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Predictive Control of Irrigation Canals Considering Well-being of Operators ⋆

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Abstract: We propose a model-predictive control (MPC) approach to solve a human-in-the-loop control problem for a non-automatic networked system with uncertain dynamics. There are no sensors or actuators installed in the system and we involve humans in the loop to travel between various nodes in the network and to provide the remote controller with measurements as well as actuating the system according to the control requirements. We compute the time instants at which the measurements and actuations should take place to yield better performance with respect to current control methods. We present simulation results using a numerical model of a real canal, the West-M canal in Arizona, and we demonstrate the superiority of the new method over previously proposed ones for such setting.

Keywords: MPC, human-in-the-loop, networked system, optimisation, uncertainty.

1. INTRODUCTION

Saving costs in large-scale networked systems may require to reduce the amount of automation available. To compensate for this, human operators need to be an active part of the system and manually perform tasks related to the measurement and actuation in the system. This situation is obvious in irrigation canals, where the risk of the equipment being stolen or damaged if left alone explains why many of these systems are still operated manually (Maestre, 2021).

To solve a human-in-the-loop control problem for an irrigation canal, prior papers by van Overloop et al. (2015); Rodríguez et al. (2017) introduced a method called mobile model predictive control (Mobile-MPC) in which a human operator travels between different locations in the canal as assigned by a controller, being both the measuring medium (cf. Lewis et al. (2009); Kaupp et al. (2005), which considered humans as sensors in sensor networks) and the actuating medium between the local sites and the remote controller due to the lack of the corresponding instrumentation. In Mobile-MPC, the remote central controller uses an event-driven MPC strategy with updated control actions. Whenever the operator arrives at an assigned location and sends measurements to the controller, the controller computes the travel time between different locations and the time required at a location to communicate new measurements and actuations as well as the next location to go.

In order to reduce the uncertainty in the network by promoting regular visits to the locations, we introduce a new penalty to the overall cost function. Moreover, the energy consumption related to the control process and a stress level relevant to the operator is added to the controller to achieve more realistic and accurate results.

The outline of this article is as follows. In Section 2, we define the considered large-scale networked system. In Section 3, the novel control algorithm is introduced. We illustrate the performance of the new controller in a numerical study in Section 4. Conclusions and future perspectives are given in Section 5.

2. NETWORKED SYSTEM MODELLING

Consider a network system described by a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Here $\mathcal{V}$ is the set of nodes (i.e. , all measurement and actuating locations in the networked system). It is assumed that at each node, measurements are taken and actuation is applied. However, the method can be easily extended to accommodate measurement-only or actuation-only nodes. Let $\mathcal{E}$ denote the set of edges of the graph such that $(v_i, v_j) \in \mathcal{E}$ if there is a direct route between nodes v_i and v_j in $\mathcal{G}$ (Jiang et al., 2019).

We define a set of possible routes for the operator to travel, which may be a subset of the total set of existing routes in the network. To define the allowed routes, sets $\mathcal{R}_{v_i \to v_j}$ are introduced

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$$\mathcal{R}_{v_i \to v_j} = \left\{ \mathcal{R}^1_{v_i \to v_j}, \ldots, \mathcal{R}^{N_{\text{routes},v_i \to v_j}}_{v_i \to v_j} \right\} \tag{1}$$

that include the allowed routes from node v_i to node v_j, in which $N_{\text{routes},v_i \to v_j} > 0$ is the number of allowed routes from v_i to v_j. Each individual route $\mathcal{R}^c_{v_i \to v_j}$, $c = 1, \cdots, N_{\text{routes},v_i \to v_j}$ is identified with a specific distance $\mathcal{D}^c_{v_i \to v_j}$ that an operator must travel along that route. It is required that there are no cycles on the routes and that each route $\mathcal{R}^c_{v_i \to v_j}$ satisfies $\mathcal{D}^c_{v_i \to v_j} \le \mathcal{D}_{\max}$, where $\mathcal{D}_{\max}$ is the maximised travel distance. Moreover, each path $\mathcal{R}^c_{v_i \to v_j}$ is identified with a particular stress level $\mathcal{S}^c_{v_i \to v_j} \in (0, 1)$ and is assigned a minimum $v^c_{\min,v_i \to v_j}$ and a maximum velocity $v^c_{\max,v_i \to v_j}$ with which an operator can travel along the route. The differences between stress levels and allowable velocities for different routes between two nodes are related to the type of different routes, e.g., empty or busy highways during different times of the day.

To introduce the time instants at which the operator actions should take place, we use a continuous-time model of the network

$$\dot{x}(t) = Ax(t) + B_{\text{u}}u(t) + B_{\text{d}}d(t) + w(t), \tag{2}$$

$$y(t) = H(t)x(t) + v(t), \tag{3}$$

where $x(t) \in \mathbb{R}^n$ denotes the state, $u(t) \in \mathbb{R}^m$ denotes the input, $d(t) \in \mathbb{R}^r$ denotes the known exogenous input, $w(t) \in \mathbb{R}^n$ denotes the unknown process noise, $y(t) \in \mathbb{R}^p$ denotes the measured output, and $v(t) \in \mathbb{R}^p$ is the unknown measurement noise. The states and control input take form as $x(t) = \left(x_1^{\text{T}}(t), \ldots, x_N^{\text{T}}(t)\right)^{\text{T}}$ and $u(t) = \left(u_1^{\text{T}}(t), \ldots, u_N^{\text{T}}(t)\right)^{\text{T}}$ for N nodes in the network. Furthermore, A, B_u, B_d, and $H(t)$ are system matrices of suitable dimensions, and the output matrix $H(t)$ is time-varying because it depends on the location of the operator in the network at a given time.

3. CONTROL ALGORITHM

In the present paper, we employ Time Instant Optimisation MPC (TIO-MPC) to improve the quality of the solution over the one resulting from the formulation proposed by van Overloop et al. (2015); Maestre et al. (2014) but, as will be shown later, the problem also contains some necessary integer variables.

Route definition Consider a network with $N_{\text{op}} \ge 1$ operators indexed by $j \in \mathcal{O} = \{1, \ldots, N_{\text{op}}\}$. Assume that at $t = \breve{t} \in \mathbb{R}$ the operators $\breve{\mathcal{O}}(\breve{t}) \subset \mathcal{O}$ take the measurements from their present location, communicate them to the controller, and receive information on what control action to apply. We assume that the time all these consecutive events take is negligible. We call $\breve{t}$ the activation time. At time $\breve{t}$, operators $j \notin \breve{\mathcal{O}}(\breve{t})$ are either travelling between the network nodes or are at a node completing some activities, having recently received instructions from the controller. We define a travel status function for operators $j \notin \breve{\mathcal{O}}(\breve{t})$ as

$$\text{st}_j(\breve{t}) = \begin{cases} 1 \text{ if operator } j \text{ is travelling,} \\ 0 \text{ otherwise.} \end{cases} \tag{4}$$

It is assumed that operators must be allowed to travel to their originally assigned location; however, the rest of their trip can be adjusted. The operators that are finishing some activities, need to be allowed $T_{\text{busy},j}(\breve{t})$ time units to complete their current activities before any new instructions assigned to them. A new schedule can be given to operators from the controller, as soon as they become free.

Define the path variable $p_j(\breve{t})$ for the operator j, consisting of N_{s} consecutive indices of nodes to be visited

$$p_j(\breve{t}) = (p_{1,j}(\breve{t}), \ldots, p_{N_{\text{s}},j}(\breve{t})),\ p_{\ell,j}(\breve{t}) \in \mathcal{V} \tag{5}$$

with $p_{1,j}(\breve{t}) = v_{\text{current},j}(\breve{t})$ for $j \in \breve{\mathcal{O}}(\breve{t})$, i.e. , the current node visited at time $\breve{t}$, and $p_{1,j}(\breve{t}) = p_{1,j}(\underline{t}^*)$ for $j \notin \breve{\mathcal{O}}(\breve{t})$ if $\text{st}_j(\breve{t}) = 1$, where $\underline{t}^*$ denotes the time of the previous activation of the controller. The elements $p_{\ell,j}(\breve{t})$ of the path variable $p_j(\breve{t})$ may be repeated so that an operator j can review and actuate a subset of possible locations many times.

In general, there are multiple possible routes between any two subsequent nodes $p_{\ell,j}(\breve{t})$ and $p_{\ell+1,j}(\breve{t})$. To consider an additional degree of freedom, the controller indicates the specific route that the operator should follow between $p_{\ell,j}(\breve{t})$ and $p_{\ell+1,j}(\breve{t})$. To do so, we introduce a complementary route index variable $r_j(\breve{t})$ as

$$r_j(\breve{t}) = (r_{1,j}(\breve{t}), \ldots, r_{N_{\text{s}}-1,1}(\breve{t})), \tag{6}$$

such that each element

$$r_{\ell,j}(\breve{t}) \in \{1, \ldots, N_{\text{routes},p_{\ell,j}(\breve{t}) \to p_{\ell+1,j}(\breve{t})}\}$$

of $r_j(\breve{t})$ determines the index of the selected admissible route between $p_{\ell,j}(\breve{t})$ and $p_{\ell+1,j}(\breve{t})$, i.e. , $r_{\ell,j}(\breve{t})$ is the index c of $\mathcal{R}^c_{p_{\ell,j}(\breve{t}) \to p_{\ell+1,j}(\breve{t})}$.

We denote by

$$T^{\text{m}}_j(\breve{t}) = (T^{\text{m}}_{1,j}(\breve{t}), \ldots, T^{\text{m}}_{N_{\text{s}},j}(\breve{t})),\ T^{\text{m}}_{\ell,j}(\breve{t}) \in \mathbb{R}, \tag{7}$$

the N_{s} time instants at which the operator should take measurements at the consecutive locations of path $p_j(\breve{t})$. Similarly to the first element of the sequence $p_j(\breve{t})$, for $j \in \breve{\mathcal{O}}(\breve{t})$ the first element of the sequence $T^{\text{m}}_j(\breve{t})$ is fixed to the current time $T^{\text{m}}_{1,j}(\breve{t}) = \breve{t}$. Further, denote the N_{s} time instants at which the operator should apply actuation at visited locations by

$$T^{\text{a}}_j(\breve{t}) = (T^{\text{a}}_{1,j}(\breve{t}), \ldots, T^{\text{a}}_{N_{\text{s}},j}(\breve{t})),\ T^{\text{a}}_{\ell,j}(\breve{t}) \in \mathbb{R}, \tag{8}$$

with the first element $T^{\text{a}}_{1,j}(\breve{t})$ to be assigned by the controller for all $j \in \mathcal{O}$, in contrast to the first element of the sequence $T^{\text{m}}_j(\breve{t})$, which is fixed for $j \in \breve{\mathcal{O}}(\breve{t})$.

The N_{s} control actions to be applied by operator j at the given locations are denoted by

$$u^{\text{op}}_j(\breve{t}) = (u^{\text{op}}_{1,j}(\breve{t}), \ldots, u^{\text{op}}_{N_{\text{s}},j}(\breve{t})),\ u^{\text{op}}_{\ell,j}(\breve{t}) \in \mathbb{R}.$$

Note that this whole sequence including the action to be applied at a current location for all operators servicing the network $j \in \mathcal{O}$ is computed given the most up-to-date measurements provided by the operator. If at some time it so happens that no actuation is needed after providing the controller with measurements at a location $p_{\ell,j}(\breve{t})$, the corresponding element of the sequence $u^{\text{op}}_j(\breve{t})$ will be $u^{\text{op}}_{\ell,j}(\breve{t}) = 0$.

Considering the variables $p_j(\breve{t})$, $T^{\text{m}}_j(\breve{t})$, $T^{\text{a}}_j(\breve{t})$, and $u^{\text{op}}_j(\breve{t})$ for all $j \in \mathcal{O}$ the control input $\widetilde{U}(\breve{t})$ is parameterised. Here, $\widetilde{U}(\breve{t})$ denotes the trajectories of the control input $u(t)$ for the whole duration T_p of the prediction window, i.e. , from the current activation time $\breve{t}$ of the controller until the end of the prediction window $\breve{t}+T_\mathrm{p}$. Thus, the following relation is achieved for $\tau \in [\breve{t}, \breve{t}+T_\mathrm{p}]$

$$u_i(\tau|\breve{t}) = \begin{cases} u^{\mathrm{op}}_{\ell,j}(\breve{t})\delta(\tau - T^{\mathrm{a}}_{\ell,j}(\breve{t})) & \text{if } v_i = p_{\ell,j}(\breve{t}), \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

in which δ denotes the Dirac impulse function. Hence, the operator should take measurements at location $p_{\ell,j}(\breve{t})$ and pass them to the controller at time $T^{\mathrm{m}}_{\ell,j}(\breve{t})$ and at time $T^{\mathrm{a}}_{\ell,j}(\breve{t})$ the control action $u^{\mathrm{op}}_{\ell,j}(\breve{t})$ should be employed at that location. Then, the operator continues to the subsequent location $p_{\ell+1,j}(\breve{t})$.

To describe the dynamics of the network, we integrate the continuous sampled-data MPC of Fontes and Paiva (2018) that employs a continuous-time model (2)-(3) of a system, but measurements are obtained from the system and new control actions are imposed at consecutive sampling times. This structure helps us defining the time instants (7) and (8) as real-valued variables.

Network uncertainty minimisation To promote regular visits to all locations in the network, we introduce an additional penalty term $J_{\mathrm{loc}}(t)$, which adds terms to the overall cost that are proportional to the time passed since each location has been visited for the last time to take measurements and change control settings, see Figure 1. Using similar concepts of a refresh time of a node (Pasqualetti et al., 2012) or a node idleness (Chahal et al., 2021), define for each $v_i \in \mathcal{V}$

$$\Delta t_i(\tau|\breve{t}) = \begin{cases} 0 & if\, \tau = T^{\mathrm{m}}_{\ell,j}(\breve{t})\, and\, v_i = p_{\ell,j}(\breve{t}), \\ \tau - t^{\mathrm{last}}_i(\tau|\breve{t}) & \text{otherwise,} \end{cases} \tag{10}$$

where $t^{\mathrm{last}}_i(\tau|\breve{t})$ is initialised as $t^{\mathrm{last}}_i(0|0) = 0$ and is updated to $t^{\mathrm{last}}_i(\tau|\breve{t}) = \tau$ whenever for any j, $\tau = T^{\mathrm{m}}_{\ell,j}(\breve{t})$ and $v_i = p_{\ell,j}(\breve{t})$ (otherwise the previously assigned value of $t^{\mathrm{last}}_i(\tau|\breve{t})$ is kept). Moreover, each time the controller gets activated since the operator is sending measurements from the new location at time t_{s+1}, the initial value is $t^{\mathrm{last}}_i(t_{s+1}|t_{s+1}) = t^{\mathrm{last}}_i(t_{s+1}|t_s)$, in which t_s implies the time of the activation immediately before.

So the cost function $J_{\mathrm{loc}}(\breve{t})$ comes in the form

$$J_{\mathrm{loc}}(\breve{t}) = \sum_{i=1}^{N} \int_{\breve{t}}^{\breve{t}+T_\mathrm{p}} \alpha_{\mathrm{loc},i} \Delta t_i(\tau|\breve{t})\mathrm{d}\tau, \tag{11}$$

in which $\alpha_{\mathrm{loc},i}$ are positive constants and set more priority at visiting some locations and less at others as needed. To minimise the above-mentioned cost function, the controller must persistently take measurements from all locations. It can also drive the time instants $T^{\mathrm{m}}_{\ell,j}(\breve{t})$, $T^{\mathrm{a}}_{\ell,j}(\breve{t})$, $T^{\mathrm{m}}_{\ell+1,j}(\breve{t})$ and $T^{\mathrm{a}}_{\ell+1,j}(\breve{t})$ closer to cause a lower performance in terms of the cost function $J_{\mathrm{MoMPC}}(t)$. Thus, by better tuning the weights (see (19)), we can enhance the overall performance. This process specifies the importance of the individual components of the entire cost function.

Operator-centric approach In the prior results of van Overloop et al. (2015); Maestre et al. (2014); Sadowska et al. (2015), there was an assumption on a constant travel speed of the human operator. However, here, the speed of the operator may vary at different parts of the path

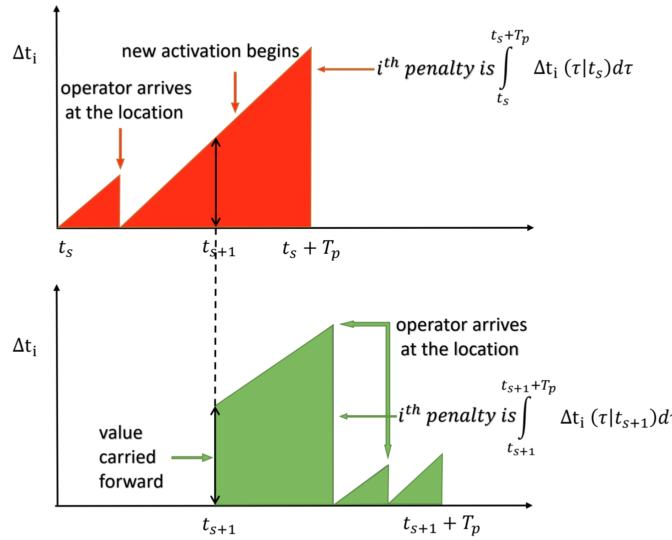

Figure 1. Definition of the variables $\Delta t_i(\tau|t)$. The i^{th} component of the penalty $J_{\mathrm{loc}}(t_s)$ ((t_{s+1}), respectively) represents the red (green, respectively) area shown.

$p_j(\breve{t})$, $j \in \mathcal{O}$ with the assumption that the operators drive between the locations. The objective of the variable speed is twofold: to enable the controller to assign the speed so as to minimise energy and, on the other hand, to minimise the travel time of the operator, which may be considered to represent a burden to the human operator. The controller determines the average speed of the operator using a variable $v^{\mathrm{op}}_j(\breve{t})$ defined as

$$v^{\mathrm{op}}_j(\breve{t}) = (v^{\mathrm{op}}_{1,j}(\breve{t}), \ldots, v^{\mathrm{op}}_{N_\mathrm{s}-1,j}(\breve{t})),\ v^{\mathrm{op}}_{\ell,j}(\breve{t}) \geq 0, \tag{12}$$

in which $v^{\mathrm{op}}_{\ell,j}(\breve{t})$ denotes the average speed for operator j when travelling from $p_{\ell,j}(\breve{t})$ to $p_{\ell+1,j}(\breve{t})$. As it is possible for two subsequent locations to be identical $p_{\ell,j}(t) = p_{\ell+1,j}(\breve{t})$, in such circumstances the corresponding speed of the operator $v^{\mathrm{op}}_{\ell,j}(\breve{t})$ must be 0. Otherwise, if the operator is assigned to go to a different location $p_{\ell,j}(t) \neq p_{\ell+1,j}(\breve{t})$, the speed $v^{\mathrm{op}}_{\ell,j}(\breve{t})$ has to be a strictly positive number.

The total time spent by an operator j on travelling between locations is defined as

$$J^{\mathrm{t}}_{\mathrm{op},j}(\breve{t}) = \sum_{s=1}^{N_\mathrm{s}-1} \frac{\mathcal{D}^{r_{s,j}(\breve{t})}_{p_{s,j}(\breve{t})\rightarrow p_{s+1,j}(\breve{t})}}{v^{\mathrm{op}}_{s,j}(\breve{t})}. \tag{13}$$

The time intervals when the operator waits between working at two consecutive locations do not contribute to the cost $J^{\mathrm{t}}_{\mathrm{op}}(t)$ in (13). However, the waiting times may be a burden to some operators like the time when they engage with wasted time during an operation (Kim et al., 2020). Hence, a second term is considered to constitute the cost function of the operator as

$$J^{\mathrm{w}}_{\mathrm{op},j}(\breve{t}) = \sum_{s=1}^{N_\mathrm{s}} \left(T^{\mathrm{a}}_{s,j}(\breve{t}) - T^{\mathrm{m}}_{s,j}(\breve{t})\right) \tag{14}$$
$$+ \sum_{s=1}^{N_\mathrm{s}-1} \left(T^{\mathrm{m}}_{s+1,j}(\breve{t}) - T^{\mathrm{a}}_{s,j}(\breve{t}) - \frac{\mathcal{D}^{r_{s,j}(\breve{t})}_{p_{s,j}(\breve{t})\rightarrow p_{s+1,j}(\breve{t}),}}{v^{\mathrm{op}}_{s,j}(\breve{t})} \right).$$

The first part in (14) stands for the waiting time at a location in between taking measurements and applying a control action and the second part accounts for the waiting times before travelling to a new location. Additionally, a third component of the operator's cost function is introduced, originating from the fact that different routes may have different associated stress levels for different operators. For instance, driving on a busy highway versus a local road, where one may prefer either of those (Farahmand and Boroujerdian, 2018). Therefore, the selection of the route $r_{\ell,j}(\check{t})$ is also taken into consideration when evaluating the burden for the operator

$$J^{\mathrm{s}}_{\mathrm{op},j}(\check{t}) = \sum_{s=1}^{N_{\mathrm{s}}-1} \mathcal{S}^{r_{s,j}(\check{t})}_{p_{s,j}(\check{t})\to p_{s+1,j}(\check{t})}(\check{t}), \tag{15}$$

where the stress level variable $\mathcal{S}$ is time-varying to allow assigning different levels for different times in response to ,e.g. , traffic congestion or weather conditions. Here, we assume that the stress levels are identical for all operators but the method can be easily extended to operator-dependent stress levels.

While involving multiple operators, we propose an additional penalty term J_{uni}, with the purpose of enhancing schedules with uniform workload between operators. The workload is defined in terms of an average of the travel time $T_{\mathrm{tr},j}(\check{t})$ given in (13) and the waiting time $T_{\mathrm{wait},j}(\check{t})$ given in (14). Thus, the total time variable for operator j sets as $T_{\mathrm{tot},j}(\check{t}) = T_{\mathrm{tr},j}(\check{t}) + T_{\mathrm{wait},j}(\check{t})$, and an average time between all operators as $T^{\mathrm{ave}}_{\mathrm{tot}}(\check{t}) = \frac{1}{N_{\mathrm{op}}}\sum_{j\in\mathcal{O}} T_{\mathrm{tot},j}(\check{t})$. It should be noted that the time is not counted for $T_{\mathrm{tot},j}(\check{t})$ when the operators are active at network nodes since at this time, they are not travelling nor waiting. The penalty takes the form

$$J_{\mathrm{uni}}(\check{t}) = \sum_{j\in\mathcal{O}} \left(T_{\mathrm{tot},j}(\check{t}) - T^{\mathrm{ave}}_{\mathrm{tot}}(\check{t})\right)^2. \tag{16}$$

The total time variable considered in (16) is related to its individual components $T_{\mathrm{tr},j}$ and $T_{\mathrm{wait},j}$. So if an operator prefers to spend different time on travelling or waiting, its preference is not a conflict with this penalty (cf. (17)).

The overall cost function for the human operators that comes in form of a burden is described as

$$\begin{aligned} J_{\mathrm{op}}(\check{t}) = \textstyle\sum_{j\in\mathcal{O}} \big(&\alpha^{\mathrm{t}}_{\mathrm{op},j} J^{\mathrm{t}}_{\mathrm{op},j}(\check{t}) + \alpha^{\mathrm{w}}_{\mathrm{op},j} J^{\mathrm{w}}_{\mathrm{op},j}(\check{t}) \\ &+ \alpha^{\mathrm{s}}_{\mathrm{op},j} J^{\mathrm{s}}_{\mathrm{op},j}(\check{t})\big) + \alpha_{\mathrm{uni}} J_{\mathrm{uni}}(\check{t}), \end{aligned} \tag{17}$$

with weighting parameters $\alpha^{\mathrm{t}}_{\mathrm{op},j}$, $\alpha^{\mathrm{w}}_{\mathrm{op},j}$, $\alpha^{\mathrm{s}}_{\mathrm{op},j}$, and α_{uni}.

Energy conservation The energy consumption cost can be represented as

$$J_{\mathrm{e}}(\check{t}) = \sum_{j\in\mathcal{O}} \sum_{s=1}^{N_{\mathrm{s}}-1} \mathcal{D}^{r_{s,j}(\check{t})}_{p_{s,j}(\check{t})\to p_{s+1,j}(\check{t})} v^{\mathrm{op}}_{s,j}(\check{t}). \tag{18}$$

We note that the two objectives (13) and (18) are in conflict since to minimise (13), the assigned speed of the operator should be maximised to allow the operator to travel faster, whereas to minimise (18) the speed of the operator should be minimised.

The final control algorithm The optimal event-driven control problem to be solved when the controller is activated and the operator is providing new measurements takes the form

$$\min_{\substack{\mathscr{U}_j(\check{t})\\ j\in\mathcal{O}}} J_{\mathrm{MoMPC}}(\check{t}) + w_1 J_{\mathrm{loc}}(\check{t}) + w_2 J_{\mathrm{op}}(\check{t}) + w_3 J_{\mathrm{e}}(\check{t}), \tag{19}$$

subject to

$$\hat{x}(\tau|\check{t}) \in \mathcal{X},\ \forall\tau\in[\check{t}, \check{t}+T_{\mathrm{p}}], \tag{20}$$

$$u(T^{\mathrm{a}}_{\ell,j}|\check{t}) \in \mathcal{U}, \text{for } \ell = 1,\dots,N_{\mathrm{s}},\ j\in\mathcal{O}, \tag{21}$$

$$T^{\mathrm{m}}_{\ell+1,j} \geq T^{\mathrm{a}}_{\ell,j} + \frac{\mathcal{D}^{r_{\ell,j}}_{p_{\ell,j}\to p_{\ell+1,j}}}{v^{\mathrm{op}}_{\ell,j}} + \Delta T^{\mathrm{arr}}_{\mathrm{d},p_{\ell+1,j}} + \Delta T^{\mathrm{dep}}_{\mathrm{d},p_{\ell,j}}, \tag{22}$$

$$\text{for } \ell = 1,\dots,N_{\mathrm{s}}-1 \text{ if } p_{\ell,j} \neq p_{\ell+1,j},\ j\in\mathcal{O},$$

$$T^{\mathrm{m}}_{\ell+1,j} \geq T^{\mathrm{a}}_{\ell,j} + \Delta T^{\mathrm{min}}_{\mathrm{d},p_{\ell,j}}, \tag{23}$$

$$\text{for } \ell = 1,\dots,N_{\mathrm{s}}-1 \text{ if } p_{\ell,j} = p_{\ell+1,j},\ j\in\mathcal{O},$$

$$T^{\mathrm{a}}_{\ell,j} \geq T^{\mathrm{m}}_{\ell,j} + \Delta T^{\mathrm{a}}_{\mathrm{d},p_{\ell,j}},\ \text{for } \ell = 1,\dots,N_{\mathrm{s}},\ j\in\mathcal{O}, \tag{24}$$

$$T^{\mathrm{m}}_{1} = \check{t},\ p_{1,j} = v_{\mathrm{current},j},\ \text{for } j\in\check{\mathcal{O}}, \tag{25}$$

$$T^{\mathrm{m}}_{1,j} \geq \check{t} + T_{\mathrm{busy},j} + \frac{\mathcal{D}^{r_{1,j}}_{\mathrm{loc}_j\to p_{1,j}(\check{t})}}{v^{\mathrm{op}}_{1,j}} \tag{26}$$

$$p_{1,j}\in\mathcal{V},\ \text{for } j\notin\check{\mathcal{O}} \text{ and } \mathrm{st}_j = 0,$$

$$T^{\mathrm{m}}_{1,j} \geq \check{t} + \frac{\mathcal{D}^{r_{1,j}}_{\mathrm{loc}_j\to p_{1,j}(\check{t})}}{v^{\mathrm{op}}_{1,j}} \tag{27}$$

$$p_{1,j} = p_{1,j}(t^*_-),\ \text{for } j\notin\check{\mathcal{O}} \text{ and } \mathrm{st}_j = 1,$$

$$T^{\mathrm{m}}_{2,j} \leq \check{t} + T_{\mathrm{max}}, \tag{28}$$

$$\text{for } \ell = 1,\dots,N_{\mathrm{s}}-1,\ j\in\mathcal{O},$$

$$v^{r_{\ell,j}}_{\mathrm{min},p_{\ell,j}\to p_{\ell+1,j}} \leq v^{\mathrm{op}}_{\ell,j} \leq v^{r_{\ell,j}}_{\mathrm{max},p_{\ell,j}\to p_{\ell+1,j}} \tag{29}$$

$$\text{and } (9), (2), (3), (10), \tag{30}$$

where the time dependence $(\check{t})$ is discarded from the constraints for brevity, loc_j is the location of a travelling operator j at time $\check{t}$,

$$\mathscr{U}_j(\check{t}) = \left(p_j(\check{t}), r(\check{t})T^{\mathrm{m}}_j(\check{t}), T^{\mathrm{a}}_j(\check{t}), u^{\mathrm{op}}_j(\check{t}), v^{\mathrm{op}}_j(\check{t})\right)$$

and w_1, w_2, w_3 are positive weighting parameters. If the next location is different from the previous one ($p_{\ell,j}(\check{t}) \neq p_{\ell+1,j}(\check{t})$), the controller can freely schedule the corresponding measurement time instants $T^{\mathrm{m}}_j(\check{t})$ and the actuation time instants $T^{\mathrm{a}}_j(\check{t})$ granted that the time instants conform with the total resulting travelling times between the locations, the times $T^{\mathrm{arr}}_{\mathrm{d},v_i}$ required after arrival to a location $v_i\in\mathcal{V}$ to derive as (2)-(3) is in (19)-(30) and as it is a continuous-time model, the times $T^{\mathrm{dep}}_{\mathrm{d},v_i}$ required at the location v_i to finish the work and to continue to the next location, see (22). On the other hand, if the operator is scheduled to stay at the same location and time ($p_{\ell,j}(\check{t}) = p_{\ell+1,j}(\check{t})$), the actuation takes place only after given a small time delay $T^{\mathrm{min}}_{\mathrm{d},p_{\ell,j}(\check{t})}$, see (23). Furthermore, constraint (24) acts as the time delay that the operator needs to get ready to apply a control action after exchanging information with the controller, constraints (25)–(27) show when the first measurement needs to be scheduled depending on whether the operator is travelling or is at a location, and constraint (28) means that a minimum of one additional location has to be scheduled for each operator within a given maximal idle time $T_{\mathrm{max}} \leq T_{\mathrm{p}}$ to provide the controller with new measurements of the system.

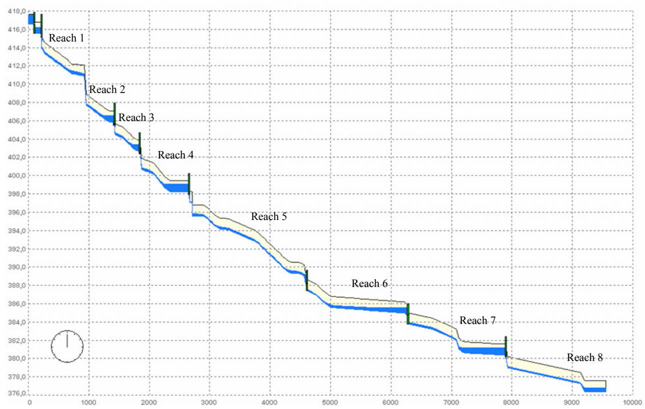

Figure 2. longitudinal profile of the West-M canal in Arizona (picture adapted from Negenborn et al. (2009b)).

4. CASE STUDY

We apply the proposed method by using a numerical model of the West-M irrigation canal in Phoenix, Arizona (Negenborn et al., 2009a). This canal consists of eight pools, see (Figure 2), but to test the controllers, pools 5 and 6 are considered as one single pool as in (Negenborn et al., 2009b). There are movable gates between the pools that the operator can raise or lower to let more or less flow through. At the inlet to the canal, there is a head gate providing water from a source. In practice, the access to the head gate is continuous since it is directly connected to the control centre and so, in this paper, we assume that measurements and actuations of the head gate are allowed continuously while the remaining gates are only serviced by a human operator.

Simulation results and discussion For using (19)-(30), we derive a discrete-time model with a sample and control step both equal to $T_{\mathrm{c}} = 4$ minutes. Actually, the purpose of discretisation is the ease of implementation. It should be noted that this way of implementation means that the time instants (7)–(8) are integer variables (i.e. , sample steps) and not real-valued variables. The genetic algorithm implemented in Matlab is therefore used to solve the optimisation problem. Subsequently, we compare the results obtained with those of the algorithms introduced in Maestre et al. (2014); van Overloop et al. (2015); Sadowska et al. (2015). We use a process model identical to the prediction model and $N_{\mathrm{s}} = 5$, and assume that there is a single operator in the network. We simulate a scenario with a prediction horizon and control horizon equal to $N_{\mathrm{p}} = 96$, and $N_{\mathrm{c}} = 16$, respectively. To enable a fair comparison, we use a simplified control algorithm to better match the settings of Maestre et al. (2014); van Overloop et al. (2015); Sadowska et al. (2015). Thus, the speed of the operator is constant, the energy consumption and the stress component are neglected, and each pair of gates is connected with a unique path. Moreover, $\Delta T^{\mathrm{arr}}_{\mathrm{d},v} = \Delta T^{\mathrm{dep}}_{\mathrm{d},v} = \Delta T^{\mathrm{a}}_{\mathrm{d},v} = 0$, see (21). In addition, $T_{\max} = N_{\mathrm{c}} T_{\mathrm{c}}$, and $\Delta T^{\min}_{\mathrm{d},v} = T_{\mathrm{c}}$, see (23). The simulation starts with off-takes in pools 1 to 6 equal to 0.2, 0.4, 0.2, 0.3, 0.3, 0.2, 0.6 (in m^3/s). Then after 6 hours, the off-takes are changed to 0.3, 0.6, 0.2, 0.1,0.5, 0.6, 0.9 in pools 1 to 6, respectively.

We compare the approaches in terms of a posteriori performance indices

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

$$J_{\Delta \mathrm{t}} = \sum_{i=2}^{8} \sum_{k=1}^{N_{\mathrm{f}}} \Delta t_i(k),$$

in which $N_{\mathrm{f}} = 360$ and the weighting matrices are $Q = 100$ and $R = 0.01I$. For the approach in Maestre et al. (2014); van Overloop et al. (2015), we have $J_{\mathrm{xu}} = 4.30 \cdot 10^4$ and $J_{\Delta \mathrm{t}} = 4.6 \cdot 10^5$, for Sadowska et al. (2015), $J_{\mathrm{xu}} = 1.99 \cdot 10^4$ and $J_{\Delta \mathrm{t}} = 7.4 \cdot 10^5$, and for the new method $J_{\mathrm{xu}} = 1.66 \cdot 10^4$ and $J_{\Delta \mathrm{t}} = 1.4 \cdot 10^6$. In addition, we compare the total waiting time and the total travel time. For the approach of Maestre et al. (2014); van Overloop et al. (2015), the waiting time is 0 since the method does not allow any waiting, and the travel time is 360. For the structure of Sadowska et al. (2015), the waiting time is 240 and the travel time is 120. Lastly, for the new methods, we have a waiting time of 271 and the travel time of 89. As evidenced by these measures, the new method can outperform the previous methods in terms of the operational objective J_{xu} and the travel time of the operator. Note that Sadowska et al. (2015) implements also TIO-MPC, so if other cost components were disregarded, the same value of J_{xu} could be achieved. We remark that with the new method, the price for improved operational performance and shorter travel time is an extended time of the operator waiting and less frequent visits to the gates. Notice in Figure 3 that for the new method, the operator only makes a handful of trips in the second half of the simulation, whereas for the other methods, and particularly for Maestre et al. (2014); van Overloop et al. (2015), the operator continues to travel between the gates frequently. If the system was subjected to uncertainties, it would be beneficial to continue taking measurements, in which case different weighting parameters would have to be selected. We also plot in Figure 4 the results obtained with the new method. It is shown that the new method ensures that the errors in the water levels with respect to their setpoints obtained in a closed-loop simulation converge to zero faster.

5. CONCLUSIONS

A human-in-the-loop control problem for an irrigation network system has been considered. The human operators act as moving sensors that obtain measurements from the current visited locations to send those to a central controller. They also perform as actuators based on the actions the controller requests. Since the human operator can only provide the controller with limited sensing and actuating actions, the actual timings of the actuations done by the human operator have been used as optimisation variables in a time instant optimisation MPC (TIO-MPC) framework. In this way, the performance of the proposed method is improved compared to the previous ones in the literature.

Future work includes engaging more human-related features possibly through experiments to obtain more precise models of the human behaviour to be used with the model-predictive controller. In addition, controller tests will be performed using a high-fidelity simulator of a networked system. Moreover, the problem of observer design for the special settings considered in the paper will be explored.

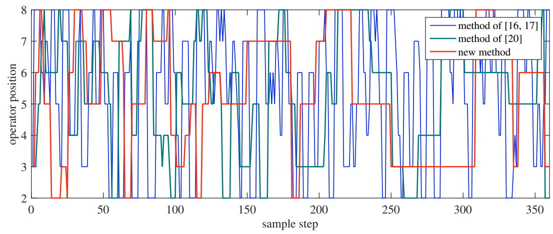

Figure 3. Comparison of the operator position for the approaches considered.

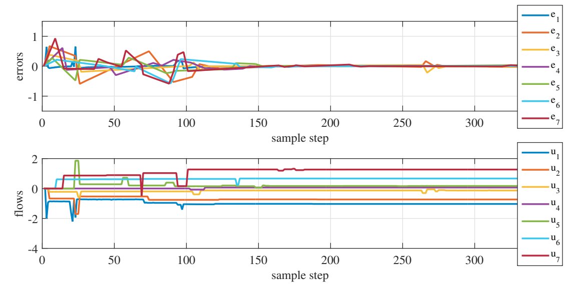

Figure 4. Simulation results obtained with the new TIO-MoMPC algorithm.

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