Pulse-based, Periodic MPC for Irrigation in Smart and Sustainable Agriculture

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Pulse-based, Periodic MPC for Irrigation in Smart and Sustainable Agriculture

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Abstract— The growing population, together with global warming and the difficulty of accessing water, makes the increase of efficient and sustainable agriculture a priority. Undoubtedly, the recent development of low-cost IoT-based sensors and actuators presents great opportunities in this direction, since these devices can be easily deployed to implement advanced monitoring and irrigation control techniques at a farm scale. This paper proposes a pulse-based, periodic, economic predictive controller. Its goal is to find the irrigation pulse trains that optimize water and energy consumption while ensuring adequate levels of soil moisture for the crops. For this purpose, the developed MPC makes use of soil moisture data at different depths, sent by a set of field sensors, and formulates a constrained optimization problem that takes into account water costs, electricity prices, and an accurate dynamical nonlinear agro-hydrological model. Its performance is tested by simulating real case studies, which show that water and energy consumption can be significantly reduced.

I. INTRODUCTION

Over the last decade, considerable progress has been made in the field of smart agriculture, including the development of promising technologies to optimize irrigation and therefore reduce water and energy consumption. One good example is the modernization of the irrigation infrastructure, which has led to pressurized irrigation networks that significantly reduce energy requirements.

Furthermore, recent advances in IoT-based devices with sensing, actuating, computation, and communication capabilities make it possible to implement advanced control techniques at farm-scale to reduce the use of water and energy. In particular, Model Predictive Control (MPC) techniques, which have been successfully applied in highly technologically equipped greenhouses [1], are now being extended to the irrigation of extensive farms.

Although the literature on this topic is surprisingly scarce, there are already some relevant developments in this direction. For instance, in [2] a robust MPC irrigation control with an affine disturbance control law is developed. The authors consider a simple water balance model and incorporate forecasts and constraints on soil moisture into it. The simulations are made using the FAO AquaCrop model[1], showing how the proposed predictive controller easily outperforms other techniques like scheduling and rule-based irrigation. In [3], a simple soil moisture model is also used, but the MPC controller is robustified with data-driven models that characterize forecast uncertainties. The results are compared with open-loop control, rule-based control strategies, and certainty equivalent MPC, with a significant reduction in water consumption.

Furthermore, [4] implements an MPC-based irrigation strategy for cotton farms, considering a heterogeneous field and defining different management zones. The performance of the controller is tested using OZCOT (a simulation model for cotton crop management), and it is compared to the results obtained with sensor-based (relay) techniques. A different approach is taken in [5], where the water dynamics in the soil are described using a linear parameter varying model and a zone-based MPC with asymmetric zone tracking penalties is proposed.

One drawback of the works referenced above is the use of simple water balance models with only one root layer to describe the dynamics of soil moisture, which may lead to problems capturing the nonlinear dynamics of the water in the soil. Moreover, there is little work in the literature regarding the predictive control and optimization at farm scale of both water and energy consumption. From the energy viewpoint, the existing works have focused only on the optimization of the energy use in pressurized irrigation networks, taking into account both the investment and operational costs [6], [7]. However, at the farm scale, an adequate dynamical model of the water fluxes is essential [8] because using the soil as a water buffer can optimize irrigation taking into account energy considerations. Finally, for efficient implementations of irrigation control techniques, it is important to consider irrigation uniformity, which irrigation tapes only guarantee for long enough, pulse-like irrigation periods.

Motivated by the above, a periodic, pulse-based, economic MPC is designed in this paper for the farm-scale of a strawberry plot to reduce the electricity and water consumption, minimizing costs. The controller makes use of an extended, multi-layer version of the model in [9] to determine the water fluxes in the soil.

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[1]http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026354/

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Furthermore, the quasi-periodic behavior of relevant farm-scale variables (crop transpiration and evaporation, as well as electricity prices) allows for optimal periodic irrigation.The controller is composed of two layers. The first one is the Real-Time Optimization (RTO) with the non-linear model cited above, and its function is computing the best economic trajectory, taking into account the periodic behavior of the main system variables, the constraints related to the soil moisture, and the cost of the electricity and water purchasing. The second layer is based on the MPC for tracking developed in [10], which guarantees convergence and recursive feasibility events when the parameters of the cost function change with time. Its adaptation makes it possible to take into account the uniformity of irrigation analyzed in [11], therefore avoiding compromising the crop growth.

The paper is presented as follows: Section II describes the agro-hydrological model that determines the water dynamics in the soil. Section III presents the formulation of the proposed controller. Section IV presents the case study results through simulations. Section V contains the main concluding remarks.

II. MODEL DESCRIPTION

To implement an advanced and efficient irrigation controller, it is crucial (and yet overlooked) to count on an appropriate dynamical model to describe the water fluxes in the soil. Here we rely on an extended version of the model in [9], further developed and tested by the authors of this paper [12] [13] . In this model, the soil is divided into $N+2$ layers: surface layer, root zone (further divided in N layers), and drainage zone is shown in Figure 1 for N = 6. The equations to describe the water dynamics are as follows:

$$\frac{d\theta_1}{dt} = \frac{1}{D_1}\left(I_{rr} + Pt - Q_{1,i}(\theta_1,\theta_2) - \frac{1}{\rho_w}E_g\right) \quad (1a)$$

$$\frac{d\theta_i}{dt} = \frac{1}{D_i}\left(\hat{Q}_i(\theta_i,\theta_{i+1}) - \frac{1}{\rho_w}\frac{E_{tr}}{6}\right), \forall i = 2\cdots N \quad (1b)$$

$$\frac{d\theta_N}{dt} = \frac{1}{D_{N+1}}\left(Q_{N,N+1}(\theta_N,\theta_{N+1}) - Q_{N+1}(\theta_{N+1})\right) \quad (1c)$$

Where θ_i denotes the volumetric water content of each layer (soil moisture), $Q_{i,i+1}$ are the water flux between layers with the nonlinear dependence of θ_i described in [9], $\hat{Q}_i = Q_{i-1,i} - Q_{i,i+1}$, D_i is the soil thickness of each layer, I_{rr} is the irrigation flow, P_t is the precipitation, Q_{N+1} is the flux out of the drainage zone, E_g and E_{tr} denote evaporation from the soil surface and transpiration from the vegetation canopy, respectively, and ρ_w is the water density.

III. MODEL PREDICTIVE CONTROL ALGORITHM

A. Predictive Control Hierarchical Structure

The structure of the proposed economic and periodic predictive controller is shown in Figure 2. The

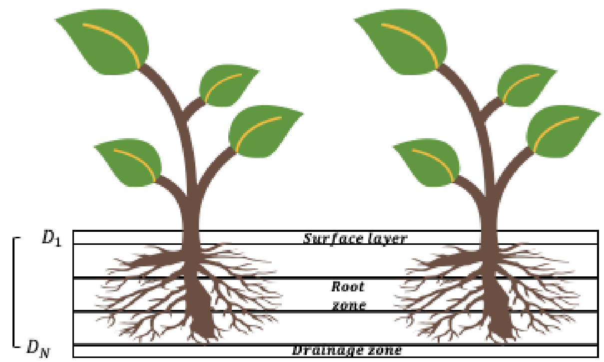

Fig. 1. A schematic of the soil layer with the proposed division in eight layers.

Tracking MPC has an optimized reference trajectory input, obtained from the previous RTO layer. This RTO encompasses a complex economic function and can use linear or nonlinear dynamics.In this paper, it uses the highly non-linear model equations (1), offering the best periodic trajectory-based in pulse train ($\delta_u^\star$) and water flux ($q^\star$) that must be tracked by the MPC.

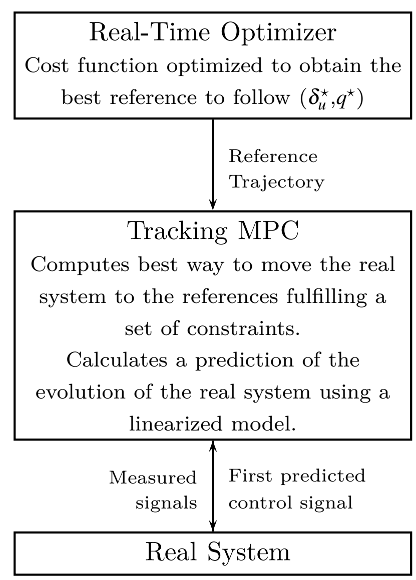

Fig. 2. Scheme of the Model Predictive Control (controller) and the Real System

The Tracking MPC layer employs a linearized model (1) to predict, at the time window equivalent to the system period (1 day), the evolution of the soil moisture, water and energy consumption, and the optimal irrigation periodic pulse train (δ_u^o), while enforcing a set of constraints (maximum and minimum for the soil moisture and maximum available irrigation flow). This layer must move the system to maintain the soil moisture as close as possible to the RTO. This periodic aspect helps the controller stability since the system does not have to stabilize at an operating point but rather a periodic trajectory. However, following a classic receding horizon paradigm, only one control action (the first) is applied, and after that, the system outputs (soil moisture) are measured again and the MPC tracking problem is recursively solved. It's important to remark that the tracking layer tries to approach the optimal references, but in general, $\delta_u^{\star}$ and δ_u^{o} can be different.

This second layer follows the developments in [10]. With this layer, the controller guarantees stability and recursive feasibility even when there are changes in certain reference parameters ($\delta_u^{\star}$).The control goal is usually to derive a control law with $\delta_u(k) = \kappa(x(k), w(k))$ to satisfy the constraints (the irrigation flow and soil moisture range) and the tracking to converge asymptotically to the RTO's nearest signal ($\delta_u^{\star}$).

This proposed controller is very interesting because, in comparison with classical tracking MPC,it increases the reachability region. Based on the non-linear model Equation (1), a Linear Time-Invariant (LTI) model is obtained from the linearization.

$$x(k+1) = Ax(k) + Bu(k) + B_d w(k) \tag{2a}$$
$$y(k) = Cx(k) \tag{2b}$$

The model equations (2b) and (2b) have four constant matrices A, B , B_d and C, where A is the system matrix, B is the control matrix, B_d represents the disturbance matrix and C represents the output matrix. The k denotes the time-variant, the $x(k) \in \mathscr{R}^8$ the states of the model, the $y(k)$ the output system, the $u(k) \in \mathscr{R}^1$ denotes the control action and the $w(k) \in \mathscr{R}^2$ the disturbances associated with this model. Considering this application, the soil moisture values in every layer are the states of the model (system output), where the last layer is dismissed because it has the same behavior as layer 7 and could use this layer to determine the water loss; the irrigation flow is the control action (system input) and the disturbances are evaporation E_g and transpiration E_{tr}.

B. Economic Predictive Controller for Periodic Pulse Train Signals

The system performance is a weighted combination of the electricity costs, water consumption, isolated pulse reduction, and soil moisture deviation from an operational point. These terms are captured by a nonlinear economic cost function, $V_p(x,u)$, which depends on both the soil moisture (system state) and irrigation water flow and pulse trains (control inputs).

It is useful to point out that the control inputs in this problem are a fixed water flux ($q^{\star}$) decided by the RTO and held during a period of 24 hours. In the tracking problem, this water flux is a parameter that only changes after a day, and the decision variable is the periodic pulse train used to decide when the irrigation system is switched on.

The control structure focuses on the periodic operation of a closed-loop system with a fixed period T of 24 hours. The quasi-periodic behavior of the main dynamic variables involved at a farm-scale (radiation, crop transpiration, electricity prices), enables us to take advantage of a periodic, real-time optimizer and tracking layer, to achieve better performance.

Remark. The controller is not a classic structure of an economic MPC, but an implementation in which the RTO takes care of economizing with the cost function, so the controller is economic.

In particular, the main goal of the controller consists of managing the irrigation to achieve optimal economic performance, minimizing a cost function that penalizes the use of water, energy, and short pulses (poor irrigation uniformity). The following optimization problem (3) generates the optimal trajectory that can operate the system, where the initial state is a free variable.

$$\begin{aligned} \min_{x(0),q,\delta_{\mathbf{u}\infty}} \quad & V_p^*(x(0), q, \delta_{\mathbf{u}\infty}) \\ s.t. \quad & x(k+1) = f(k, x(k), q, \delta_u(k)), && \text{(3a)} \\ & (x(k), q, \delta_u(k)) \in Z_r, \quad \forall k \geq 0, && \text{(3b)} \end{aligned}$$

where the set Z_r is a closed polyhedron that contains the above-mentioned constraints that affect the soil moisture, irrigation flows, and pulse trains. The optimal state and control action trajectories[2] are $\mathbf{x}_\infty^{\star}$ and $\delta_{\mathbf{u}\infty}^{\star}$ respectively. In general, problem (3) has an infinite number of decision variables. However, given the periodic nature of the dynamics, the constraints, and the cost function, the optimal solution can be obtained from the solution of the following optimization problem at any given time instant k, which is denoted as $\mathscr{P}_P(x(0), q, \delta_u; w)$.

$$\begin{aligned} \min_{x(0),q,\delta_{\mathbf{u}}{}^{\mathbf{T}}} \quad & \sum_{k=0}^{T-1} V_p^*(x(0), q, \delta_{\mathbf{u}}{}^{\mathbf{T}}) \\ s.t. \quad & x(k+1) = \int_0^{T_m} f(x(0), q, \delta_u(t), w(t))\, dt && \text{(4a)} \\ & (x(k), u(k)) \in Z_r, \quad \forall k \geq 0, && \text{(4b)} \\ & x(0) = x(T) && \text{(4c)} \end{aligned}$$

where T_m is the sampling time. The optimal solution $(x(0)^{\star}, q^{\star}, \delta_{\mathbf{u}}{}^{\mathbf{T}\star})$ of the problem (4) ($\mathscr{P}_P(x(0), q, \delta_u; w)$) is used by the tracking optimization problem, which is denote as $\mathscr{P}_N(x, \delta_u, w)$. The goal of this problem is to move the real system as near as position to the optimal trajectory $(x(0)^{\star}, q^{\star}, \delta_{\mathbf{u}}{}^{\mathbf{T}\star})$, taking into account that $q^{\star}$ is a parameter in this optimization problem.

[2]Bold letters denote trajectories of signals over the prediction horizon/period.

$$
\begin{aligned}
\min_{x_0^r, \delta_{\mathbf{u}}{}^r, \delta_{\mathbf{u}}} \quad & V_N(x, \delta_{\mathbf{u}}, \mathbf{w}; x^r(0), \delta_{\mathbf{u}}{}^r, \mathbf{w}) \\
s.t. \quad & x(0) = x && \text{(5a)} \\
& x(k+1) = Ax(k) + B_u q^\star \delta_u(k) + B_d w(k) && \text{(5b)} \\
& y(k) = Cx(k) + Dq^\star \delta_u(k) \quad k \in \mathbb{Z}_N && \text{(5c)} \\
& (x, \delta_u) \in Z_r && \text{(5d)} \\
& x(N) = x^r(N) && \text{(5e)} \\
& x^r(k+1) = Ax^r(k) + B_u q^\star \delta_u^r(k) + B_d w(k) && \text{(5f)} \\
& (x^r, \delta_u^r) \in Z_r && \text{(5g)} \\
& y^r(k) = Cx^r(k) + Dq^\star \delta_u^r(k) \quad k \in \mathbb{Z}_T && \text{(5h)} \\
& x^r(0) = x^r(T) \quad k = 1..T && \text{(5i)}
\end{aligned}
$$

where $\mathbf{x}^r$ and $\delta_{\mathbf{u}}{}^r$ are reachable trajectories by the linear model of the controller used to avoid the problematic situation (loss of recursive feasibility, etc.) for the MPC controller. Note that the trajectory produced by the RTO does not have to be reachable by the system, that is why this structure is used. For more details, see [14].

The cost function of this tracking controller is defined as follows:

$$
\begin{aligned}
V_N(x^r(0), \delta_{\mathbf{u}}{}^r, \delta_{\mathbf{u}}) &= V_S(x^r(0), \mathbf{x}^r, \mathbf{x}, \delta_{\mathbf{u}}{}^r, \delta_{\mathbf{u}}) \\
&+ V_T(x_0^r, \delta_{\mathbf{u}}{}^r)
\end{aligned}
$$

and

$$
\begin{aligned}
V_S(\mathbf{x}^r, \mathbf{x}, \delta_{\mathbf{u}}{}^r, \delta_{\mathbf{u}}) &= \sum_{i=0}^{N-1} \|x(i) - x^r(i)\|_Q^2 \\
&+ \|\delta_u(i) - \delta_u^r(i)\|_R^2 && \text{(6a)} \\
V_T(x_0^r, \delta_{\mathbf{u}}{}^{\mathbf{r}}) &= \sum_{i=0}^{T-1} \|x^r(i) - x_T^\star(i)\|_W^2 \\
&+ \|\delta_u^r(i) - \delta_u^{T\star}(i)\|_S^2 && \text{(6b)}
\end{aligned}
$$

Generally, in the tracking optimization problem, the initial soil moisture is an argument, and taking into account the large reachability region of this controller and the soil moisture admissibility size, there is very reduced chance that the optimization problem becomes unfeasible.

Considering the equations of the optimization variables (5), which are divided into two parts, the first part is the MPC trajectory and the second is the reachable trajectory. This second part must be near or converge to the reference (RTO) and has to be reachable by the MPC. To achieve the mentioned above, the constraints are the following: the (5a) force that the predicted trajectory of the initial state is equal to the system state. The (5b)-(5c) provide the input trajectories and predicted state, respectively; (5d) determine the range of the state and control action value. The (5e) imposes the periodicity; in (5f) the predicted state must track the reachable reference in T steps; (5g) determines the range of the state and control action value of the reachable trajectory; and (5i) imposes the periodicity; the reachable initial state must be equal to the reachable state in T.

Please note that we are using a nominalm MPC, which could lead to unfeasibilities. We avoid this here using soft constraints in lower constraints of the soil moisture.

C. Economic Cost Function for Farm

The cost function is composed of four main terms. The first term weights deviations in the soil moisture from optimal values established as the minimum values that do not compromise crop growth. The second term minimizes the irrigation water cost, taking into account the electric cost. The third term weighs the use of water. Finally, the last term focuses on minimizing the train pulses.

$$
\begin{aligned}
V_p^*(\mathbf{x}, \mathbf{u}) &= wp_1 f_1(x^{op}; \mathbf{x}) + wp_2 f_2(\mathbf{u}) \\
&+ wp_3 f_3(\mathbf{u}) + wp_4 f_4(\mathbf{u})
\end{aligned}
$$

$$
l f_1(\mathbf{x}) = \sum_{k=0}^{T-1} \|x(k) - x^{op}\|_Q \tag{7a}
$$

$$
f_2(\mathbf{u}) = \sum_{k=0}^{T-1} C_{elec}(k) u(k) \tag{7b}
$$

$$
f_3(\mathbf{u}) = \sum_{k=0}^{T-1} C_{water} u(k) \tag{7c}
$$

$$
f_4(\mathbf{u}) = \sum_{k=0}^{T-1} \|\nabla \delta_u(k)\| \tag{7d}
$$

where C_{elec} is a time-varying electric cost, C_{water} is a fixed cost associated to the water per m^3, and x^{op} are the operational point values of the soil moisture, $\nabla \delta_u$ reduces increments in u, tries to move the signals of the control actions between 0 and 1 or values closer to integers, and wp_i are the corresponding weights, where i= 1,2,3,4.

IV. SIMULATIONS RESULTS

A. Case Study

The case study in this paper corresponds to a strawberry farm located in Almonte (Spain), with a specific greenhouse type, called tunnel greenhouses, in which the precipitation/rainfall does not affect the crop.

The typical irrigation pattern of the local farmers is to apply water in pulses of 30–40 min [11]. Note that this specific crop type (strawberry) needs sandy soil, and according to [15], sandy soil drains faster than other types of soil, so the farmers have to irrigate at specific times of the day so that water can be available before it is completely drained (between 8:00 a.m to 4:00 p.m, when the crop needs water to transpire).

The strawberry crops need more water in the month of June, and during this month, farmers apply water between 60 to 90 minutes a day. In this case, we apply

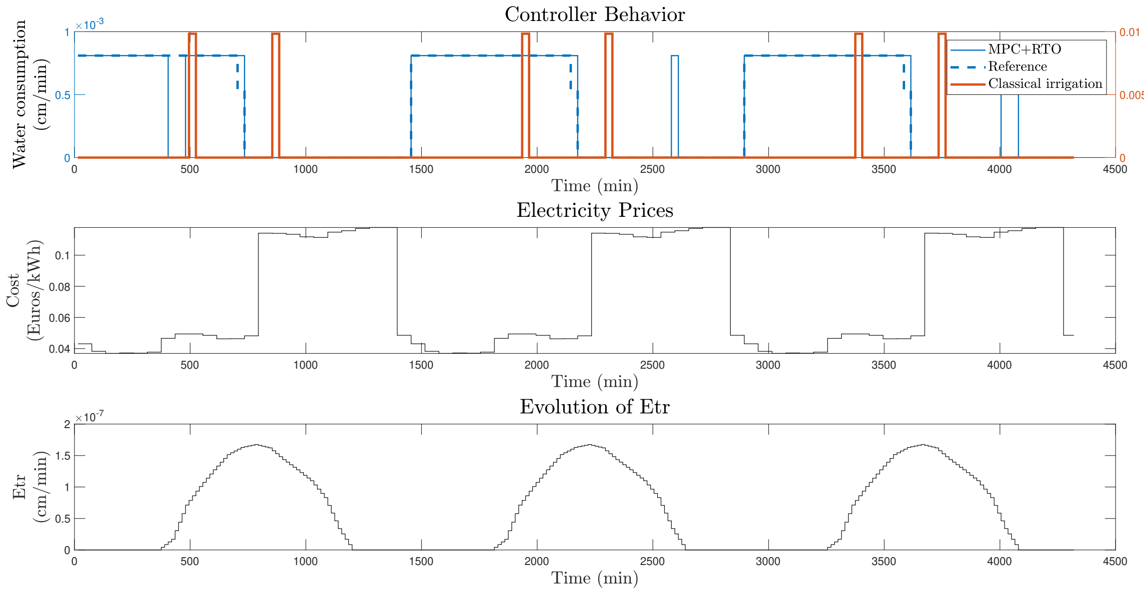

Fig. 3. (a) Scaled irrigation flow by the MPC Controller, optimal consumption by th RTO and classical irrigation strategy during 3 days (b) Electricity prices (c) Evolution of the Etr

water in pulses of 35 min twice a day. The strategy expressed above is classical irrigation, which is going to be used from now.

The classical irrigation strategy exposed above and the controller irrigation strategy proposed in this paper are compared to the performance in terms of water usage and electricity costs. The water cost and electricity tariff are used from [16] and presented in Fig. 3(b).

Considering the equations (1), the term P_t is assumed zero, because the strawberries are cultivated under plastic (tunnel greenhouse), so rainfall does not affect the water balance. Moreover, according to [16] for this specific case-study, the crop evapotranspiration ET_c is only due to plant transpiration E_{tr}, because there is no evaporation from the soil E_g is equal to zero. Besides, simulations are carried out considering a June cloudless day and real values for strawberries. These values are shown in minutes in Fig. 3(c).

Regarding the soil characterization, its hydraulic parameters are chosen according to surveyed values of sandy soils during the month of June [17]. These values are shown in Table I (a). The thickness of the eight soil layers are D=[3 6 6 6 6 6 6 1] cm. Finally, it is considered homogeneous soil and crops, an ideal and uniform irrigation network, and filling/emptying dynamics.

B. Simulations and Discussion.

We compare two irrigation strategies. The first strategy is the proposed controller system, while the second strategy is the above-mentioned classical irrigation. Both scenarios take into account the same characteristics, and

TABLE I

Table of soil hydraulic parameters and controller constraints and weights values

Soil hydraulic parameters			
Variables	Distribution	Values	Units
θ_{sat}	uniform	0.395	cm^3/cm^3
K_{sat}	uniform	1.056	cm/min
ψ_{sat}	uniform	12	cm
B	uniform	4.05	-
Constraints and weights			
	RTO	MPC	
Variables	Range/values		Units
(x_{max}, x_{min})	[0.29 0.175]	[0.29 0.175]	%
(u_{min}, u_{max})	[0.09 -]	[0 -]	cm/min
$(wp_1, ..wp_5)$	[0.01 10^6 10^6]	[0.01 10^{12} 1 10^9 0]	-
E_g	0	0	cm/min

the simulations are 3 days long (4320 minutes). We assumed that the pump consumes 1 kWh/m^3 to simplify the simulation.

The linearized model's system matrices A, B, C values used in the tracking layer are shown in our previous paper [3] [12], in which linearization is performed around the equilibrium points, which in this application is the Field Capacity (FC), so x_{eq}= [0.1745,0.1749,0.1753,0.1757,0.1760,0.1762,0.1764] $\frac{cm^3}{cm^3}$, u_{eq}=0, E_{tr}=0 and E_g=0. The tracking layer has restrictions very near to operational points x_{op} to check the controller performance. In this case, $x_{op} = x_{eq}$.

The used constraints and weights are summarized in Table I (b). A soft constraint in soil moisture [0.1570

[3]The system matrices are not placed in this paper due to space issues.

0.1574 0.1578 0.1581 0.1584 0.1586 0.1588 0.1588] $\frac{cm^3}{cm^3}$ is considered.

The prediction horizon is chosen equal to the period, that is $N = T = 96$ (24 hours). The cost matrices are chosen as $Q = \mathscr{I}_1$, $R = 5000 \cdot \mathscr{I}_1$, where $\mathscr{I}_n$ is the identity matrix of dimension n.

Simulation results show the comparison between a classical irrigation strategy and the proposed controller. Figure 3(a) presents the water applied by the classical irrigation and the controller strategies together with the reference (best trajectory) provided by RTO. Note that the MPC and RTO (reference) signal is scaled. The system is forced to comply with the periodicity so if have to irrigate to fulfill the periodicity, it will irrigate and that happens in some minutes, the controller irrigates in higher electricity prices, looking at figures 3(a) and 3(b), it can be check in the controller strategy how the predictive controller tries to pump water when electricity prices are lower despite to the mentioned above.

A summary of the obtained results is presented in Table II. In (a), presents the results per m^2 in 30 days during the whole month of June, (b) estimates results in large scale, we consider a tunnel greenhouse with $330m^2$ (case study), so, the crop need during the whole month is around 157.51 l/m^2. Therefore, the controller strategy saves 14.13% of water and 51.48% of electricity cost in comparison to the classical irrigation strategy. These results show that the total water saving and electricity costs will be considerable on large scale.

TABLE II

Table of case study comparison between Classical Irrigation and the proposed MPC

Simulation Results ($1m^2$)			
Studied terms	Classical Irrigation	MPC Irrigation	Units
Water usage	206.6	177.4	l
Electricity cost	16.81	8.157	€
Water cost	0.07231	0.06209	€
Simulation Results(Tunnel Greenhouse)			
Study terms	Classical Irrigation	MPC Irrigation	Units
Water usage	68178	58542	l
Electricity cost	5547.3	2691.81	€
Water cost	23.86	20.49	€

V. CONCLUSIONS

In this work, an economic, pulse-based, periodic MPC controller was successfully applied to an irrigation system at a farm scale. The controller used a highly nonlinear agro-hydrological model and an economic cost function because minimizes the water applied therefore electricity costs. In order to compare the results of the controller with the classical irrigation strategy, it can observe the significant reduction of water applied in the crop and the electricity costs. Even considering homogeneous soil and crops, ideal and uniform irrigation network, and filling/emptying dynamics, these effects would also augment the water consumption of the classical irrigation strategy, so total saving could be still similar. The simulations results of the controller show a good performance and on a large scale can give considerable returns.

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