# Human-in-the-loop control of an irrigation canal using time instant optimization model predictive control

A. Sadowska, P.-J. van Overloop, J.M. Maestre, and B. De Schutter

***Abstract*— In the paper we discuss the recently introduced Mobile Model Predictive Control approach for an irrigation canal. Mobile MPC is a configuration of MPC that explicitly incorporates the role of the human operator traveling between the gates as ordered by a remote centralized controller. The operator provides the controller with up-to-date measurements from the locations visited and acts as the actuator as required by the remote controller. Mobile MPC provides a solution in between fully manual and fully automatic canal operation, as the first one may give poor performance and the second one might be impracticable in some situations, where it is not possible to rely on the equipment installed in the field. In the current paper we improve the performance of the original Mobile MPC approach by allowing the controller to decide the exact time instants when the operator should arrive at a specific gate and change the gate's settings as well as we include a penalty in the objective function for the controller to minimize the workload of the human operator. We show that the new approach yields enhanced performance in comparison to the previous method, and we demonstrate the benefits of the new method as opposed to the previous one in a case study.**

## I. Introduction

Irrigation canals are cascade-connected networks consisting of a number of pools with movable gates in between the pools to transport water downstream from a source to farmers. Various automatic control methods for irrigation canals are discussed in [5], [11], [12], [17], [18], [22], [23]. These control methods may rely on simple solutions such as PI controllers but may also resort to an application of more sophisticated control approaches such as model predictive control (MPC) [4], [14]. MPC is a powerful control method that has been adapted to a broad spectrum of applications, including process control, power systems, and water resources management. However, MPC for irrigation canals relies on regularly obtaining measurements from the local sites as well as actuators installed at every gate to apply the required control actions in every control step. Such a configuration poses a serious problem if one cannot depend on the equipment left in the field or if there is simply no equipment in the first place. Therefore, despite the advances in the field of controlling an irrigation canal in theory, in practice the functioning of the canal commonly relies on manual operation by human operators traveling between the gates and raising or lowering the gates depending on whether more or less flow is needed. Such an approach, while very popular for practical reasons, may result in a rather poor performance as the operators can only use local information available to them in their subjective judgement how the gates' settings should change. Consequently, a bridge is needed between the automatic control methods and the manual human-operator-based methods in order to provide a practicable solution yielding an adequate performance.

In fact, control methods where a human factor is incorporated in the control system design are quite scarce and many aspects still have not been studied. However, it has been argued that introducing human-in-the-loop control brings a number of benefits to the control design [2] and is a logical progression of how control systems are designed [1]. Whereas some work on human interactions with a control system has been done for certain settings [3], [9], [10], [13], it remains still an open question how to integrate in the control problem formulation the important role played by human operators.

To deal with such a challenging control problem, a new configuration referred to as Mobile MPC has been recently proposed [15]. It relies on the explicit consideration of a human operator and is motivated by a practical observation associated to (not exclusively) the field of irrigation and concerning the problem that sensors, actuators, or communication links placed in outdoor conditions may be prone to excessive wear and tear and consequently to malfunctioning due to the harsh environment they operate in with little financial resources to maintain them well, as well as to a theft or an intentional damage by passers-by. Therefore, automatic operation of the gates is not always possible despite the fact that it can bring superior performance over subjective rule-based control of a human operator. Hence, in Mobile MPC an operator travels from one location to another to serve as both the measuring and the actuating medium, and communicates with a remotely located controller using a mobile device to send the measurements and to receive the control actions to be applied as well as the next location where the operator should go to. In this way, no equipment needs to be installed at the local sites and instead the operator carries a simple portable device; moreover, communication links do not need to be placed either. The central controller is designed using the principles of the MPC taking into account the time that is needed to travel from every one location to another, and the time needed at a site to perform the job. This controller works in an event-driven manner, with events associated with the operator arriving at a new location as well

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as other circumstances that may require a sudden reaction of the controller.

Mobile MPC as introduced in [15] is suitable for the aforementioned settings with human operators taking an active part in the control process; however its performance could be improved. The improvement that we propose is to add another degree of freedom to the controller: we allow the controller to also decide on the exact time instant at which the operator should perform its job at a specific location as opposed to deriving the times directly from the information about the traveling times between the gates and the amount of time needed at each gate to perform the required activities. By letting the operator wait sometimes before proceeding to a next location, the performance can be enhanced as the time instants at which changes at local sites take place can be better synchronized with the dynamics of the canal. Indeed, good performance and specifically maintaining water levels close to setpoints are important in the considered application to enable efficient discharge flows to the water users (offtakes).

We employ here a linear model of a canal [17], [19] describing the relation between water levels in pools and flows between the pools so that the flows serve as control inputs in the model. Using time instant optimization MPC (TIO-MPC) [6], [21], we parametrize the flows through the gates in terms of the specific required time instants and flow changes assigned by the controller. To use continuous time instants, we use sampled data MPC, as opposed to [15], where discrete-time MPC was considered. We also regard more human-related aspects in the control design. In particular, we add a penalty on a number of location changes in the path that the operator needs to take, with the aim to ease the workload of the operator, and we consider a delay between when a measurement is taken and a control action is applied as would occur in reality.

In Section II we describe the original Mobile MPC approach. In Section III we point out some weaknesses of the original Mobile MPC approach and in response we introduce the new and improved method for human-in-the-loop TIO-MPC of an irrigation canal. Section IV demonstrates the performance of our method and compares it with the existing solution in a simulation-based case study. Our concluding remarks are given in Section V.

## II. Mobile MPC

Mobile MPC [15], see Fig. 1, employs a human operator, who travels along the canal from one gate to another according to a sequence of gates ordered by the control center. At each location, the operator takes the measurements, communicates them to the control center using a mobile device and in return receives new control actions that should be applied and an instruction where to go next.

The canal is assumed to consist of $N$ pools with indices from the set $\mathcal{I} = \{1, \ldots, N\}$, and can be described with a linear discrete-time model

$$x(k+1) = Ax(k) + B_\mathrm{u} u(k) + B_\mathrm{d} d(k), \tag{1}$$

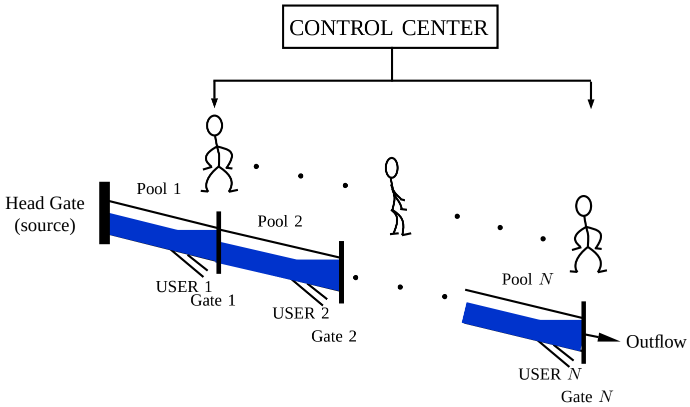


Fig. 1. Mobile MPC configuration for an irrigation canal.

where $x(k) \in \mathbb{R}^n$ denotes the state, $u(k) \in \mathbb{R}^m$ the control input, $d(k) \in \mathbb{R}^p$ the external input acting on the canal (e.g. a rainfall), and $A$, $B_\mathrm{u}$ and $B_\mathrm{d}$ are matrices of appropriate dimensions (see e.g. [12], [17] for more details). In particular, the state vector $x(k)$ contains information about the deviation of the current water level in each pool with respect to the setpoints and the control input $u(k) = (u_1(k), \ldots, u_N(k))^T$ denotes the flow changes in each pool at step $k$. Note that the flows through the gates relate nonlinearly to specific gate settings. Yet, following the standard convention, it is assumed throughout this paper that flows can be directly set up and fixed by the operator.

Let $N_\mathrm{p}$ and $N_\mathrm{c}$ denote the length of the prediction and control horizons, respectively, with $N_\mathrm{c} \leq N_\mathrm{p}$, and let $N_\mathrm{s}$ be the number of gates to be scheduled for the operator at the current step $k$ starting at the current location $i_\mathrm{current}(k) \in \mathcal{I}$. Moreover, let $M \in \mathbb{N}^{N\times N}$ be the matrix with traveling times between the gates in sample steps, such that $M_{i,i} = 0$ and $M_{i,j}$ denotes the traveling time between gate $i$ and $j$. Denote further the time that is needed at each gate to perform all required activities (identical for all gates) by $T_\mathrm{o}$.

The optimal control problem in Mobile MPC consists in solving at each control step the following mixed-integer programming problem

$$\min_{\widetilde{U}(k), p(k)} \sum_{j=0}^{N_\mathrm{p}-1} \big(x^T(k+j+1|k)Qx(k+j+1|k) + u^T(k+j|k)Ru(k+j|k)\big)\,, \tag{2}$$

$$\text{s.t. } x(k+j+1|k) \in \mathcal{X}, \text{ for } j = 0, \ldots, N_\mathrm{p}-1, \tag{3}$$

$$u(k+j|k) \in \mathcal{U}, \text{ for } j = 0, \ldots, N_\mathrm{p}-1, \tag{4}$$

$$p(k) \in \mathcal{P}_{i_\mathrm{current}(k), N_\mathrm{s}, T_\mathrm{o}, M}(k), \tag{5}$$

$$a(p(k), k+j|k) \neq i \implies u_i(k+j|k) = 0, \tag{6}$$

$$x(k+j+1|k) = Ax(k+j|k) + B_\mathrm{u}u(k+j|k) + B_\mathrm{d}d(k+j|k). \tag{7}$$

Here, $\widetilde{U}(k) = (u^T(k|k), \ldots, u^T(k+N_\mathrm{p}-1|k))^T$, with $u(k+j|k) = (u_1(k+j|k), \ldots, u_N(k+j|k))^T$. The notation $(k_1|k_2)$ is used to denote predictions for step $k_1$ made at step $k_2 \leq k_1$. Constraints (3) and (4) represent the operational constraints on state and input, respectively. Moreover, $p(k) \in \mathbb{N}^{N_\mathrm{s}}$ denotes the desired path as found at step $k$, which

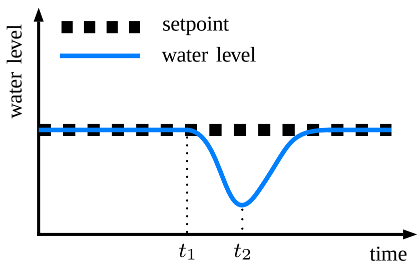


Fig. 2. Problems that may appear in the standard approach to Mobile MPC: because $t_1 \neq t_2$, the water level deviates temporarily from the setpoint.

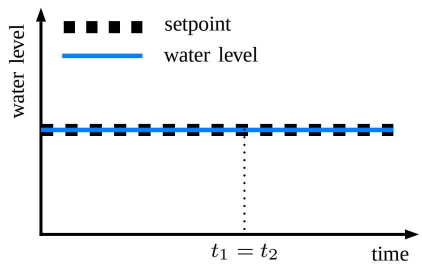


Fig. 3. Adequate performance when the new approach to Mobile TIO-MPC proposed in the paper is applied: since $t_1 = t_2$, no deviation in the water level with respect to the setpoint is observed.

must be a subset of all paths of length $N_\mathrm{s}$ starting from the current location, $i_\mathrm{current}(k)$, which is the first element of $p(k)$. In addition, $\mathcal{P}_{i_\mathrm{current}(k),N_\mathrm{s},T_\mathrm{o},M}(k)$ denotes a set of all admissible paths of length $N_\mathrm{s}$ that are accessible from the current place $i_\mathrm{current}(k)$ which is indeed the first element of all admissible paths, given the duration $T_\mathrm{o}$ and the traveling times $M$ with repetitions permitted. Importantly, the path variable is defined so that whenever the operator finishes working at one location, he/she is immediately sent to the next one with no waiting in between. Further, $a(p(k), k+j|k)$, $j = 0, \ldots, N_\mathrm{p} - 1$, denotes the availability of the operator at step $k + j$ given a selected path $p(k)$. It returns $0$ if the operator is free at prediction step $k+j$. If the operator is working at prediction step $k + j$, the availability function returns the index of the gate where the operator is. Using the availability function $a(\cdot, \cdot|k)$ in (6), the input sequence $\widetilde{U}(k)$ is determined in that if the operator is not at gate $i$ at step $k + j$, the value of $u_i(k + j|k)$ needs to be 0. Otherwise, if the operator is at a given gate, the specific input $u_i(k + j|k)$ needs only to satisfy (4). The sets $\mathcal{X}$ and $\mathcal{U}$ in (3) and (4), respectively, are convex sets determined by physical and operational limitations of the system, such as maximal and minimal permissible water levels. In addition to Mobile MPC, the head gate is controlled using standard MPC with a control step $T_\mathrm{c}$. Standard MPC for the head gate and Mobile MPC for the pools are coordinated and solved together when an operator appears at a local site at an integer multiple of the control step $T_\mathrm{c}$, i.e. when the MPC problem for the head gate is solved.

## III. Mobile TIO-MPC for Irrigation Canals with Humans in the Loop

We now examine some weaknesses of the Mobile MPC method introduced in Section II and consequently we introduce a new method - Mobile TIO-MPC - that offers a performance improvement upon the original Mobile MPC.

### A. Problem with Mobile MPC

To ensure effective water offtake flows to the users in the canal pools, water levels need to be maintained around the setpoints. We discuss now the situation depicted in Fig. 2. In the picture, the water level at the downstream end of a pool is shown as a function of time. Assume that at time $t_1$ the operator modifies the flow through the gate in a pool thus increasing the outflow from the pool. However, the flow change should ideally happen at time $t_2 > t_1$ because e.g. this is the time instant when an extra inflow due to an earlier flow change at the upstream gate arrives at the location. This causes the water level to drop temporarily starting from time $t_1$ because an increased outflow from a pool occurs before an increased inflow to that pool arrives to the downstream end of a pool to compensate it. The situation starts to improve at time $t_2$ when the extra inflow presents itself at the location. Understandably, if the gate change could occur exactly when the extra inflow from the upstream gate appears, i.e. $t_1 = t_2$, the water level would not drop, as shown in Fig. 3. However, the solution presented in Section II only allows for this if the corresponding travel times between the gates are exactly matching, with no possibility to let the operator wait for a while in between two locations to obtain the aforementioned synchronization and to enjoy its benefits. This observation has motivated our development of the new, improved algorithm i.e. Mobile TIO-MPC for an irrigation canal, where the precise time instants of the human operator's actions are determined by the controller and synchronized with the system's dynamics, thus improving the achievable performance.

### B. New control approach description

Given the importance of maintaining water levels in an irrigation canal close to their setpoints to enable adequate offtake performance, we propose to enlarge the solution space in the Mobile MPC problem (2)-(7), and to consider explicitly as a control input to be found by the predictive controller the time variable that specifies the time instant when the operator should arrive at a given gate and communicate the measurements to the control center. Therefore, that time variable does no longer have to necessarily follow directly from the traveling times between any two locations as in the solution presented in Section II, but extra gaps are also permitted to improve the performance.

Because of the human operator's presence in the system, we also consider an additional penalty on the number of location changes on the specific path that the operator needs to take. The idea behind this is to relax the working conditions of the operator, since it is the operator who has to travel to all locations to take measurements and to change the gates' settings. Furthermore, driven by reality, the control algorithm introduced here takes into consideration the fact that there is a delay between the moment that the measurements are taken and the moment when a control action is applied.

We use continuous sampled-data MPC [8], [16], [20], which naturally complements the use of real variables as time instants (see [7] for an alternative approach). To that end, instead of using a discrete-time model of a canal (1), we use an equivalent continuous time model

$$\dot{x}_{\mathrm{c}}(t) = A_{\mathrm{c}} x_{\mathrm{c}}(t) + B_{\mathrm{c,u}} u_{\mathrm{c}}(t) + B_{\mathrm{c,d}} d_{\mathrm{c}}(t), \tag{8}$$

where the tag 'c' is added to distinguish the variables of the continuous-time model (8) from those of the discrete-time model (1). Similarly to the discrete-time model, the control input in (8) can be written as a collection of $N$ elements $u_{\mathrm{c}}(t) = (u_{\mathrm{c},1}(t), \ldots, u_{\mathrm{c},N}(t))^T$ for $N$ gates in the canal.

To introduce the time instants as control inputs, we use the concept of TIO-MPC [6], [21], which is an approach that was first introduced for traffic control, and was later applied in water management to control discontinuous control structures (e.g. pumps that can only be either on or off). Such control structures would normally dictate posing the MPC problem as a mixed-integer programming problem with 0-1 states to be determined for the whole prediction horizon. In contrast, when using TIO-MPC for a discontinuous control structure, the time instants when the changes to the structure's state should occur are optimized for a selected number of changes, resulting in a real-valued programming problem.

Recall that the path variable defined in (5) contains $N_{\mathrm{s}}$ elements of $\bar{\mathcal{I}} = \mathcal{I} \setminus \{1\}$ (excluding the first gate i.e. the head gate) as follows:

$$p(t) = (p_1(t), \ldots, p_{N_{\mathrm{s}}}(t))^T, \; p_\ell(t) \in \bar{\mathcal{I}},$$

and specifies the sequence of indices of the gates that the operator should go to from the current location $p_1(t) = i_{\mathrm{current}}(t)$. We note that the indices in the path variable $p(t)$ may be repeated, as indeed it may be worthwhile to visit a subset of possible locations a few times. For tractability reasons and in particular to reduce the search space, we limit the set of locations that could be visited with the help of introducing an integer parameter $N_{\mathrm{limit}}$. Any following location scheduled for the operator $p_{\ell+1}(t)$ can be at most $N_{\mathrm{limit}}$ locations away from the preceding location $p_\ell(t)$, i.e.

$$|p_{\ell+1}(t) - p_\ell(t)| \leq N_{\mathrm{limit}}, \; \ell = 1, \ldots, N_{\mathrm{s}} - 1. \tag{9}$$

Denote by

$$T(t) = (T_1(t), \ldots, T_{N_{\mathrm{s}}}(t))^T, \; T_\ell(t) \in \mathbb{R},$$

the time instants when the operator should arrive at the $N_{\mathrm{s}}$ gates to apply the necessary changes. Since the first element of the sequence $p(t)$ is fixed to $p_1(t) = i_{\mathrm{current}}(t)$, the first element of the sequence $T(t)$ is accordingly fixed: $T_1(t) = t$. Denote further the $N_{\mathrm{s}}$ control actions to be executed by the human operator by

$$u^{\mathrm{human}}(t) = (u_1^{\mathrm{human}}(t), \ldots, u_{N_{\mathrm{s}}}^{\mathrm{human}}(t))^T, \; u_\ell^{\mathrm{human}}(t) \in \mathbb{R},$$

where, following the introduced convention, $u_1^{\mathrm{human}}(t)$ denotes the action to be applied at the present gate $i_{\mathrm{current}}(t)$, which, contrary to $p_1(t)$ and $T_1(t)$, is not fixed but is to be found by the controller at time $t$. We use $p(t)$, $T(t)$, and $u^{\mathrm{human}}(t)$ to parametrize the control input $\widetilde{U}_{\mathrm{c}}(t)$, which, similarly to the profile $\widetilde{U}(k)$ in the discrete-time case in Section II, denotes the trajectories of the control input $u_{\mathrm{c}}(t)$ from the activation time $t$ until the end of the prediction horizon $t + N_{\mathrm{p}} T_{\mathrm{c}}$. Consequently, the following parametrization of the input $u_{\mathrm{c},i}(t)$ for the given prediction horizon results

$$u_{\mathrm{c},i}(\tau|t) = \begin{cases} u_\ell^{\mathrm{human}}(t)\delta(\tau - (T_\ell(t) + T_{\mathrm{d}})) & \text{if } i = p_\ell(t), \\ 0 & \text{otherwise,} \end{cases} \tag{10}$$

for $\tau \in [t, t + N_{\mathrm{p}} T_{\mathrm{c}}]$ and in which $\delta$ denotes the dirac impulse function. The new parameter $T_{\mathrm{d}} \in \mathbb{R}$ represents the time delay between when a measurement is taken, and a control action is applied. Hence, the operator should arrive at gate $p_\ell(t)$ at time $T_\ell(t)$ to take measurements and communicate the measurements to the controller, and at time $T_\ell(t) + T_{\mathrm{d}}$ the gate position should be changed according to $u_\ell^{\mathrm{human}}(t)$. Afterwards, the operator has $T_{\mathrm{o}}$ time units to finish the required activities at the current gate, before proceeding to the next gate (cf. (17)).

With the help of the path variable $p(t)$, the number of location changes scheduled for the operator who travels from one gate to another can be determined. We want to minimize the number of location changes within the control horizon, as it represents the workload for the human operator on a prospective predicted path $p(t)$. Let $n_{N_{\mathrm{c}}}(t)$ denote the number of elements in the path variable $p(t)$ that are scheduled within the control horizon. i.e. such that $T_\ell(t) \leq t + N_{\mathrm{c}} T_{\mathrm{c}}$. It can be found by solving a constrained integer programming problem $n_{N_{\mathrm{c}}}(t) = \mathrm{argmax}_\ell \ell$ subject to $T_\ell \leq t + N_{\mathrm{c}} T_{\mathrm{c}}$ and $2 \leq \ell \leq N_{\mathrm{s}}$. We assume that $n_{N_{\mathrm{c}}}(t) \geq 2$, which means that at least one action apart from the one to be done presently needs to be scheduled within the control horizon (so $T_2(t) \leq t + N_{\mathrm{c}} T_{\mathrm{c}}$) to enforce a minimal state update frequency. Consequently, the additional penalty $J_{\mathrm{operator}}(t)$ on the number of location changes that the operator needs to do within the prediction horizon is expressed as

$$J_{\mathrm{operator}}(t) = \sum_{s=1}^{n_{N_{\mathrm{c}}}-1} \mathbb{1}_{p_{s+1}(t) \neq p_s(t)} \tag{11}$$

and serves the purpose of minimizing the workload of the operator. The indicator function $\mathbb{1}_A$ returns 1 if event $A$ is true and 0 otherwise. Further, the cost function in (2) is reformulated to match the continuous-time settings

$$J_{\mathrm{MoMPC}}(t) = \int_t^{t+N_{\mathrm{p}}T_{\mathrm{c}}} \big( x_{\mathrm{c}}^T(\tau|t) Q x_{\mathrm{c}}(\tau|t) + u_{\mathrm{c}}^T(\tau|t) R u_{\mathrm{c}}(\tau|t) \big) \, \mathrm{d}\tau. \tag{12}$$

The optimal control problem to be solved at each new location the operator visits is then

$$\min_{p(t), T(t), u^{\mathrm{human}}(t)} J_{\mathrm{MoMPC}}(t) + \alpha J_{\mathrm{operator}}(t), \tag{13}$$

subject to

$$x_{\mathrm{c}}(\tau|t) \in \mathcal{X}, \; \forall \tau \in [t, t + N_{\mathrm{p}} T_{\mathrm{c}}], \tag{14}$$

$$u_{\mathrm{c}}(\tau|t) \in \mathcal{U}, \; \forall \tau \in [t, t + N_{\mathrm{p}} T_{\mathrm{c}}], \tag{15}$$

$$\dot{x}_{\mathrm{c}}(\tau|t) = A_{\mathrm{c}} x_{\mathrm{c}}(\tau|t) + B_{\mathrm{c,u}} u_{\mathrm{c}}(\tau|t) + B_{\mathrm{c,d}} d_{\mathrm{c}}(\tau|t), \; \forall \tau \in [t, t + N_{\mathrm{p}} T_{\mathrm{c}}], \tag{16}$$

$$T_{\ell+1}(t) \geq T_\ell(t) + T_{\mathrm{o}} + T_{\mathrm{d}} + M_{p_\ell(t), p_{\ell+1}(t)}, \quad \text{for } \ell = 1, \ldots, N_{\mathrm{s}} - 1, \tag{17}$$

$$T_1(t) = t,\ p_1(t) = i_{\text{current}}(t), \tag{18}$$
$$T_2(t) \leq t + N_{\text{c}} T_{\text{c}}, \tag{19}$$
$$\text{and (9), (10)}, \tag{20}$$

in which $\alpha$ is a positive parameter weighting the importance of the objective $J_{\text{MoMPC}}(t)$ against $J_{\text{operator}}(t)$ in the multi-objective optimization problem. At every new location, the current measurements are sent to the control center and used by the controller to solve (13)-(20). The controller then furnishes the operator with the required modifications $u_1^{\text{human}}(t)$ to be executed at the current location $i_{\text{current}}(t)$ and provides the operator with the new location $p_2(t)$ to go to to as well as the specific time instant $T_2(t)$ when the operator should arrive at the next scheduled gate.

Similarly to the approach presented in Section II, in the approach introduced in this section the head gate is controlled using standard MPC with a control step $T_{\text{c}}$. Accordingly, the head gate flow is coordinated with the solution to Mobile TIO-MPC problem (13)-(20).

The difference between the new approach introduced in this paper and the earlier approach of [15] (see Section II) is that the new method allows for more freedom in terms of when the actuation takes place, while the method presented in Section II requires that the system is actuated whenever there is a possibility for this, i.e. the operator has finished work at one location and so is free to carry out new tasks. The small motivating example given in Section III-A shows that it is crucial for systems like this with limited and event-triggered measurements and actuation provided by the operator to actuate the system at the right time given the system dynamics.

## IV. Numerical comparison with the previous method

In this section we give simulation results of the new method presented in the paper for human-in-the-loop control of an irrigation canal and compare its performance with that of the previously introduced method [15], which is shown to outperform the manual-only operation. In the implementation, we approximate the continuous sampled-data model (13)-(20) with a discrete-time model using control step of $T_{\text{c}} = 5$ minutes. To compare the methods, we use the a posteriori cost function defined as

$$J_{\text{post,MoMPC}} = \sum_{k=1}^{N_{\text{f}}} \left( x^T(k) Q x(k) + u^T(k) R u(k) \right),$$

where $N_{\text{f}} = 288$ denotes the total number of simulation steps, which corresponds to 24 hours. The weighting matrices are $Q = 0.01I$ and $R = 0.0001I$. In addition, we evaluate how many location changes are ordered to the operator in the original method and in the newly proposed one (cf. (11)). We thus consider the following complementary performance index

$$J_{\text{post,operator}} = \sum_{s=1}^{n_{\text{overall}}} \mathbb{1}_{p_{s+1}^{\text{overall}} \neq p_s^{\text{overall}}},$$

where $p^{\text{overall}} = (p_1^{\text{overall}}, \ldots, p_{n_{\text{overall}}}^{\text{overall}})^T$, $p_s^{\text{overall}} \in \bar{\mathcal{I}}$, is the sequence of all $n_{\text{overall}}$ gates visited by the operator during the simulation.

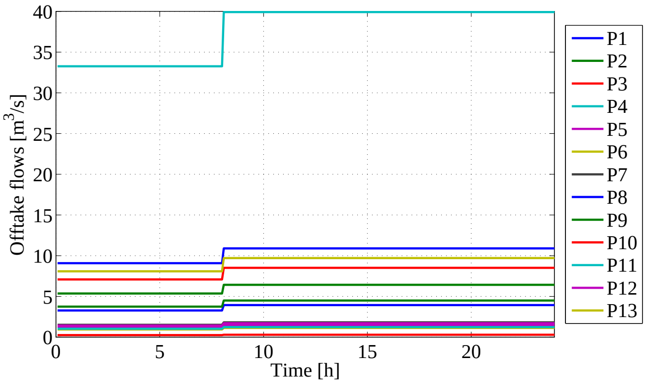


Fig. 4. Offtake profile in the case study.

TABLE I

Comparison between the performance obtained with the original method and the new proposed approach.

| | original method | newly proposed method |
|---|---|---|
| $J_{\text{post,MoMPC}}$ | 71.17 | 8.59 |
| $J_{\text{post,operator}}$ | 101 | 46 |

As in [15], we simulate a scenario with $N_{\text{s}} = 5$, $N_{\text{p}} = 72$, and $N_{\text{c}} = 30$. We use a model of an existing irrigation canal located in Dez in Iran and consisting of 13 gates (including the head gate). A number of disturbance offtakes are employed in the canal to assess the proposed method, see Fig. 4.

The comparison results are given in Table I, while Figs. 5 and 6 depict the system behavior with the new method. As expected, the new method results in a better performance than the originally proposed solution. Moreover, the results also indicate that in closed-loop operation, the operator's work is more relaxed with fewer location changes to take for the newly proposed method. Hence, the case study demonstrates that the new method introduced in the paper attains a twofold improvement. First, the closed-loop performance is better in terms of meeting the canal operation criteria (cf. (12)). Second, the improved performance comes together with eased working conditions of the operator, which improves the quality of work of the human operator.

## V. Conclusions

We have proposed a new method based on MPC for an irrigation canal with a human operator explicitly included in the control design. The operator travels along the canal and provides measurements and actuation. We have introduced a control method, which uses the time instants of when the operator's actions should take place as the optimization variables to synchronize the time instants with the system dynamics and thus achieve a good performance. The performance of the new method in comparison to the original solution are demonstrated in a simulation-based case study. This confirms the improved performance that the new method offers over the previous method.

We have aimed to minimize the workload of the human

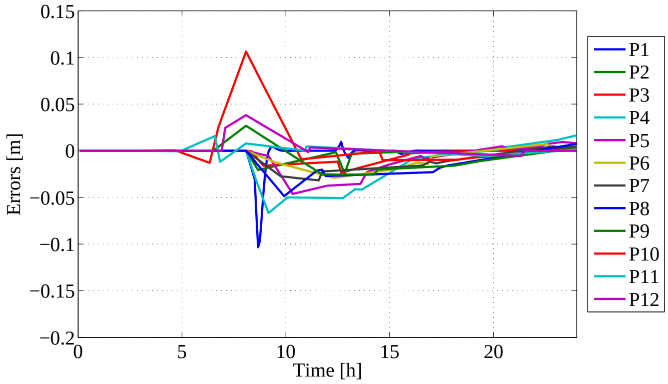


Fig. 5. Deviations in the water levels with respect to their respective setpoints.

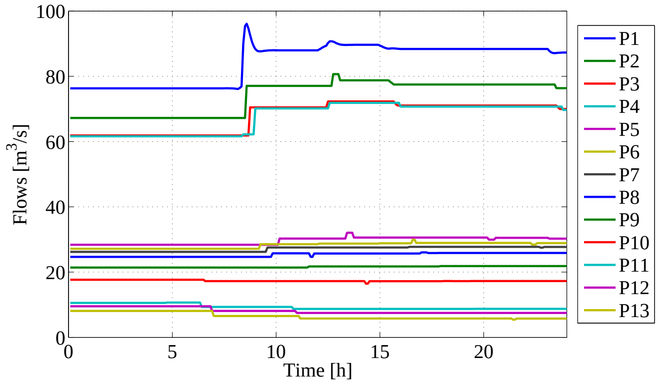


Fig. 6. Flows through the gates.

operator by using a penalty on the number of location changes that the operator needs to take in order to ease the working conditions of the operator. We also explicitly model a delay between the moment when the operator takes the measurements and sends them to the controller, and when the control action is applied. In the future, more human-related aspects such as inaccuracy of the human actions will be added to the control design to bring the problem formulation and the proposed solution closer to the realistic situation. Moreover, estimation techniques will be studied and adapted or extended to the particular settings to update the state of the whole system based on measurements from the individual locations.

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