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An MHE-based MPC strategy for simultaneous energy generation maximization and water level management in inland waterways

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Abstract: This paper proposes a combined control and state estimation strategy for inland waterways, aiming at simultaneously attaining the optimal water level management and maximizing hydroelectricity generation. The latter can be realized by turbines installed in canal locks that harness the energy generated during lock filling and draining operations. These two objectives are of opposed nature, as maximization of energy generation can be achieved by maximizing the number of lock operations, which in turn leads to unbalanced water levels upstream and downstream of the lock. To address this issue, the multi-objective optimization problem is formulated . Then, model predictive control (MPC) and moving horizon estimation (MHE) are designed to maintain navigation conditions in the canals while maximizing energy production. Finally, the proposed strategy is applied to a realistic case study based on part of the inland waterways in the north of France.

Keywords: Inland waterways, water level regulation, hydroelectricity generation, turbines, model predictive control, moving horizon estimation.

1. INTRODUCTION

Real-time management and control of inland waterways has received increased attention given its environmental, economic and social consequences. Inland waterway networks are large-scale systems consisting of artificial canals and natural rivers, and are used primarily for the transportation of passengers and freight (Segovia et al., 2018), giving valuable services in modern society. Thus, maintaining service availability is an imperative requirement.

Inland waterway networks are multivariable dynamic constrained systems characterised by the connection of various subsystems (actuators, lock operations, nodes and reaches). Moreover, their management aims to guarantee the navigability condition while minimizing the operational cost and extending equipment lifespan. This is a complex challenge, and can be formulated as a multi-objective optimization problem. Furthermore, inland waterways are affected by complex phenomena such as rainfall and demand uncertainty. Therefore in order to achieve a satisfying management of the inland waterways advanced control methods need to be used (Litrico et al., 2008).

One of the most popular control strategies for water systems is model predictive control (MPC). Generally, the control action sequence is determined by solving an optimal control problem that minimizes the considered control objectives and respects constraints (Pour et al., 2019b). Therefore, MPC offers an appropriate framework to control water systems and improve performance, since it allows to compute optimal control actions ahead of time. Van Overloop et al. (2010) used MPC at a national scale to guarantee navigation, provide water during dry times and preserve against high river flows and sea tides. The connection between water supply and reliability of sewer systems was tackled using MPC by Pour et al. (2020). An economic MPC was designed by Pour et al. (2019a) to minimize the economic costs associated with water treatment and pumping for water distribution networks. On the other hand, some states might not be measurable, which requires the use of an observer. While there are many approaches to estimate the states, moving horizon estimation (MHE)is employed in this work. Their combination is certainly attractive because the MHE is also expressed as an online optimization problem that can explicitly deal with constraints (Copp and Hespanha, 2017).

On a separate note, the energy crisis and climate evolution caused by the depletion of fossil fuel energy sources has driven researchers to investigate renewable energy sources in the last few decades. Several studies have investigated the design and control of systems involving the use of wind or tidal energy, the aim of which is similar to the problem of canal lock hydropower conversion into electrical

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energy (Zhou et al., 2013), (Yin et al., 2016). Canal lock hydropower could be considered as one type of renewable energy source (Zhang et al., 2017). The hydraulic turbine is then placed inside of a lock, and harnesses hydraulic energy to generate electricity. The possibility of installing turbines in canal locks has been discussed by Desy and Virta (2005). Wind and photovoltaic energy sources are completely weather-dependent, while canal lock hydropower is predictable. According to the different sizes of locks and canals, the flow rate changes. Therefore, the energy variation for a particular turbine can be anticipated. For instance, in the *Hauts-de-France* region, there are more than 200 canal locks. Hence, using the power generated during lock operations to feed turbines (and thus generate hydroelectricity) could have a meaningful impact on diminishing the dependency on non-renewable energy sources. In the literature, a number of different methods have been studied, such as the optimization of the profit of power production for a cascade of hydro-electric power stations (Ribeiro et al., 2012) and the design of an MPC to regulate the turbine discharge of river power plants based on navigational constraints (Setz et al., 2008). However, these approaches do not consider the transport delay of the system explicitly, and the economic part is addressed as a constraint, and not as an optimization objective.

The main contribution of this paper is the combined use of MPC and MHE to maximize energy production and regulate the water levels in inland waterways, thus extending the results of Segovia et al. (2020) and Guekam et al. (2021). The hydraulic turbine is installed in a canal lock to exploit the unused hydraulic energy to generate electricity. Then, the number of lock operations should be increased to maximize energy generation, although these lead to unbalanced water levels at both lock sides. It is crucial to take into account that the navigation is allowed only if the level of each reach is inside an interval known as the navigation rectangle. Hence, by applying the proposed MPC-MHE approach, the energy produced is maximized. At the same time, not only the navigation conditions in the upstream and downstream reaches are maintained, but also the rest of operational goals can be attained. Finally, the real case study considered in this paper to show the effectiveness of the proposed approach is part of a real inland waterways of the *Hauts-de-France* region.

The rest of the paper is structured as follows. In Section 2, the control-oriented model and the control problem are presented. The proposed MPC-MHE approach is described in Section 3. In Section 4, the results of applying the proposed strategy to the real case study are discussed, which enables to draw conclusions in Section 5.

2. PROBLEM STATEMENT

2.1 Control-oriented model of inland waterways

Numerous modelling methods dealing with inland waterways have been proposed in the literature (see Weyer (2001), Segovia et al. (2019), Horváth et al. (2014)). Considering the set of compositional elements (as e.g., actuators, lock operations, nodes and reaches) and the modeling methodology of each component in the inland waterways proposed in Segovia et al. (2019), the control-oriented model of inland waterways can be described as a set of linear discrete-time difference-algebraic equations with multiple delays for all time instant $k \in \mathbb{Z}_+$:

$$x(k+1) = Ax(k) + B_u u(k) + B_d d(k) + \sum_{\tau_i \in S} \Big(A_{\tau_i} x(k-\tau_i) + B_{u\tau_i} u(k-\tau_i) + B_{d\tau_i} d(k-\tau_i) \Big), \tag{1a}$$

$$y(k) = Cx(k) + D_u u(k) + D_d d(k) + \sum_{\tau_i \in S} \Big(C_{\tau_i} x(k-\tau_i) + D_{u\tau_i} u(k-\tau_i) + D_{d\tau_i} d(k-\tau_i) \Big), \tag{1b}$$

where $x(k) \in \mathbb{R}^{n_x}$ are the water volumes (m^3), $u(k) \in \mathbb{R}^{n_u}$ represents the manipulated flows (m^3/s), $y(k) \in \mathbb{R}^{n_y}$ denotes the water levels (m) and $d(k) \in \mathbb{R}^{n_d}$ are the lock operations (m^3/s), which can be regarded as disturbances. Moreover, τ_i denotes the time delay of the i-th canal, and set $S = \{\tau_1, \tau_2, ..., \tau_p\}$ denotes multiple delays, one for each canal. Then, $u(k-\tau_i)$ and $d(k-\tau_i)$ describe the i-th delayed effect of the control actions and disturbances, respectively. Furthermore, $A, A_{\tau_i}, B_u, B_{u\tau_i}, B_d, B_{d\tau_i}, C, C_{\tau_i}, D_u, D_{u\tau_i}, D_d$ and $D_{d\tau_i}$ are time-invariant matrices of suitable dimensions dictated by the network topology.

Moreover, the physical nature of some variables, e.g., flows, water levels, openings and elevations, as well as other elements in the waterways, impose some constraints on the system. In the inland waterways, the system variables in (1) are constrained by the following physical limitations:

$$\underline{u} \le u(k) \le \overline{u}, \tag{2a}$$

$$\underline{y}_{ref} - \alpha(k) \le y(k) \le \overline{y}_{ref} + \alpha(k), \tag{2b}$$

where $\overline{u}$ and $\underline{u}$ are the upper and lower opening/elevation limits of the actuator. Besides, $\alpha(k)$ is a relaxation variable, and $\overline{y}_{ref}$ and $\underline{y}_{ref}$ denote the upper (HNL) and lower (LNL) bounds of the normal navigation level (NNL) values, respectively.

2.2 Operational control problem of waterways

The main goal of inland waterways management is to guarantee that the transportation of passengers and freight is performed safely. To ensure smooth transport chains, the water levels need to be maintained inside the navigation rectangle i.e., an interval around the normal navigation level. Furthermore, water resources must be dispatched optimally, i.e., minimizing their losses. To this end, cross structures are installed to regulate the levels of the reaches.

At the same time, harnessing the energy that is generated during lock filling and draining operations, and reusing this energy by means of a turbine, is another important operational objective regarded in this work. Indeed, during filling and draining processes, the water level in the lock will reach the same level as the upstream and downstream lock side, respectively. Afterwards, the ship can move into the lock chamber. Placing a hydraulic turbine inside of a canal lock makes it possible to recover the unused hydraulic energy to generate electricity. However, each lock operation leads to unbalanced water levels between the reaches upstream and downstream of the lock. More water from the upstream reach is sent to the downstream reach, lowering the upstream level, and thus increasing the downstream level. The navigation is allowed only if the level of each reach is inside the navigation rectangle. Utilizing the power generated during the operation of the lock in the existing canal equipment is invaluable. This energy is considered as a side benefit obtained during the lock operation that allows the ship to navigate through.

Therefore, the above-mentioned objectives could be achieved by formulating a multi-objective control problem. MPC is a suitable technique to control inland waterways due to its capability to perform online optimization, and its simple yet powerful design framework. Consequently, the set of operational goals can be formulated and achieved as the minimization of a multi-objective cost function, which can be built as the weighted sum of several terms, each of them related to a particular objective. Based on the operational goal stated for inland waterways, the following conditions can be considered:

- Keep water levels close to the setpoints:
$$\ell^y(k) \triangleq \left(y(k) - y_{ref}\right)^\top W_y \left(y(k) - y_{ref}\right), \quad (3)$$
where y_{ref} is the vector of NNL values and W_y expresses the weighting term that indicates the priorities of maintaining the water levels.
- Maximize energy production by increasing number of lock operations. However, there is an upper bound on the number of lock operations that can be performed, which can be denoted as $\overline{d}^{lo}$. Then, the difference between the actual and the maximum number of lock operations must be minimized.
$$\ell^{ep}(k) \triangleq \left(\overline{d}^{lo} - d^{lo}(k)\right)^\top W_{ep} \left(\overline{d}^{lo} - d^{lo}(k)\right), \quad (4)$$
where $d^{lo} \in d$ denotes the specified disturbances related to the specific lock that contains the turbine, and W_{ep} is a diagonal positive definite matrix.
- Minimize cost of operating equipment:
$$\ell^e(k) \triangleq u(k)^\top W_e u(k), \quad (5)$$
where W_e is a diagonal positive definite matrix that defines the priority of such control objective.
- Smoothe control actions:
$$\ell^{\Delta u}(k) \triangleq \Delta u^\top(k) W_{\Delta u} \Delta u(k), \quad (6)$$
where $\Delta u(k) \triangleq u(k) - u(k-1)$, and $W_{\Delta u}$ is a diagonal positive definite matrix.
- Penalize relaxation of navigability condition:
$$\ell^\alpha(k) \triangleq \alpha^\top(k) W_\alpha \alpha(k), \quad (7)$$
where W_α is a diagonal positive definite matrix.

Each of the previous operational goals is formulated for all canals in the network. Then, the multi-objective function L can be defined as:

$$L = \sum_{k=1}^{N_p} \left(\ell^y(k) + \ell^e(k) + \ell^{\Delta u}(k) + \ell^\alpha(k) + \ell^{ep}(k)\right), \quad (8)$$

where N_p is the prediction horizon.

3. PROPOSED APPROACH

3.1 MPC formulation

The MPC design follows classical methods (Camacho and Bordons, 2013). Considering the system constraints, the cost function is minimized by solving the optimization problem over the prediction horizon. By following the receding-horizon strategy, the first value of the control input vector is obtained from the solution and is applied to the system, discarding the rest of components. The same procedure is repeated for the following time instants.

Therefore, the MPC requires to solve the following finite-time horizon optimization problem (FHOP):

$$\min_{u(k),d^{lo}(k),y(k),\alpha(k)} \sum_{i=k}^{k+N_p-1} \Big(\ell^y(i|k) + \ell^e(i|k) + \quad (9a)$$
$$\ell^{\Delta u}(i|k) + \ell^\alpha(i|k) + \ell^{ep}(i|k)\Big),$$

subject to:

$$x(i+1|k) = Ax(i|k) + B_u u(i|k) + B_d d(i|k) + \quad (9b)$$
$$\sum_{r=1}^{N_r} S_r \Big(B_{u\tau} u(i-\tau_r|k) + B_{d\tau} d(i-\tau_r|k)\Big),$$
$$i \in \{k, ..., k+N_p-1\},$$
$$y(i|k) = Cx(i|k) + D_u u(i|k) + D_d d(i|k) + \quad (9c)$$
$$\sum_{r=1}^{N_r} S_r \Big(D_{u\tau} u(i-\tau_r|k) + D_{d\tau} d(i-\tau_r|k)\Big),$$
$$i \in \{k, ..., k+N_p-1\},$$
$$\underline{y} - \alpha(i|k) \leq y(i|k) \leq \overline{y} + \alpha(i|k), \quad (9d)$$
$$i \in \{k, ..., k+N_p-1\},$$
$$\underline{u} \leq u(i+1|k) \leq \overline{u}, i \in \{k, ..., k+N_p-1\}, \quad (9e)$$
$$\underline{d}^{lo} \leq d^{lo}(i+1|k) \leq \overline{d}^{lo}, i \in \{k, ..., k+N_p-1\}, \quad (9f)$$
$$u(l|k) = u_{MPC}(l|k), l \in \{k-\tau, ..., k-1\}, \quad (9g)$$
$$d^{lo}(l|k) = d^{lo}_{MPC}(l|k), l \in \{k-\tau, ..., k-1\}, \quad (9h)$$

where $\mathbf{S}_r$ is a selector matrix that allows to choose the appropriate output subject to the delayed control (Guekam et al., 2021), and $\underline{d}^{lo}$ and $\overline{d}^{lo}$ set the lower and upper bounds on the allowed number of lock operations, respectively. Moreover, $k \in \mathbb{Z}_{\geq 0}$ is the current time instant, $i \in \mathbb{Z}_{\geq 0}$ is the time instant during the prediction horizon, $(k+i|k)$ indicates the predicted value of the variable at instant $k+i$ using information available at instant k, and $l \in \mathbb{Z}_{\geq 0}$ indicates the use of previous data computed by the MPC, where the time interval is different from that specified by i.

With all this, the MPC is solved online to obtain the optimal sequences $\mathbf{u}^*(k) = \{u(i|k)\}_{i \in \mathbb{Z}_{[k,k+N_p-1]}}$, $\mathbf{y}^*(k) = \{y(i|k)\}_{i \in \mathbb{Z}_{[k,k+N_p-1]}}$, $\boldsymbol{\alpha}^*(k) = \{\alpha(i|k)\}_{i \in \mathbb{Z}_{[k,k+N_p-1]}}$ and $\mathbf{d}^{lo*}(k) = \{d^{lo}(i|k)\}_{i \in \mathbb{Z}_{[k,k+N_p-1]}}$. Taking into account the receding horizon philosophy, only the first value $u^*(k|k)$ and $d^{lo*}(k|k)$ from the optimal input and disturbances sequences $\mathbf{u}^*(k)$ and $\mathbf{d}^{lo*}(k)$ are applied to the system, respectively.

Remark 1. When considering dynamical systems, an important question to address is the question of stability, where the states of the dynamical system can drift arbitrarily far from the equilibrium. A lot of attention has been dedicated to this problem. It is noteworthy to remark that an optimal controller is not necessarily stabilizing. To investigate this issue for (1), one can simply consider the extended system without input and perturbation:

$$X_k = [x_k, x_{k-1}, ..., x_{k-\tau_p}] \tag{10}$$

$$\mathcal{A} = \begin{bmatrix} A & A_{\tau_1} & \cdots & A_{\tau_{p-1}} & A_{\tau_p} \\ I & 0 & \cdots & 0 & 0 \\ 0 & I & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} \tag{11}$$

It can be verified that (11) is Hurwitz for the canal under consideration. Therefore, instability cannot occur in the present work, as the system is asymptotically stable without input and disturbance, and the admissible input and disturbances are bounded.

3.2 MHE formulation

As not all the system states are always directly measurable, they must be estimated from the available data by using an observer. In this work, the MHE is used to fully reconstruct the system states. The fundamental principle of this method is to formulate the estimation problem as a quadratic program utilising a moving estimation window of constant size (Rao et al., 2001). In fact, only the most recent inputs and outputs are considered, which are shifted in time to exploit the most recent information.

Therefore, according to the previous explanation, and bearing in mind that the MHE is coupled to the MPC given by (9), (12) corresponds to the optimization problem solved by the MHE to estimate the states $\hat{x}_{MHE}$.

$$\min_{\hat{\mathbf{x}}_k} W^\top(k-N_e+1|k)P^{-1}W(k-N_e+1|k) + \tag{12a}$$
$$\sum_{i=k-N_e+1}^{k} \Big(W^\top(i|k)Q^{-1}W(i|k) + V^\top(i|k)R^{-1}V(i|k) \Big),$$

subject to:

$$W(k-N_e+1|k) = \hat{x}(k-N_e+1|k) - x(k-N_e+1) \tag{12b}$$

$$W(i|k) = \hat{x}(i+1|k) - \Bigg(Ax(i|k) + B_u u(i|k) + \tag{12c}$$
$$B_d d(i|k) + \sum_{r=1}^{N_r} S_r \Big(B_{u\tau} u(i-\tau_r|k) + B_{d\tau} d(i-\tau_r|k) \Big) \Bigg),$$
$$i \in \{k-N_e+1, ..., k\},$$

$$V(i|k) = y(i|k) - \Bigg(Cx(i|k) + D_u u(i|k) + \tag{12d}$$
$$D_d d(i|k) + \sum_{r=1}^{N_r} S_r \Big(D_{u\tau} u(i-\tau_r|k) + D_{d\tau} d(i-\tau_r|k) \Big) \Bigg),$$
$$i \in \{k-N_e+1, ..., k\}$$

$$y(i|k) = y(i), \; i \in \{k-N_e+1, ..., k\}, \tag{12e}$$

$$\underline{x} \leq \hat{x}(j|k) \leq \overline{x}, \; j \in \{k-N_e+1, ..., k+1\}, \tag{12f}$$

$$\underline{d}^{lo} \leq d^{lo}(i+1|k) \leq \overline{d}^{lo}, i \in \{k-N_e+1, ..., k\}, \tag{12g}$$

$$x(m|k) = \hat{x}_{MHE}(m|k), \; m \in \{k-N_e-\tau+1, ..., k-N_e\}, \tag{12h}$$

$$u(m|k) = u_{MPC}(m|k), \; m \in \{k-N_e-\tau+1, ..., k-N_e\}, \tag{12i}$$

$$d^{lo}(m|k) = d^{lo}_{MPC}(m|k), m \in \{k-N_e-\tau+1, ..., k-N_e\}, \tag{12j}$$

where N_e denotes the size of the estimation window, and R^{-1} and Q^{-1} are the weighting matrices inverses of appropriate dimensions associated with the confidence in the measurements and quality of the model, respectively. The value $x(k-N_e+1)$ in (12a) corresponds to the most probable initial state, and can be determined based on the knowledge of the system, while $\hat{x}(k-N_e+1|k)$ is the first value of the optimal state sequence, estimated by the MHE at time instant k. The error in this initial estimate, given by $\hat{x}(k-N_e+1|k) - x(k-N_e+1)$, is weighted by matrix P^{-1}, which indicates the confidence into the initial state, and its tuning is linked to satisfying estimation boundedness (Copp and Hespanha, 2017). Moreover, $y(i)$ are the measured water levels.

Thus, (12) is solved, and the optimal sequence $\hat{\mathbf{x}}^*(k) = \{\hat{x}(i|k)\}_{i \in \mathbb{Z}_{[k-N_e, k+1]}}$ is determined. However, as was the case for the MPC, only one value in the sequence is kept, i.e., the last value of the sequence, $\hat{x}(k+1|k)$.

Fig. 1. Escaut river (orange line) and locks (black wedges)

4. CASE STUDY

4.1 Description of the system and experiment design

The combined control and state estimation approach proposed in Section 3 is tested on the Escaut river, a border river between France and Belgium that is principally used for navigation. Its upstream part is managed by *Voies Navigables de France*, the French company responsible for promoting river logistics and responsible for overall water management. A schematic representation of the system is given in Fig. 1, featuring several locks (represented by black wedges) that enable vessel navigation.

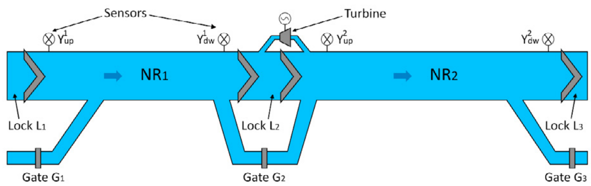

Fig. 2. Schematic representation of the system

Table 1. Characteristics of the system

Reach	NNL	n_r	m	W	Q_0	s_b	D	L
NR_1	3.2	0.035	0	50	1	0.0001	3	6.4
NR_2	2.8	0.035	0	50	1	0.0001	3	2.6

Near the city of Valenciennes, the project *Ilot Folien*[1] aims at creating a new eco-neighbourhood. Among the envisaged developments is the reuse of the energy generated during lock operations in the nearby waterways. To this end, a turbine prototype has been designed for this lock. Hence, maximizing lock operations leads to a maximization of hydroelectricity generation. However, as lock operations disturb the levels, the maximum number of lock operations (and thus the amount of hydroelectricity generated) is limited by the navigability constraint, i.e., levels must be kept within the navigation rectangle.

The considered system consists of two navigation reaches, NR_1 (between Trith-Saint-Léger and Valenciennes) and NR_2 (between Valenciennes and Bruay-sur-l'Escaut). Both reaches are equipped with a lock (for navigation purposes) and a controlled gate (for water level regulation). The only lock equipped with a generator is L_2. Likewise, sensors are available at the end of each canal, and provide the controllers with water level measurements. The characteristics of the generator are provided in Zhang et al. (2018). A schematic representation of these two reaches is depicted in Fig. 2.

The physical parameters of the reaches are summarized in Table 1[2], where n_r [$m^{1/3}$/s] is Manning's roughness coefficient, m (dimensionless) is the side slope of the cross section ($m = 0$ for rectangular shape), W [m] is the average width of the reaches, L [km] is the length, s_b (dimensionless) is the bottom slope and Q_0 [m^3/s] is the average discharge along the reach. Note that, as the reaches are part of a canalized river, their cross sections are assumed to present a rectangular profile with a constant roughness coefficient. Although the model could be further refined, e.g., by means of a bathymetry survey, these modeling assumptions allow to reproduce the dynamics of the reaches with enough accuracy. Furthermore, the NNL of each reach corresponds to the normal depth given in Table 1, while HNL and LNL are defined in relation to the NNL, such that HNL = NNL + 0.15 m and LNL = NNL - 0.15 m.

As mentioned before, one of the most important goals of this work is to maximize energy production. To achieve

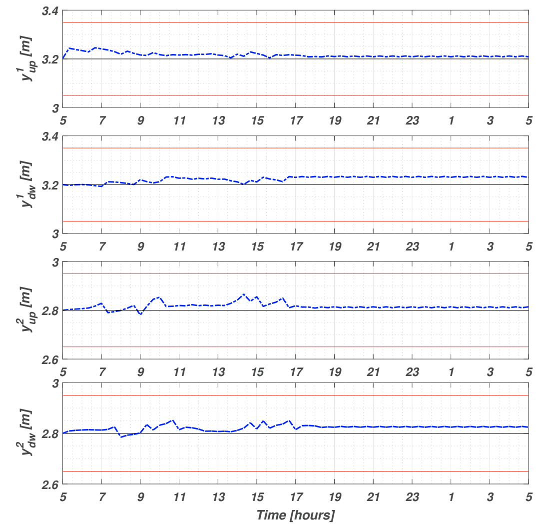

Fig. 3. Water levels (blue dash-dot lines), NNL (black solid line), and LNL and HNL (red solid line)

this goal, the number of lock operations performed by L2 should be increased. In the considered case study, there are three locks: the operation of L1 and L3 is assumed known and denoted as d_1 and d_3, respectively. The known lock operations due to navigation demand are depicted in blue line in Fig. 6. The second lock operation of L2 (d_2) is considered as a decision variable (to maximize energy generation), and that there is a fixed part coming from navigation demand. Note that navigation is only allowed between 6 am and 8 pm, and hence navigation resumes the following day at 6 am.

The linear discrete-time multiple-delay equations (1) are used in both MPC and MHE. It is worth noting that a sampling time $T_s = 20$ min has been used, which is reasonable given the slow system dynamics. Both reaches consider the same sampling time and present the same time delay. Moreover, the sizes of both prediction horizon N_p and estimation window N_e are considered equal to twelve samples (four hours). The result analysis is given for a time period of twenty-four hours.

The flow supplied by the gates is bounded between 0 and 7 m^3/s. The weights of the cost function (8) are set as follows: $W_y = 20$, $W_{ep} = 1$, $W_e = 10$, $W_{\Delta u} = 5$, and $W_\alpha = 1$, and are established by reiterative tuning until the appropriate performance is obtained. It is worth noting the relative importance of the objectives, which can be realized by the selected weights. Furthermore, precipitation and infiltration effects are not considered in the simulation. Finally, simulation results based on real data are obtained using the Gurobi 9.2 optimization package[3] and Matlab R2016b (64 bits), running in a PC Intel(R) Core(TM) i7-5500 CPU at 2.4 GHz with 12 GB of RAM.

4.2 Results and discussion

In order to analyze and assess the proposed approach, it is necessary to consider the water levels of each reach and the number of lock operations performed by L2. Indeed, as outlined before, keeping the water levels close to the

[1] https://www.valenciennes.fr/fileadmin/Public/Documents-PDF/Enquete-publique/ile-folien/Etude-impact-ILE-FOLIEN-V7.pdf

[2] http://www.fluviacarte.com/fr/voies-navigables/region-nord-1/voie-escaut-536

[3] https://www.gurobi.com/

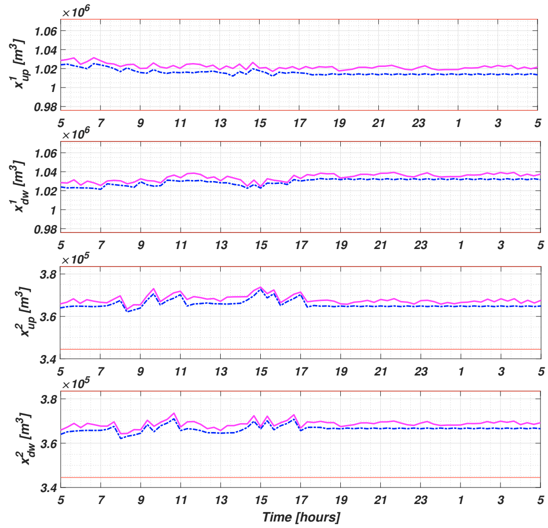

Fig. 4. State estimates (purple solid lines) and computed states (blue dash-dot lines)

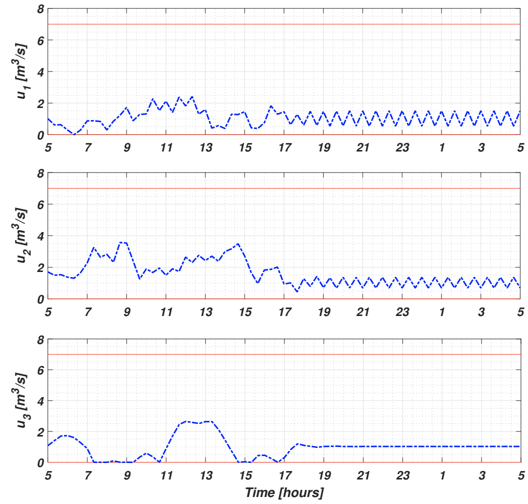

Fig. 5. Optimal control actions (blue dash-dot lines) and bounds (solid red lines)

NNL is the most important control objective, the second one being the maximization of lock operations performed by L2 (d_2). Note that *up* and *dw* are used in the figures to denote the upstream and downstream ends of a reach, respectively.

The evolution of the levels, which results from applying the control actions computed by the MPC, is depicted in Fig. 3. The results show that the levels in both reaches stay close to the NNL and inside the navigation rectangle despite the disturbances. Note that the levels are allowed to oscillate around the NNL (and within the bounds) to allow for the maximization of d_2 during the navigation period.

It can be noted that the initial upstream level of NR_1, i.e., y^1_{up} is higher than the NNL. Hence, the gate G1 (control action u_1) must close, and the gate G2 (u_2) must open to withdraw water from NR_1. During the non-navigation period, the gates maintain the average discharge Q_0 given in Table 1. Furthermore, the performance of the controller can be quantified computing the error between the water levels and the NNL by means of the following indices:

$$TP = 1 - \frac{1}{N_p}\sqrt{\sum_{k=1}^{N_p}\left(\frac{y_k - y_{ref}}{\frac{1}{2}\left(\overline{y}_{ref} - \underline{y}_{ref}\right)}\right)^2} \qquad (13)$$

which are equal to 0.9890 for NR_1 and 0.9806 for NR_2, thus allowing to highlight the satisfactory performance of the control strategy.

On the other hand, the optimal control actions computed by the MPC are depicted in Fig. 5. There is a certain oscillation around the value 1 m^3/s in the first and second gate, which can be considered as a constant value according to the rules given by the waterways manager.

Then, the optimal gate actions are applied, and their effect on the system (water levels) is measured. The MHE is solved by considering the most recent input-output information window, which allows to estimate the states. Fig. 4 illustrates the comparison between state estimates and states computed using the simplified model.

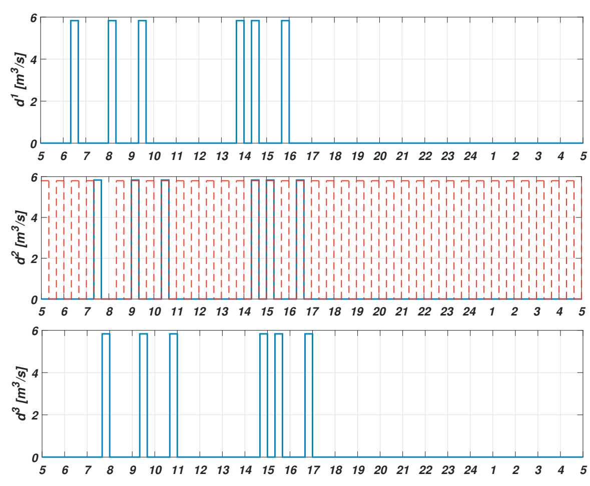

Fig. 6. Evolution of lock operations: known (blue solid lines) and optimized for hydroelectricity generation (red dashed lines)

The evolution of lock operations is represented in Fig. 6. As mentioned above, the navigation demand on locks L1 (d_1) and L3 (d_3) are assumed to be known disturbances, while lock filling and draining operations for d_2 can be optimized to maximize energy generation (aside from the navigation demand on lock L_2). The most important result regarding this figure concerns the issue of maximizing energy production in L2, which is represented in the second lock operation d_2 (red line) and the behaviour of lock operation without maximizing the lock operation is shown in blue line. It can be seen how lock operations at L2 are maximized during the navigation period, but always ensuring that the levels are kept within the navigation rectangle. Note that each lock operation generates 6.21 MJ Leontidis et al. (2016). Then, the total energy generated by using MPC-MHE is 211.4 MJ, while the total energy production without maximizing the local operation is

37.26 MJ. Energy production is improved while tracking performance is maintained.

5. CONCLUSIONS

This paper focused on a combined MPC and MHE approach for maximizing hydroelectricity generation while ensuring navigability of inland waterways. A dynamic model of the process, which is characterized by a delayed descriptor formulation, was used. Hydroelectricity generation was tackled by using a turbine inside of a lock, and the amount of lock operations was maximized while ensuring that the levels were never outside the navigation interval. Simulation results on part of the inland waterways in the north of France allowed to demonstrate the effectiveness of the methodology.

Future research regards the consideration of a detailed mathematical model of the turbine, which could be merged into the dynamic model of the inland waterways. This would allow for a finer control strategy, which should improve the accuracy and performance of the approach.

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