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# Potential of model predictive control of a polder water system including pumps, weirs and gates

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## ABSTRACT

This work presents an assessment of the potential of model predictive control (MPC) of a Dutch polder system. The system drains to the Linge river and includes 13 weirs, 4 hydraulic gates and 4 large pumping stations each equipped with multiple pumps, managed by the Water Board Rivierenland. The management of the system must comply with several goals: keep the water levels within the bounds of safety, pump out the excess water at minimum cost or $CO_2$ emission, but always have enough water for irrigation and shipping. To achieve these goals there are weirs regulating the water level in different pools, pumping stations to pump water in and out and gates to let water in and out by free flow when possible. These pumping stations consume large amounts of energy. We propose multi-objective mixed-integer optimization by using goal programming to prioritize different operational objectives. For the control of the pumps mixed-integer optimization is used, which makes it possible to not only model the energy consumption of the pumps while in operation, but also to model if the pumps are turned on or off. The control system is implemented using RTC-Tools, an open-source software tool to implement MPC. It is demonstrated that the proposed control system implementation can comply with the operational goals of the water board: keeping the water levels within the bounds while reducing the operational costs. The proposed control system has been tested numerically on data from the year 2013, and it is shown that it highly outperforms the current operation.

## 1. Introduction

Low-lying countries have to constantly discharge water to keep their land dry by pumping excess water to the sea, while all the demands of the different users of water should be satisfied. With global warming and increasing sea level this task is going to present more challenges. Operational water management provides solutions for achieving the desired distribution of water taking into account, the amount, the time and the location. The distribution of water occurs by operating hydraulic structures such as pumps, weirs and gates. During the management of a system with such structures, several factors have to be taken into account: safety, ecology, and requirements related to agriculture, navigation, and recreation. Multi-objective programming techniques can solve such problems. RTC-Tools is a decision support system for water management, able to use multi-objective optimization and multi-objective programming techniques [1]. In this work the development and use of additional components of this decision support system are described and an application is presented.

Model predictive control (MPC) has been used to control different kind of water systems [2]. MPC is especially suitable for water systems due to its capability of dealing with model-based predictions, known disturbances (such as weather forecasts or tidal motion, day-ahead energy price forecasts), unknown disturbances (such as unknown inflows or water level changes caused by unmodeled processes) and finally time delay. Its first use was for irrigation and drainage systems [3–5]. It is often used for reservoir operation [6,7] and not only for water quantity but also for quality control [8]. Due to the complexity and price of the development and infrastructure, there are only few real implementations [9].

MPC has been used in water systems including pumps to minimize their power consumption, but they were mainly drinking water systems and the dynamics of the pump was often not taken into account in the modeling phase. The pump-dynamics is a discrete, non-linear and non-convex process, which implies that it is computationally hard to solve and multiple local optima exist. In many polder systems, the pump head and pump discharge both may vary over 50% to 100% of the design duty point of the pumping stations. Therefore, correct modeling of the pump

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behavior (head, discharge and power) is essential to minimize energy cost or energy consumption. [10] use stochastic model predictive control on a reservoir–pump–wind–turbine system, but the dynamics of the pumps are not taken into account. One way to overcome the heavy computational burden is to not minimize the energy used by the pumps directly, but the number of switching intervals [11] or total on-time of the pumps [12]. [13] used a similar approach for a water distribution system (modeled by system identification) in which the number of pumps turned on was minimized. The disadvantage of these approaches is that they are hard to combine with other objectives and to integrate into a complex system. There are some studies that include pump-dynamics into the optimization. [14] uses continuous optimization for drinking water systems, and uses post processing to discretize and then to obtain the pump-schedule. [15] does use discrete optimization, that is non-linear, but also non-convex, thus optimality of the solution is not guaranteed. [16,17] uses discrete optimization, convex modeling and linear (and thus convex) pump modeling.

In this work convex, discrete, non-linear optimization is used, which is able to approximate the pump dynamics well and enables real time implementation. There are two contributions of this paper:

(1) development of a modeling framework of a water system containing hydraulic structures and pumps. The modeling framework includes:

- Convex modeling of each part of the water system
- The pumps are modeled including the pump curves in order to achieve efficient pumping, which is different from what is erroneously assumed by most: always pumping at maximum efficiency.
- The on–off state of the pumps is included in the optimization, therefore it became a mixed-integer problem that is solved in real-time.
- The multiple objectives are approached using goal programming instead of using weights on the objectives, therefore the wishes of the water managers can be directly translated to goals and the results are reflecting the expectations better.

The pump modeling approach has been discussed in detail in [18].

(2) presentation of a feasibility study of the optimization of the complete water system using historical data. Due to the way of modeling the network, it is possible to always arrive at a solution that is physically possible and within acceptable computation time. This fact allows the application of this control technique in real situations.

The rest of the article is organized as follows: first the modeling explained in general including the water system and the hydraulic structures. Then the case study of the Linge River is introduced, including the objective function specific for the system. Then the test scenario is described, and finally the results are presented and the work is concluded.

## 2. Methodology

### 2.1. Framework for model predictive control and optimization

The optimization and the model predictive control are implemented using RTC-Tools (Real Time Control Tools). RTC-tools is an open-source, real-time control toolbox that can be used as a decision support system (DSS) for the control of a water system. As such, it comprises of a computational model of the system, an optimization algorithm, a platform for data aggregation, and a user interface. Among the desirable properties that a DSS should have, the ability to produce consistent, explainable, computationally efficient solutions is a fundamental one. RTC-tools guarantees this provided that the system is modeled in a convex way. Indeed, under mild technical assumptions, a convex optimization problem has a unique optimal value and an optimal solution can be found via a deterministic, polynomial time algorithm. A convex optimization problem can be written in the following form:

$$\begin{aligned}\underset{x}{\text{minimize}}\quad & f_0(x)\\ \text{subject to}\quad & f_i(x)\le 0,\ i=1,\dots,m,\\ & h_i(x)=0,\ i=1,\dots,p,\end{aligned}\tag{1}$$

where $x \in \mathbb{R}^n$ is the optimization variable, $f_0 : \mathbb{R}^n \mapsto \mathbb{R}$ is the convex objective function, $f_i : \mathbb{R}^n \mapsto \mathbb{R}$ are the convex inequality constraints and $h_i : \mathbb{R}^n \mapsto \mathbb{R}$ are the affine equality constraints. The next step is to describe the operation of the pump is in such form.

In this implementation discrete variables are needed to represent, for example, whether a pump is on/off or whether the water level downstream of a pump is higher or lower than the upstream level. As soon as integer variables are introduced in an optimization problem this becomes, potentially, very computationally expensive to solve. Indeed, mixed-integer programming is a NP-complete problem and its complexity grows exponentially with the number of discrete variables [19]. However, there are well-established exact algorithms and relatively efficient solvers for linear and quadratic mixed-integer programs. RTC-Tools is currently using the following solvers: CPLEX [20], Gurobi [21] and CBC [22]. They are solving quadratic mixed-integer optimization problems containing first-order and convex second-order functions. They are also used in this paper and can be written as:

$$\begin{aligned}\underset{x}{\text{minimize}}\quad & c_i f_0(x)\\ \text{subject to}\quad & f_i(x)\le 0,\ i=1,\dots,m,\\ & h_i(x)=0,\ i=1,\dots,p,\\ & c_i\in[0,1],\ i=1,\dots,n\end{aligned}\tag{2}$$

where $f_i : \mathbb{R}^n \mapsto \mathbb{R}$ are first order of convex second-order functions and $h_i$ are affine functions.

#### 2.1.1. Multi-objective programming technique

RTC-tools can deal with multi-objective problems by applying lexicographic goal programming. This is a useful multi-objective programming technique when various, conflicting objectives are present and there is a clear hierarchy on the priority of these objectives [23,24]. For example, keeping the water level between certain boundary levels should be preferred over minimizing energy usage or pump operating costs. Starting with the most important goal, the algorithm will perform subsequent optimization runs to optimize each goal while not compromising the results of the previous priorities. The advantage of this approach compared to the conventional approach where the objectives are in one objective function with different weight is the clarity of importance of the objectives. In case of using more objectives on one function, how far the objectives are reached depends on the weighing factors. For example how far the water level stays within a certain bound versus minimizing pumping costs. The balance can be different in different situations while the weighting factor is the same. In goal programming, it can be clearly described how important is to keep the water level in the bound (and which bound exactly). Using goal programming approach such wishes of the users can be reached: The water level should be definitely below 20 cm NAP, and using the least possible energy. This wish would be difficult to implement with one objective function using weights. Keeping the water level within the desired bounds is modeled as an objective and not as a constraint. The reason for this formulation is to allow the water level to exceed those bounds if there is no possible operation to avoid it. If these were hard constraints, a solution to the optimization problem would not be feasible and a suggested control action would be lacking. Using the water level bounds as objectives provides the best possible control action in order to keep the water levels as close as possible to the bounds even if they have to be exceeded. In this way there is always a feasible solution if it is physically possible, which is crucial for implementation in real cases.

The optimization problem in Eq. (2) describes the water system. In order to be able to make such description all components of the water system are described using convex or linear equations and are used in the optimization problem as objective or constraints. In the following section it is shown how each component of the water system is described in such optimization framework.

### 2.2. Modeling of the components of the water system

#### 2.2.1. Flow modeling

For each branch in a water system a mass-balance model is used. Each branch acts as a reservoir and the water level is determined as the integral value of the incoming and outflowing water. Note that it is straightforward to extend the system to an Integrator Delay model [25], adding a time-delay to the mass-balance model. The mass-balance model can be written as:

$$A\frac{dh}{dt} = Q_{in}(t) - Q_{out}(t) \tag{3}$$

where $A$ is the backwater surface, $h$ is the water level of the branch, $Q_{in}$ and $Q_{out}$ are the in- and outflow discharge, respectively. All values are in SI units.

#### 2.2.2. Pump modeling

The pump modeling includes the model of the hydraulics and the energy consumption of the pumps. The modeling is nonlinear and convex. The boundaries of the working area of the pump are modeled with convex second and first order functions. The energy consumption $E$ of the pump is modeled as

$$E = \sum_{t_d=0}^{t_{dn}} P_{app}(Q(t_d), H(t_d))\Delta t \tag{4}$$

where $P_{app}$ is the power approximation, a second order convex function of the discharge $Q$ and head $H$, and $\Delta t$ is the length of the discrete time step. The working area of the pump is used as constraints, such that any $Q$ - $H$ pair correspond to a physically possible working point of the pump. This enables the computation of the shaft speed as post processing. The pump modeling is described in detail in [18].

#### 2.2.3. Weir modeling

The discharge over weirs is described by the general weir equation [26]:

$$Q = C_d 2/3B\sqrt{2g}(h - h_w)^{3/2} \tag{5}$$

where $Q$ is the discharge over the weir, $C_d$ is the weir discharge coefficient (approximated as 0.61), $B$ is the crest width, $g$ is the acceleration of gravity, $h$ is the water level, $h_w$ is the crest height. For the weir discharge coefficient the most common value from literature is used [27,28]. This value of the discharge coefficient performs well even compared to more sophisticated equations [29,30]. The actual decision variable used is the discharge, and the weir height is calculated as post-processing. The physical constraints of the weir are introduced as inequality constraints and deduced from Eq. (5). The result of this approach is that for crest heights that are different from the minimum and maximum crest height, the complete non-linear weir equation is used (Eq. (5)), while for the minimum and maximum crest height the following linear approximation suffices:

$$Q = C_{lin1}(h - h_w) + C_{lin2} \tag{6}$$

where $C_{lin1}$ and $C_{lin2}$ are coefficients for the linearization. The detailed weir modeling is described in [31].

#### 2.2.4. Sluice gate or free orifice modeling

The discharge through a sluice gate can be written as [26]:

$$Q = C_{dg}Bw\sqrt{2g(h - h_b)} \tag{7}$$

where $C_{dg}$ is the sluice gate discharge coefficient, $B$ is the width of the gate, $w$ is the opening of the gate and $h_b$ is the bottom elevation. As the square root function is convex, it can be directly used as an inequality constraint in the optimization. This inequality constraint enforces that the discharge is less than or equal to the actual orifice flow:

$$Q \leq C_{dg}Bw\sqrt{2g(h - h_b)}. \tag{8}$$

Moreover, it can be easily rewritten in the following convex way:

$$\begin{aligned} &Q^2 - C_{dg}^2 Bw^2 2g(h - h_b) \leq 0 &&\text{if } h > h_b,\\ &Q = 0 &&\text{otherwise.} \end{aligned} \tag{9}$$

Meaning that, depending on the water level value, either the first or the second constraint should be applied to the optimization problem. Such type of constraints can be easily formulated using the big-M approach typical of mixed-integer linear programming. The idea is to have a integer variable $\delta \in \{0, 1\}$ that indicates whether the first or the second constraint should be activated. That is, $\delta = 1$ if and only if $h > h_b$ and $\delta = 0$ otherwise.[1] We can then reformulate (9) as

$$Q^2 - C_{dg}^2 Bw^2 2g(h - h_b) - M(1 - \delta) \leq 0, \tag{11}$$

where $M = \max_h(C_{dg}^2 Bw^2 2g(h - h_b))$.

Adding another constraint enforcing positive discharge, the discharge is between zero and the curve defined by Eq. (7). Physically it means that the gate opening is chosen to be variable: when the opening is zero the discharge is zero, while the opening is at its maximum when the flow is equal to Eq. (7). Moreover, for any flow in between it is possible to find a physically realizable gate opening. Actual gate opening values are calculated as post-processing.

### 2.3. The whole optimization problem

Using the equations of the different structures the whole optimization problem can be constructed. The detailed description of the mixed-integer optimization problem can be found in [18]. The objective function ($f_0$) of the second-last step of the goal programming is the combined energy of all pumps that they consume during the time horizon. All other physical processes discussed in the section above are present as equality of inequality constraints. For example the water movement (Eq. (3)) is used as equality constraint. The free flow model of the weirs (Eq. (6)) is used as inequality constraint, as the weirs are movable and therefore the discharge could be any value between the possible physical bounds.

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[1] This is easily implementable as

$$\begin{aligned} &h - h_b - M(1 - \delta) \leq 0,\\ &h - h_b + M\delta \geq 0, \end{aligned} \tag{10}$$

where $M = \max_h(h - h_b)$.

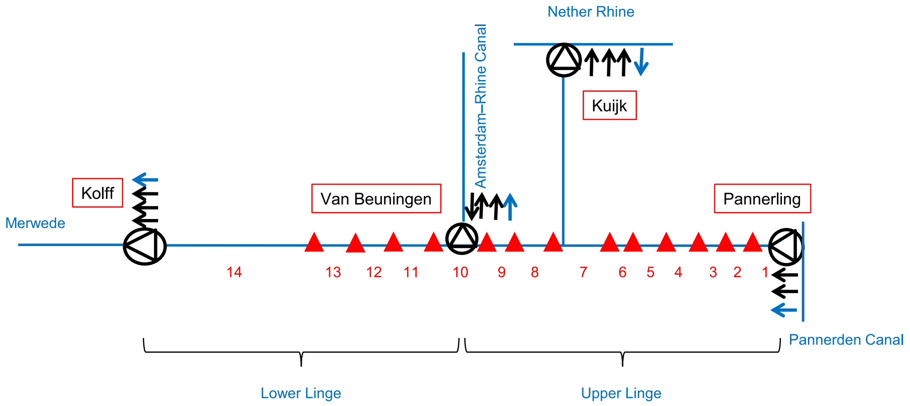

**Fig. 1.** The Linge River, the weirs are denoted with red triangles, the four pumping stations are indicated, and the direction of the pumping and free flow is noted with black and blue arrows, respectively. The number of black arrows denotes the number of pumps.

**Table 1**
Characteristics of pumping stations.

| Pumping station | Location (branch) | Number of pumps and directions | Direction of free flow |
|---|---|---|---|
| Pannerling | 1 | 2 in | In |
| Kuijk | 7 | 3 out | In |
| van Beuningen | 10 | 1 in, 2 out | Out |
| Kolff | 13 | 3 out | Out |

## 3. Case study

### 3.1. Description of the study area

This study focuses on the water management of the Linge river with its four pumping stations. This area is managed by Water Board Rivierenland, one of the 21 water boards in The Netherlands. The 98 km-long Linge is located in the South of the Netherlands, between two branches (Waal and Nether Rhine) of the Rhine river. The Linge carries water from the Pannerden Canal to the Beneden Merwede, while allowing the drainage of the surrounding polders, supplying water to agricultural activities and being used for navigation. The Upper Linge has several pools divided by weirs, while the Lower Linge has long meandering parts (Fig. 1). Apart from the weirs, there are four pumping stations to be managed along the Linge. Upstream pumping station Pannerling is responsible for letting water in (or pumping in) to the Linge. Kuijk pumping station is also located at the Upper Linge and it can pump water out or let water freely in. The next pumping station in downstream direction, Van Beuningen pumping station, is mainly used to pump out, or discharge freely from the Linge to the Amsterdam-Rhine Canal. It can also pump water in whenever it is needed. Kolff pumping station is located at the downstream end of the river, and can pump water out or discharge it freely to the Beneden Merwede. The complex combination of possibilities of the pumping stations and inlets are summarized in Table 1.

The aim of the management of the Linge is to store and transport the water from the polder dewatering, provide water for agriculture in dry periods while maintaining the water level within a desired range (with a bandwidth of 20 cm) in order to ensure safety, navigation and to preserve ecology. These goals can be satisfied by controlling the settings of pumps, weirs and gates. These variables directly determine the water levels and flow in the Linge. Operating pumps requires considerable energy and money. The purpose of this study is to propose a management system for the Linge river such that the aims are achieved while spending the least possible amount of money.

### 3.2. Building the model of the Linge river

The model of the Linge river is built with the following components: 14 branches, 13 weirs, 4 pumping stations and 4 gates (Fig. 1). The branches and the weirs are modeled as described in the methodology section. The four pumping stations contain several types of pumps. Most of them are variable speed pumps, except for van Beuningen station, in which there are constant speed pumps. Two stations (Kolff and Kuijk) are diesel engine driven, while the other two (van Beuningen and Pannerling) are driven by electric motors. The diesel price is constant, while the price of the electricity changes in time, and it is known in advance for the next 24 h. The information about the day-ahead energy price is used in the optimization. At some of the pumping stations free flow is possible depending on the outside water level. In the model the amount of free flow can be chosen by the optimization provided the outside water level is lower than the inside and it is not exceeding a prescribed maximum. The optimization of the water system is performed by RTC-Tools, and for that purpose, the modeling is also performed by RTC-Tools modeling library [18,32,33]. According to these modeling principles the working area of the variable-speed pumps is defined as a range of possible combinations of discharge and head $(Q, H)$. For this example the bounds of the working area are the following four curves: (1) the minimum shaft speed (2) the maximum shaft speed and two curves related to minimum efficiency. This could be improved by replacing these curves with physically more relevant ones like minimum flow rate, cavitation and maximum power.

The model built from the components has four water level boundary conditions and fourteen discharge boundaries. The water level boundary conditions are the water levels of the water bodies: the water level of (1) Pannerden Canal, (2) Beneden Merwede, (3) Amsterdam-Rhine Canal, (4) Nether Rhine. The Beneden Merwede is subject to tidal variations up to 40 cm. The discharge boundary conditions are the in- and outflows to all fourteen branches; these flows depend on the dewatering of the polders or the water used for agriculture. In real-time control these values can be predicted with rainfall-runoff and hydraulic models by using the weather forecast as input. In this case study we use historic data for flow rates in and out of the branches. The control action variables (decision variables) are the operation of the hydraulic structures: (1) the discharge of 11 pumps grouped into four pumping stations, (2) the flow under the four gates that are installed parallel to the pumps, and (3) the flow over the 13 weirs, where pump shaft speeds, the gate openings and the weir height are the result of the post-processing. The controlled variables are the 14 water levels and the cost of energy consumed by the pumps.

### 3.3. Optimization of the Linge river

As described in Section 2.1 the optimization uses a multi-objective programming, called goal programming. The first goal to be solved is that the water levels should stay within the given bounds; formally the exceedance of the water level bounds are minimized. The second goal is that the water level at the last optimization step is no higher than the middle of the aforementioned range. This goal is used to avoid the water levels reaching the upper boundary at the end of the optimization horizon, which would occur as it is a cheaper solution. If water levels cannot be contained in a range, this goal creates only options that do not cause further violation of the first goal. As a third goal the pumping cost is minimized, that is the product between the energy consumed and the forecast of the energy price, summed up during the optimization period.

Such optimization problem has the following formulation:

$$\begin{aligned} \text{minimize} \quad & \sum_{p\in\mathcal{P}}\sum_{t_d=0}^{t_{dn}} P^p_{app}(Q,H)\Delta t\omega^p(t) \\ \text{subject to} \quad & \text{Mass-balance equations (3)}, \\ & \text{Weir equations (6)}, \\ & \text{Sluice and orifice equations (11)}, \\ & \text{Pump modeling constraints [18]}, \\ & h^*_{lb} \le h \le h^*_{ub}, \end{aligned} \qquad (12)$$

where the values of $h^*_{lb}$ and $h^*_{ub}$ are determined via the goal programming procedure explained above and the objective function is composed as following: for each time step $t$ and each pump $p$ the associated pumping cost is formulated as the approximated energy consumption of a pump $P^p_{app}(Q,H)\Delta t$ multiplied by its energy price $\omega^p(t)$. Summing up for each timesteps in the time horizon and the set of all the pumps $\mathcal{P}$, we obtain the total pumping cost.

Finally, the last goal smooths out the rapid changes in the water level by minimizing the time derivative of the water level. This smoothing results in less movement by the structures which helps to avoid wear and tear of the hydraulic structures.[2]

The models are simplified physical models, therefore the parameters of these models come from the geometry of the river and the hydraulic structures. The possibly conflicting objectives are managed by the goal programming. The order of the goals is chosen such that it reflects the importance of the management objectives of the Linge river. We refer to our extensive description of goal programming in Section 2.1.1 and [23]. The tunability of this approach lies in the definition of the goals and the decision on their order. This has been done in consultation with the operators of the system and resulted in the following goals and order of priorities:

1. keep the water level within the prescribed bounds
2. the water level at the last time step cannot be higher than the middle of that prescribed bound
3. the pump costs are minimized
4. the water level changes are minimized

As water level bounds is the first goal, this one has the highest priority. The second goal is an often-used end-point goal to avoid the water levels increasing in the end of the horizon. With the minimization of the pumping costs as the third goal the solutions are preferred where excess water can be discharged without using the pumps in situations when the outside water level is low enough to allow free flow. As the minimization of the costs is the third goal in line, keeping the water levels within the desired bounds is a priority. Cost reduction is only achieved if a solution can be found that is cheaper than the original one and not causing the water levels to exceed the bounds more than in case of the original solution.

In some problem formulations water level bounds are implemented as constraints. But if, for instance, water inflow is too high to maintain water levels within these bounds, the optimization would become infeasible and no control action is given. In the goal programming formulation when the bounds cannot be kept there is still a control action provided that minimizes the water level exceedance.

Note that, as we implement lexicographic goal programming we run an optimization problem for each priority (without the need of adding arbitrary weighting factors to the optimization function to differentiate among the priorities). Moreover, since the target water level goal is of highest importance, when we optimize for subsequent priorities like pump costs the target water level becomes de-facto a constraint. Indeed, if during the first priority optimization run we find that the water level targets can always be satisfied, then such must be the case for all the subsequent priorities. And this is implemented via a constraint as explained in [23]. However, if for some reason the water level goals cannot be met, we compute the minimum violation and at each subsequent priority we ensure that such violation of the water level targets is not exceeded (and this is also implemented as a constraint).

Another advantage of goal programming lies in its transparency. Priorities are much easier to communicate with operators than weighing factors. Clear communication with operators is crucial for the adoption and implementation of the MPC solution in practice.

The physical limitations of the system are implemented as constraints: the physically minimum and maximum water levels, the equations of the water movement and the structures.

### 3.4. Test scenario

Model predictive control is used, that is, the optimization is carried out in a receding horizon manner: for every optimization run the following 12 h are optimized with hourly time step. In a real scenario, the optimization is re-run at least every hour, to anticipate water-levels deviating from modeled values and to incorporate new weather forecast data or updated energy prices. Since the current test is used to assess the potential of MPC, the test case makes use of historic inflow data and the system response is computed rather than measured. A 6-h interval for a re-run was adopted in order to balance between calculation time and how often the forecast data is likely to change. This method allows the incorporation of new boundary conditions at every 6 h. To show the potential of the method we optimize the entire year 2013. The following data is known 12 h ahead at every optimization step: (1) day-ahead energy price, (2) inflows, (3) water level bound (given as historical data for this study). The results of the year calculation are compared to the current management, or an approximation thereof, which is called "base scenario". In this comparison it is assumed that the inflows to the system are known, which in reality are predictions. Pumps and weirs are assumed to be controllable instantly in both the optimization and the base scenario. In reality, starting or stopping a pump, or changing the setting of a weir takes some time. The lead time for starting a pump depends on the type of the drive and the limitations in system dynamics and maximum motor current. All pumps in this study start up slowly, with their shaft

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[2] Suppose that the optimization problem (12) finds as optimal value $p^*$, then the goal programming routing of RTC-Tools will add the extra constraint $\sum_{t_d=0}^{t_{dn}} P_{app}(Q,H) \le p^*$.

speeds increasing gradually in case of a diesel engine drive or an electric motor with frequency converter, or increasing in steps up to a fixed shaft speed in case of an electric motor with a voltage reducing device such as a soft starter, a star-delta starter, a series inductance, or combinations thereof. Such start-up procedures limit the inrush current and starting torque of a motor, and prevent potentially damaging system dynamics such as slamming of check valves. In practice, the lead time for a pump start is always below 20 s.

### 3.5. Base scenario

In the base scenario we attempt to reproduce the current management techniques as closely as possible. The base scenario contains PID controllers for the weirs and rule-based control for the pumps: if the suction water level exceeds a certain level, the pump is switched on and if the suction water level drops below a threshold the pump is turned off. In reality the pumps are controlled by operators, and there was no data available about the actual control. The base scenario was developed to emulate the behavior of the operators as closely as possible. The reference model has been developed in the package WANDA (https://www.deltares.nl/en/software/wanda/), an advanced, interactive software package to support the hydraulic design process of pipeline systems with open channels and hydraulic structures. WANDA was preferred with respect to other software packages for its modeling flexibility and abilities to simulate advanced low-level control systems and pump energy consumption. (RTC-Tools does not have a similar simulation option.) WANDA was used to model the open channel system of the Linge in a manner very similar to the RTC-Tools model. Channel features and boundary conditions are identical; the only difference between the two models being the way the system is managed. In the RTC-Tools model, the management of the pumps and weirs is optimized, while in the base scenario a feedback control is used. The weirs along the Linge are managed with a local PID controller calibrated in order to keep their upstream water level between the bounds. The other structures are managed by an interval controller with respect to the downstream (Pannerling) or upstream (Kolff and Kuijk) water level. The interval controllers are set in order to keep the water levels within the given bounds. Before switching on a pump, the controller checks whether it is possible to discharge by free flow. If that is possible, free flow is preferred as long as the conditions allow it. Alternatively, the pumps are switched on. Pumps are only modeled at Pannerling and Kolff pumping stations, as the flow conditions for 2013 did not require the use of pumps at van Beuningen and Kuijk pumping stations. The feedback control of the weirs and the pumping stations have been set in consultation with the operators of the Water Board Rivierenland.

The base scenario is validated with available data of real pumping hours and costs for pumping station Kolff (Table 2). The total operating hours are in the same order of magnitude in the base scenario and in reality. The same applies to the total cost. In reality, the three pumps at Kolff were used more or less equally to prevent premature wear in one of the pumps. In the base scenario pump 1 was always turned on first and pumps 2 and 3 followed if required. Since the three pumps are identical, the order of their use was irrelevant in the simulation. What is important in this respect is that the overall working hours and cost are in the same order of magnitude. Van Beuningen station was marginally used, and data about the other two stations was not available.

Though the intention was to re-create the operation of the pumps as closely as possible using rule-based (feedback) control, there are several reasons why the base scenario is different from the reality. In reality operators turn on and off the pumps, they have their own reasoning behind it, therefore it cannot be mimicked by standard rules. For instance, in reality, pumps were preferably not used during the night because of a lack of supervision. In the feedback control this was not the case.

**Table 2**
Operating hours and costs of diesel for the three pumps of Kolff pumping station (2013): real, measured data and results of base scenario with feedback control modeling.

| Pumping station | Real | | Base (feedback control) | |
|---|---|---|---|---|
| | Cost (k€) | Runtime (h) | Cost (k€) | Runtime (h) |
| Kolff 1 | – | 642 | – | 1196 |
| Kolff 2 | – | 739 | – | 350 |
| Kolff 3 | – | 541 | – | 42 |
| Total | 195 | 1922 | 188 | 1588 |

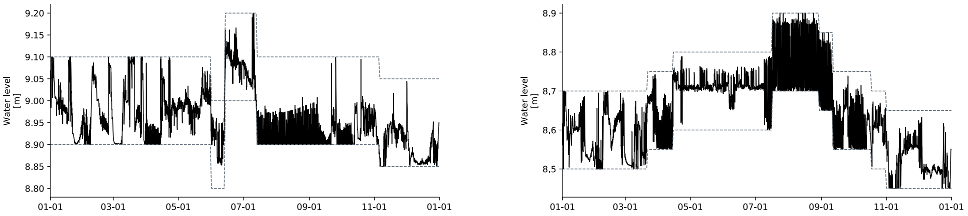
The main contribution of this paper is a modeling framework that allows to use optimization of complex water systems including pumps which can lead to mixed integer problems and a case study using real data. The Long-term calculations are to demonstrate this concept and to show that they indeed can be implemented on a real system and are fast enough to make calculations in real time. The base scenario is not a perfect representation of reality but given the availability of the data the agreement is considered satisfactory. Even if reality is not exactly represented in the base scenario, the comparison is still between two control methods (feedback and optimized) applied on exactly the same system scenario.

## 4. Results

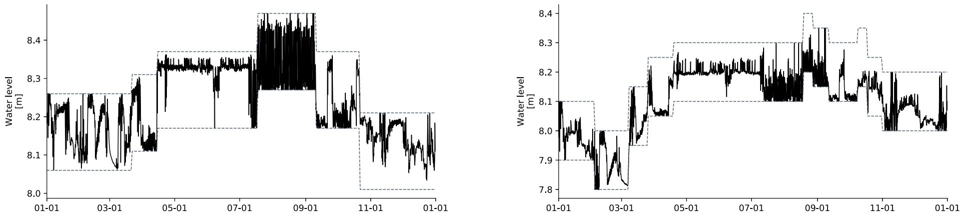
In this section the results of the application of the proposed control system are discussed and compared to the base scenario. First, the main objective is evaluated: keeping the water levels within the prescribed bounds. Then, the other objective, to save as much cost as possible is discussed.

The main objective of the management of the Linge is achieved: the water levels stay within the given bounds (Figs. 2–3). In most of the branches during the yearly operation the minimum and maximum water level changes, but the bandwidth remains constant: 20 cm. In several branches most of the time the water level stays in the middle of the bounds (branches 4–6, listed in Fig. 2 and branches 8–13, listed in Fig. 3), while in some branches it tends to fluctuate more and in others it stays near to the maximum bound. This is an allowed behavior, as no additional preference was expressed for the water level staying in the middle of the bound rather than at the top. On the other hand, traditional feedback control of the hydraulic structures, as implemented in the base scenario, was not able to keep the water levels within the bounds due to the fact that the feedback control cannot anticipate on excessive future inflow coming from rainfall run-off. Some examples are shown in Fig. 4, where the water level exceeds the bounds at several occasions. Similar violations also occurred in reality, the bounds could not always be kept.

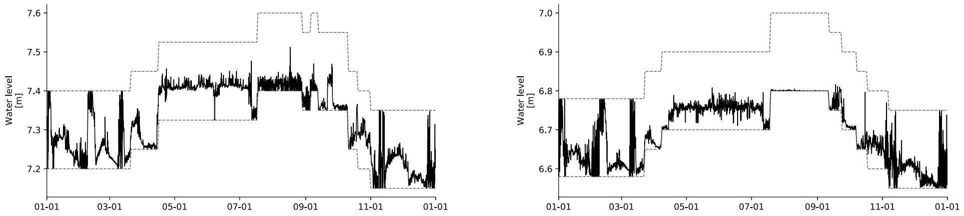
The other aim for the control system is to spend the lowest possible amount of money on pumping. The comparison of the costs between the base scenario and the proposed control method is shown in Tables 3 and 4. Kolff pumping station consumes less than 15% of the energy of the base scenario. The more upstream a pumping station is located, the less energy it consumes. In total, 80% of the costs are saved by using optimization. In the following, the reasons for this large saving are explained. While the first three reasons consider the management of the individual pumping stations, the last two show that optimizing the management of the pumps in a water system is more than running the individual pumps efficiently.



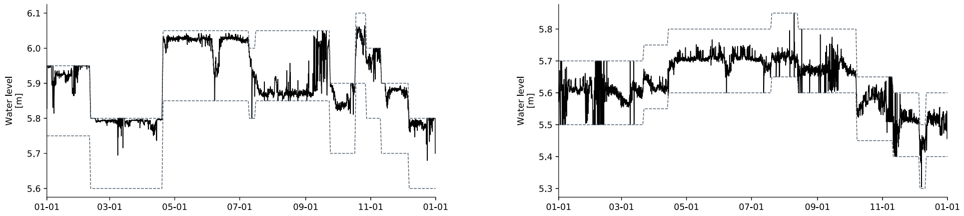
(a) branch 1 (b) branch 2



(c) branch 3 (d) branch 4



(e) branch 5 (f) branch 6



(g) branch 7 (h) branch 8

**Fig. 2.** Result of model predictive control (MPC): Water levels in branches 1–8 with black line, the minimum and maximum bounds on water level with gray dashed line.

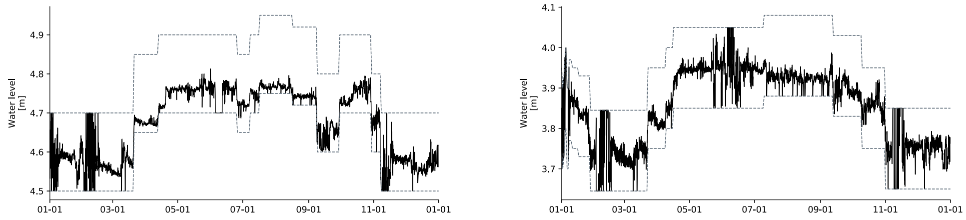
**Table 3**
Energy usage of pumping stations.

| Pumping station | Feedback control (MWh) | MPC (MWh) |
|---|---|---|
| Pannerling | 70 | 11 |
| Kuijk | 0 | 23 |
| Beuningen | 0 | 49 |
| Kolff | 608 | 83 |
| Total | 678 | 166 |

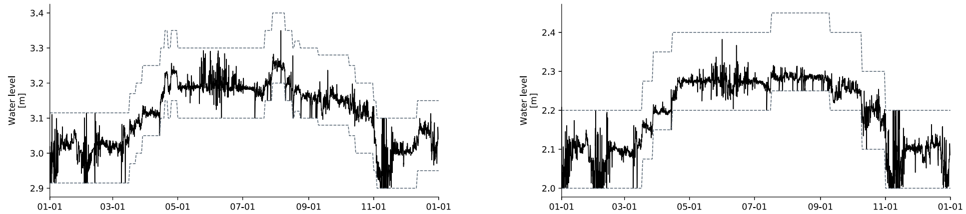
**Table 4**
Cost of pumping stations.

| Pumping station | Feedback control (k€) | MPC (k€) |
|---|---|---|
| Pannerling | 3.6 | 0.4 |
| Kuijk | 0 | 7 |
| Beuningen | 0 | 2 |
| Kolff | 188 | 26 |
| Total | 191.6 | 35.4 |

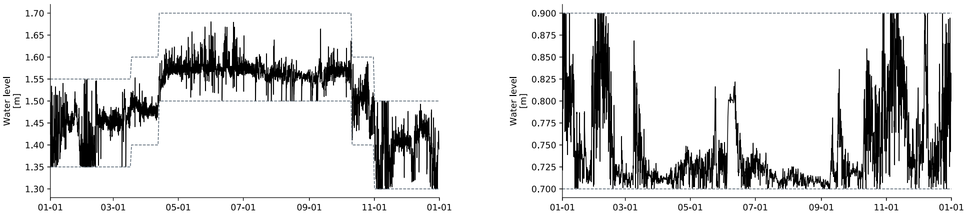
1. Pumping efficiently
   The pumps controlled by optimization operate at higher efficiencies and at lower specific energy. An example is the Kolff pumping station, whose working area and operation are shown in Fig. 5. The working area is shown within the bounds, and is colored according to the specific energy. A lower value of the specific energy is equivalent to a higher efficiency, and thus to cheaper pumping. The red triangles show the (Q,H) operating point for each hour of pumping. The left graph in Fig. 5 shows all the instances when pump no. 2 was on in 2013 according to the optimization. It can be seen that most operating points are located in the



(a) branch 9 (b) branch 10

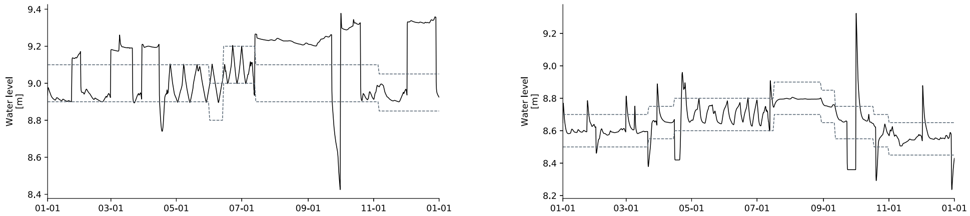


(c) branch 11 (d) branch 12

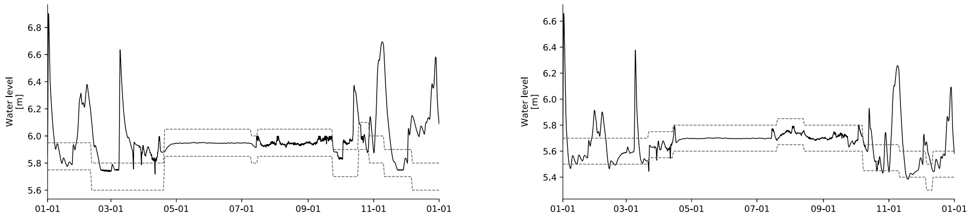


(e) branch 13 (f) branch 14

**Fig. 3.** Result of model predictive control (MPC): Water levels in branches 9–14 with black line, the minimum and maximum bounds on water level with gray dashed line.

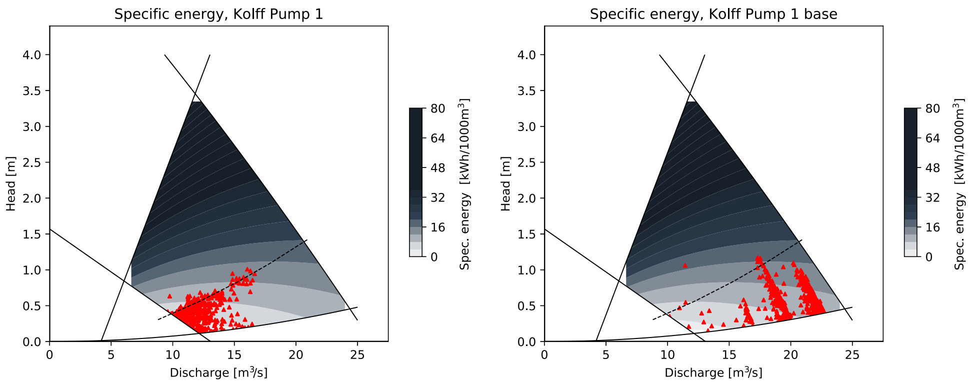


(a) branch 1 (b) branch 2



(c) branch 7 (d) branch 8

**Fig. 4.** Result of conventional feedback control: Water levels in branches 1, 2, 7 and 8 with black line, the minimum and maximum bounds on water level with gray dashed line.



(a) Optimization (MPC)

(b) Feedback control

**Fig. 5.** Operating points of pump no. 1 of pumping station Kolff, for the year 2013 (triangles) plotted within the operating range showing specific energy. The dashed line is the best efficiency line.

lowest region of the graph. The dashed black line indicates operating conditions with maximum efficiency for a given head value. Operating points at higher head are located along the best efficiency line. As it is a diesel pump, the energy price is constant, thus pumping cheap is equivalent to consuming the least amount of energy. The right graph in Fig. 5 shows the pump operation in the base scenario. The operation points are located in regions of higher specific energy than those of the optimization.

2. Pumping at low energy price
   In the above example a diesel pump was analyzed, where the energy price was constant. However, if the energy price is not constant, as is the case for a pump driven by an electric motor, the cost of pumping not only depends on the specific energy, but also on the energy price. The optimized operation of electric pumping station Van Beuningen is shown in Fig. 6. The price of electricity is also indicated in the graph: the more purple the triangle is, the higher the energy price. It can be seen that the operating points no longer follow the best efficiency line, especially when energy price is low. Operating points during high energy price are either closer to best efficiency line or occur at lower head vales when specific energy is low.
   Therefore to achieve cost-effective operation, the changing price of electricity should be taken into account. In reality and in the base scenario the energy price was not taken into account in the operation of the pumping stations.
3. Preference for electric drives
   The price of electricity is less than the price of diesel (in this case study the diesel price was 0.31€/kWh and the mean value of the electricity price was around 0.04 €/kWh) therefore using electric motor driven pumps is the cheaper option. This can also be seen from the data in Table 4. The energy used by van Beuningen station is 60% of that of Kolff, while the cost is only 8%. The optimization can take this into account, and pump a large amount of the water out of the system by Beuningen pumping station (which is located in the middle of the system), while it is not used in the base scenario.
4. Pump at low tide
   This reason is related to the operation within the system. Pumps use less energy if they have a smaller head to overcome. As the water is pumped from the Linge to the Beneden Merwede, which is affected by tide, the head is influenced by the time of pumping. Therefore pumping at the right time, i.e. at low tide can save energy. An example of the Kolff pumping station is shown in Fig. 7. The upper figure shows the water level at the suction side of the pumping station (i.e. branch 14) and its bounds, and in gray the outside water level in the Merwede is shown. The middle figure is the discharge pumped, while the lower figure is the free flow. Pumping mainly occurs during the winter. During these times the level of the Merwede is often higher than the Linge for an extended period of time, thus the only way to remove excess water is by pumping. This time also corresponds to the time of the highest inflows. Fig. 8 zooms into the month of January of the same pumping station. The gray line in the upper plot shows the tidal motion in the water level of the Merwede. From January 7th, the level of the Merwede crosses the level of the Linge during the tidal cycles. This means that, during the lower tide of the Merwede, water can be freely let out through the gate and no pumping is necessary. Thus the peak flows of the gate flow correspond to the tidal cycles of the level of the Merwede. Pumping also occurs at low tide, when the head is smaller. In order to avoid pumping at high tide, Kolff pumping station pumps at low tide as much as possible, letting the water level in branch 14 decrease, and at high tide the water level slowly increases. However, in the base scenario the tide is not considered in pumping decisions: Fig. 9. The pump is turned on and off much less often than in case of the optimized control.
5. Buffering and anticipating
   The other point related to the management of the whole system is the capacity of buffering water and hence wait until the best conditions to pump. The control system is able to anticipate on tide and electricity prices, therefore it can store water or pump water out to the minimum level when it is needed. This flexibility allows for the choice of the most economic pumping period and improve safety at the same time. An illustration of this feature can be seen in June 2013, when the level outside Beuningen pumping station is very high (Fig. 10). The pumping is postponed until the last possible moment, this can be seen in the increase of the upstream water levels on June 5th (Fig. 10). Once the water level reached the highest bound, it is lowered periodically during cheaper energy periods.
   The buffering mechanism is also achieved by controlling the weirs between the canal pools. The second plot of Fig. 8 shows the upstream weir flow with black line. It is a controlled flow, as opposed to the base scenario (Fig. 9) where the weir flow is not controlled.
   An additional advantage of MPC, not related to cost saving, is the increased ability to prevent flooding. The control

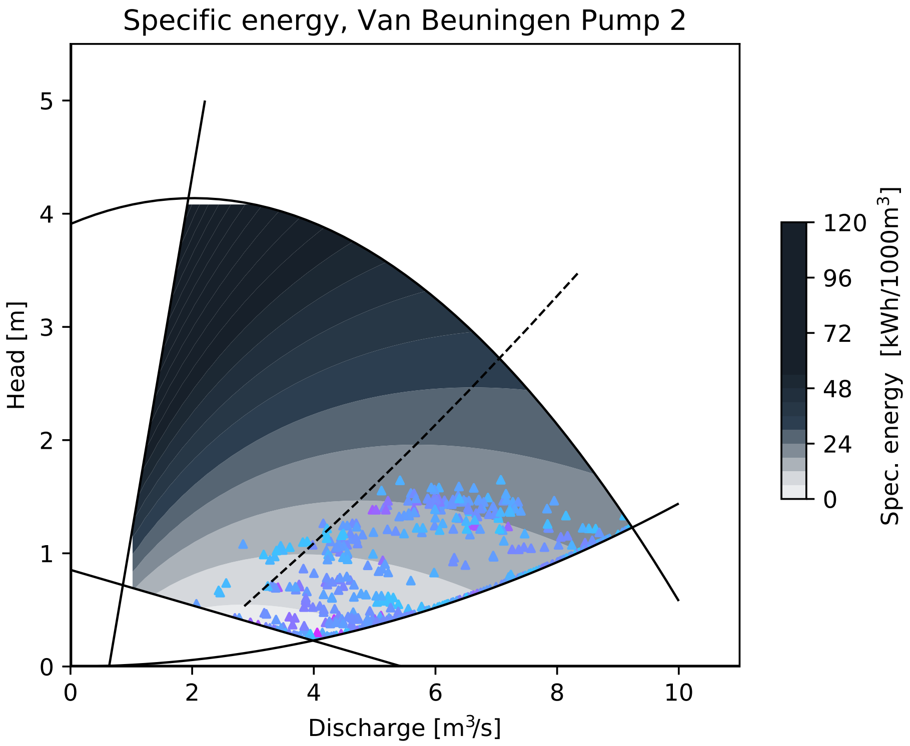


**Fig. 6.** Operating points of pump no. 2 of pumping station Van Beuningen, for the year 2013 (triangles) plotted within the operating range showing specific energy. The color of the triangles corresponds to the electricity price: blue is the lowest and purple is the highest price. The dashed line is the best efficiency line.

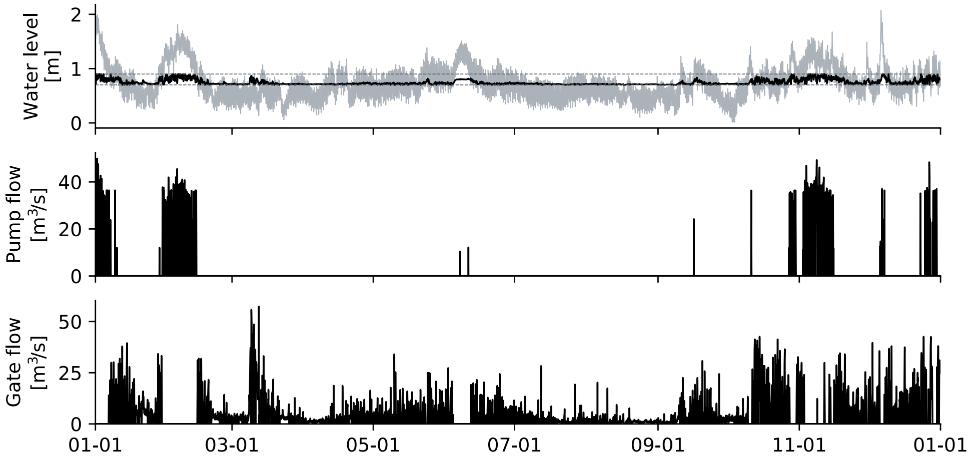


**Fig. 7.** Optimized control (MPC) of Kolff pumping station during 2013, with black color the water level of the Linge, and with gray the Beneden Merwede (river where the water is pumped into from the Linge).

system can anticipate future wet periods by creating extra storage capacity in the polder, something a feedback control system cannot (Figs. 8 and 9).

These reasons explain why the optimization method is more economical than the current operation. However, the 80% saving should be taken with care, and it is based on several assumptions. These assumptions and their effects are discussed in the following section.

## 5. Discussion

In this section the results are discussed, their meaning and limitations and also the possible steps and challenges for implementation are listed.

The resulting 80% energy saving, though it can be explained, might be an overestimation. It is important to mention that this number depends on several assumptions. If these assumptions are removed, the saving will decrease. The assumptions are the following:

1. During the calculation a perfect forecast was used. That is, for inflows the historic data was used. In practice, these inflows are a result of rainfall-runoff models, that are fed with weather forecasts. Therefore this information has a considerable uncertainty in practice.
2. The advice of the decision support system was tested using simple models for the pumps, weirs and open water channel flow. In fact, these were the same models onto which the decisions were applied. In practice, these decisions would be applied on a real system. Before doing that, they

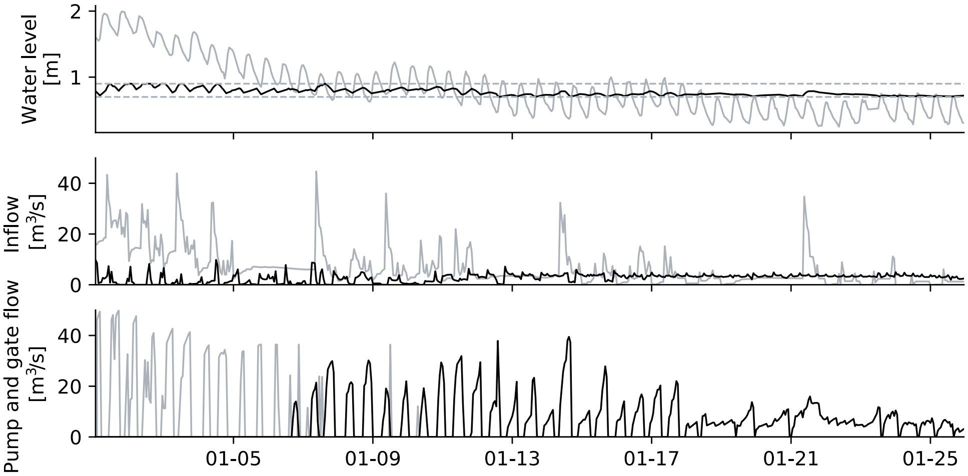


**Fig. 8.** Optimized control (MPC) of Kolff pumping station, zoomed into January 2013. In the first plot with black color the water level of the Linge and with gray color the outside water level, in the second plot with black color the upstream flow and with gray color the lateral inflow form the polders, and on the third plot with gray color is the pump discharge and black the free flow through the gate.

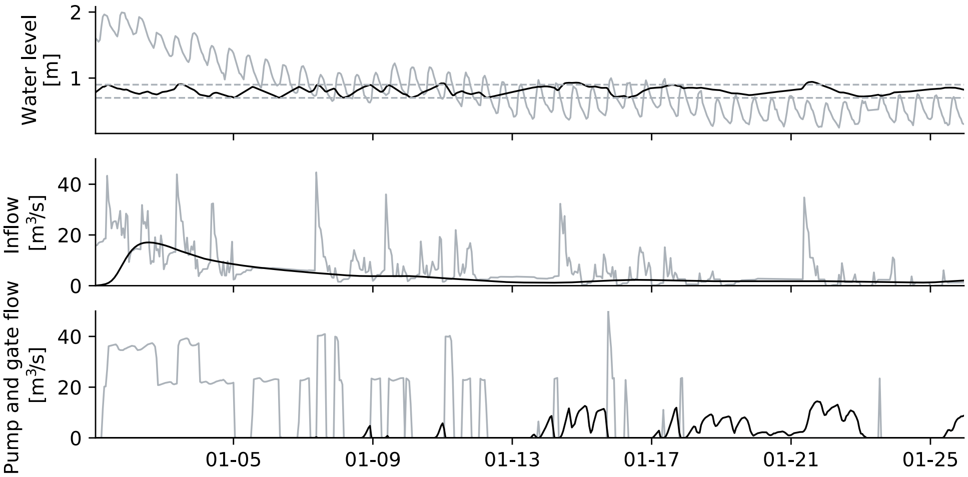


**Fig. 9.** Base scenario (feedback control) of Kolff pumping station, zoomed into January 2013. In the first plot with black color the water level of the Linge and with gray color the outside water level, in the second plot with black color the upstream flow and with gray color the lateral inflow form the polders, and on the third plot with gray color is the pump discharge and black the free flow through the gate.

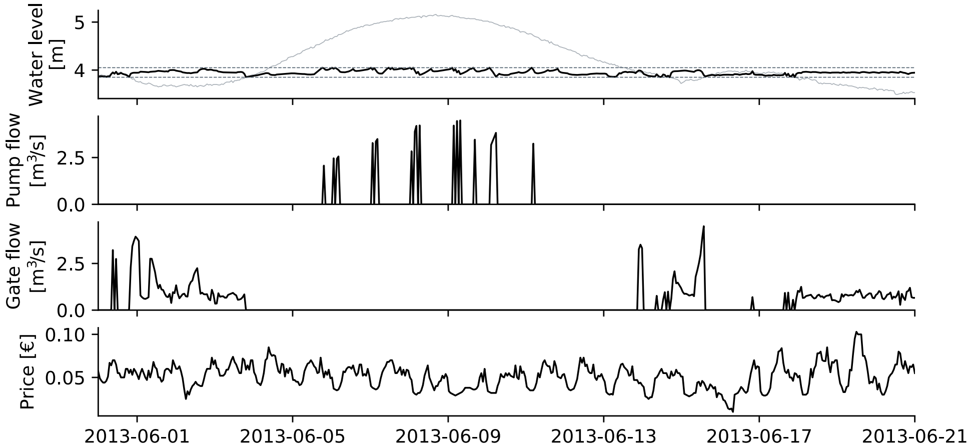


**Fig. 10.** Optimized control (MPC) at van Beuningen pumping station during 2013, with black color the water level of the Linge, and with gray the Amsterdam-Rhine Canal (river where the water is pumped into from the Linge).

should be tested in a more realistic model of the system, for example a 1D hydrodynamic model. This is a so-called closed-loop test, which is future work.

3. The cost and time it takes to turn pumps on and off are not considered. In practice, a start-up procedure may include stages in which a vacuum pump runs to evacuate

air from the suction piping, or an auxiliary oil or grease pump is used to lubricate the bearings. A slowly increasing shaft speed to limit the shaft power, and the opening of a valve or a gate, also take time. It depends on the type of pump, on its construction in the pumping station, and on the circumstances of its use. The time delay and the cost involved in starting up and shutting down a pump are easily incorporated in the MPC.

An uncertainty in the weather forecasts (and thus the inflow into the Linge) leads to an uncertainty in the water levels in the Linge. But what leads to major savings in the optimization is still perfectly predictable: (1) the tidal movement in de Beneden Merwede, (2) the electricity price for the next 24 h and (3) the advantage of using electric drives over diesel engine drives. The real scenario and the base scenario (in 2013) proved that pump capacity available in the four pumping stations is enough to prevent water levels from rising above the maximum bounds even in extreme cases (except for a few occasions). What happens then is that pumps run at their maximum shaft speeds. In case water inflow is higher than expected, shaft speeds of the pumps have to be increased to pump at a higher capacity. The pumps will then no longer run at or near to their best efficiency line. Referring to Fig. 5 (Kolff), operating points will shift to the right (higher discharge at equal head). For instance:

- if Kolff operates at 0.25 m of head, the energy consumption might increase from 4 to max 6 kWh/1000 m$^3$ (+50% max).
- if the pump operates at 0.5 m of head, the energy consumption might increase from 6 to max 8 kWh/1000 m$^3$ (+33% max)
- if the pump operates at 0.75 m of head, the energy consumption might increase from 11 to max 13 kWh/1000 m$^3$ (+18% max)

Another possibility is that pumps have to operate at high instead of low tide, or at high instead of low electricity price. At these unfavorable conditions:

- Kolff uses 100% more energy if operating at high tide of 0.65 m instead of low tide at 0.25 m
- Kolff uses 85% more energy if operating at high tide of 0.9 m instead of low tide at 0.5 m
- Kolff uses 50% more energy if operating at high tide of 1.15 m instead of low tide at 0.75 m
- electric-drives use 100% more energy (3 cts/kWh -> 6 cts/kWh), but it only affects Beuningen and Pannerling

Suppose, in a very conservative estimate, that the specific energy consumption is always higher by 100% due to unexpected higher inflows or due to unfavorable conditions, then the total cost in 2013 would increase from 35.4 to 71 k€, which is 37% of the 192 k€ for the base scenario. It would still give us a 63% reduction in total cost.

Addressing the above mentioned issues is the next step towards implementation. To address the first assumption, the same scenario can be calculated, but using historic weather forecasts and rainfall-runoff models to make decisions using information that was available at the time. Secondly, the system can be tested in closed-loop as described in point 2. And finally costs and time delays involved in the turning on and off of the pumps can be included. Though this is the first step towards the implementation, there are already several independent uses of such a system. For example, it can be a useful tool to answer questions such as: How much energy can be saved by using wider bounds on water level? How much money or CO2 emissions can be saved by installing a different kind of pump? How to make the operation of the system more sustainable? Such questions can be answered quantitatively by simple adjustments in the model.

## 6. Conclusion

A mixed-integer model predictive control based decision support system, RTC-Tools, is applied for a case study of a drainage system including several pumps, weirs and gates. This water system should be operated such that the water levels are kept within the prescribed bounds and the expenses on pumping are minimal. The proposed operation was numerically tested on data from the year 2013. The controller was able to keep the water levels within the bounds while saving 80% of the costs. The main reasons of this saving are using the pumps more efficiently, pumping at low tide, pumping at low energy price, and being able to anticipate and use the storage capacity of the river to wait for the best moment to pump. This setup also allows the testing of different operation scenarios, for example more flexible bounds on water levels or the replacement by a different pump. Future steps towards implementation include testing with weather forecast in closed-loop. In such tests MPC will use weather forecasts and is connected in closed-loop to a calibrated 1D-hydrodynamic model of the Linge system using the real weather conditions. MPC could then be applied using 1-h timesteps with 12 h receding horizon prediction time. The savings might decrease, however, this is a promising result for further investigation.

## CRediT authorship contribution statement

**K. Horváth:** Writing – review & editing, Writing – original draft, Investigation. **B. van Esch:** Funding acquisition, Supervision, Writing – review & editing. **T. Vreeken:** Software, Methodology. **T. Piovesan:** Software, Methodology. **J. Talsma:** Software, Data curation, Investigation. **I. Pothof:** Funding acquisition, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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