpoint, it has more functionality than PI control.

2. Control flexibility: MPC is able to consider system constraints that may be present within the optimization, for example, the maximum allowed pollution concentration. Because MPC can react in advance based on the prediction, extra leeway can be created before the real concentration peak arrives. This is extremely important, especially when water quality deviation margins are small and the constraints are easily violated. The constraint violation may be unavoidable or be mitigated through very tight control when applying PI control.
3. Implementation difficulty: It is not sufficient for MPC to only use measurements. MPC needs a proper model to predict the future behavior. In reality, it is difficult to obtain all the information required by the model, such as to anticipate the lateral flow and its concentration. Therefore, other models are needed to generate these inputs first, for example rainfall-runoff model coupled with certain water quality model. Since PI control reacts only when deviations occur, measurements are enough to fill the controller. This makes the implementation of PI control much easier.

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