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Exploring the Capabilities of Adaptive Model Predictive Control in Irrigation Systems

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Abstract— **This work addresses the problem associated with the variability of the parameters involved in irrigation control systems for real crops. Factors such as soil compaction, climatic variability or phenological state of the crops, among others, significantly influence the dynamics of these systems, challenging the implementation of model-based controllers in real use cases. In this context, an Adaptive Model Predictive Control scheme is proposed, which makes it possible to update the model by employing a recursive system identification. A comparison with a conventional predictive controller employing a constant model is made. The study is based on models identified from data collected in a production farm in Seville, Spain. The validation of the proposed strategy and the comparison between the adaptive MPC and the conventional MPC are performed by means of simulations. The results demonstrate the potential applicability and effectiveness of Adaptive MPC in real farming conditions.**

I. Introduction

Agriculture stands as one of the most important productive sectors in the world, serving as an indispensable pillar for the global economy and food security and being responsible for around 70% of the total fresh water consumption [1]. With anticipated population growth and climate change effects, water scarcity and competition for resources will become more pronounced. This highlights the need for proper irrigation control, not only for the significant consumption of this resource, but also because over-irrigation can yield counterproductive consequences, leading to an increase in energy consumption, reduction of crop yields and contamination of aquifers by fertilizers [2].

In response to these challenges, and with the recent developments in the Internet of Things (IoT), a large number of studies have been conducted to implement advanced controllers into irrigation systems with the aim of reducing water and energy consumption. Among the various strategies for implementing these advanced control techniques, Model Predictive Control (MPC) [3] has emerged as a particularly successful choice, showing its effectiveness not only in technologically advanced greenhouses [4] but also in conventional farms. An example of the above can be found in [5], where an MPC controller was successfully implemented in an agricultural field in Ecuador, showcasing its practicality in real-world farming scenarios. Additionally, another study [6] underscores the effectiveness of model-based smart irrigation control systems in improving water use efficiency in tomato production. A comparison between manual and open-loop irrigation methods highlights the significant advantages offered by the model-based controller approach.

However, despite notable progress in the application of MPC in irrigation management, the dynamic nature of these systems, influenced by factors such as soil compaction, climate fluctuations, and crop phenological stages, introduces a very significant variability, which in turn poses a substantial challenge to the practical implementation of model-based controllers, potentially constraining their performance and compromising crop yields.

To overcome this problem, several MPC-based strategies have been proposed. Notably, some studies (see for instance [7] and [8]) have focused on robust MPC, which shows adaptability when confronted with disturbances and uncertainties in control the system. Alternatively, other authors have explored stochastic MPC controllers, which are capable of characterizing uncertainties in forecast errors of evapotranspiration and precipitation, as observed in [9] and [10]. Finally, to avoid the use of precomputed models and to perform online learning from data, some researchers have discharded MPC based controllers and have opted instead for machine learning algorithms (see for instance [11] or [12]).

This paper addresses the control problem associated to the variability in the irrigation system dynamics by employing an MPC based scheme designed to minimize water consumption while adapting to dynamic system changes. While not a novel concept, as this control strategy is a widely utilized methodology in fields such as robotics [13] and process industries [14], the primary contribution of this paper lies in introducing Adaptive Model Predictive Control (Adaptive MPC) to the domain of irrigation systems, an area where it remains largely unexplored, as far as our current understanding extends.The proposed controller continuously updates the prediction model through a recursive system identification, using data collected from the field.

Furthermore, its validation is performed in a simulation case based on real data from a crop field owned by the company Bioalverde located in Seville (Spain). The simulation analysis includes comparing the controller performance to a conventional MPC, which employs a static linear model. Consequently, the results obtained will offer evidence of the practical suitability and efficiency of Adaptive MPC and its applicability potential in real crops.

The paper is organized as follows: Section II describes the control problem, including the involved system dynamics and modeling. Section III introduces the formulation of the proposed Adaptive MPC. Section IV describes the real farm

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where the data for the controller validation was collected, including the deployed set of sensors, actuators and communication network, and also the models associated to the observed irrigation dynamics. Section V uses these models to analyze the results of the proposed control strategy and carry out a comparison with a conventional MPC. In Section VI the results obtained from the simulations are shown and analyzed. Finally, Section VII contains the main conclusions and future work.

II. Problem formulation

A. System dynamics and irrigation model

To successfully execute the implementation of a model-based predictive control strategy, it is imperative to procure an appropriate model of the irrigation. In these systems, the most relevant dynamics are linked to evolution of the soil moisture in cultivated plots, which can be characterized through the Volumetric Water Content (VWC), that is, the ratio of water volume to soil volume.

A commonly used dynamic model in this context consists of different layers, predominantly three: the surface layer, root zone, and drainage layer. One representative example of this can be found in [15], where a model based on Richards equations considering agro-hydrological interactions between soil, crops, and the atmosphere, is developed and carefully tested. Another possibility to enhance model accuracy is the inclusion of sub-layers within the root (see [16] or [17]), although this requires placing more soil moisture sensors.

However, soil models based on physics and agro-hydrological interactions require a large number of parameters, such as hydraulic conductivities, soil porosity, and soil texture. While laboratory experiments can measure these parameters, real cultivated soils are very often subjected to changes due to factors such as crop growth, temperature, rainfall, and machinery operations. These changes affect soil parameters and consequently modify the system dynamics. Proof of this is that the soil moisture data used in this work were obtained from a real farm during two distinct time periods, followed by the identification of their nonlinear models. The resulting models exhibited significant differences, highlighting the necessity of implementing adaptive MPC to continuously adjust the model in response to inherent variations in system dynamics.

To reflect the previously mentioned time-varying nature of the irrigation system dynamics, the following nonlinear, unknown discrete-time model is introduced:

$$x(k+1) = f(x(k), u(k), k), \tag{1}$$

where $x(\cdot) \in \mathbb{R}^{n_x}$ represents the state, describing measurements of the moisture levels of the different layers of the soil, $u(\cdot) \in \mathbb{B}^{n_u}$ denotes the binary control input related to pumps or solenoid valves in the irrigation system and $f : \mathbb{R}^{n_x} \times \mathbb{B}^{n_u} \times \mathbb{R} \rightarrow \mathbb{R}^{n_x}$ is an unknown, nonlinear, time-varying function characterizing the irrigation dynamics. Note that the time dependence of the model is due to climatological, agrohydrological and soil parameters whose variation is slow or neglectible compared to the dynamics produced by changes in the state $x(k)$ or the control inputs $u(t)$.

B. Prediction models inferred from data

Given the complexity of accurately obtaining or measuring all the parameters that become time-varying the irrigation system, a practical solution is to use past sequences of the state and the control inputs to identify linear and nonlinear models.

1) Linear model: state predictions are obtained with the following linear discrete-time model:

$$\hat{x}(k+1) = A(k)x(k) + B(k)u(k), \tag{2}$$

where $A(k) \in \mathbb{R}^{n_x \times n_x}$ and $B(k) \in \mathbb{R}^{n_x \times n_u}$ are the time-varying state matrix and the time-varying input matrix respectively. A recursive algorithm has been proposed for the matrices identification, in order to priorize the recent data in the identification process. Since the iterative identification method can be a computationally exhaustive process and the time-varying nature reflected in $A(k)$ and $B(k)$ is the slowest dynamics of the system, Equation 2 can be modified with a slight increment in the prediction error by:

$$\hat{x}(k+1) = A_{k_0}x(k) + B_{k_0}u(k), \tag{3}$$

where $A_{k_0} \in \mathbb{R}^{n_x \times n_x}$ and $B_{k_0} \in \mathbb{R}^{n_x \times n_u}$ are the state matrix and the input matrix respectively that were identified by minimizing the prediction error (least square method) at time $k_0 < k$. Note that if k reaches values much higher than k_0, the prediction error may not be negligible. In these cases, a new identification of the system would be necessary to reduce the prediction error.

2) Nonlinear model: in order to obtain a more realistic simulator of the system and considering the slowest dynamics of the time varying nature applied to model presented in Equation 1, a static nonlinear discrete-time model is defined as follows:

$$\hat{x}(k+1) = f_{k_0}(x(k), u(k)), \tag{4}$$

where $f_{k_0}(\cdot,\cdot) = f(\cdot,\cdot,k_0)$ is a nonlinear function that was identified at time k_0.

III. Proposed Controller

Adaptive MPC is an advanced control strategy for dynamic systems, particularly useful in scenarios where the system dynamics is not fully known and can even change over time.

The block diagram of the proposed control scheme can be observed in Figure 1, whose different components are explained next [1].

[1]The absence of a reference input in the controller is due to the fact that, in irrigation control, the objective of the controller is to maintain the moisture levels withing an acceptable range, rather than following specific references

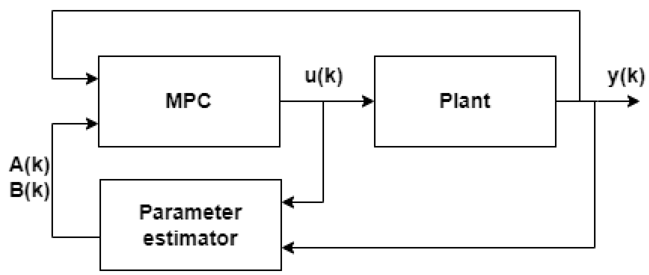

Fig. 1. Structure of the Adaptive MPC.

1) Parameter estimator: the variability of the system dynamics over time, both due to its nonlinear nature and to system changes, can be captured via a linear state-space model with time-varying matrices $A(k)$ and $B(k)$, as in Equation 2.

A recursive least squares (RLS) algorithm with a forgetting factor has been chosen for the estimation of the elements of the state-space matrices, as discussed in [18] and [19]. Its recursive formulation allows an implementation with reduced computational burden, and the inclusion of the forgetting factor enables the algorithm to give less importance to old data, which is crucial in the case of parameters that vary over time.

To implement the RLS algorithm, the following vectors and matrices are defined. The estimation of the parameters vector $\hat{\theta}(k)$ is defined as:

$$\hat{\theta}(k) = [vec(A(k)) \quad vec(B(k))]^T, \tag{5}$$

where the components of $\hat{\theta}(k)$ are the elements of the $A(k)$ and $B(k)$ matrices stacked into a single vector, $\Phi(k)$ is a matrix such that multiplied by the previous estimation of the parameters vector, that is $\hat{\theta}(k-1)$, results in a prediction of the output, denoted as $\hat{y}(k)$, thus:

$$\hat{y}(k) = \Phi(k)\hat{\theta}(k-1). \tag{6}$$

The iterative equations that conform the RLS algorithm are:

$$K(k) = P(k-1)\Phi(k)^T \left(\delta I + \Phi(k)P(k-1)\Phi(k)^T\right)^{-1} \tag{7}$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)(y(k) - \Phi(k)\hat{\theta}(k-1)) \tag{8}$$

$$P(k) = (I - K(k)\Phi(k))\, P(k-1)/\delta \tag{9}$$

In Equation 7, the weighting or gain matrix, defined as $K(k)$, is calculated from $\Phi(k)$, the error estimation covariance matrix, denoted as $P(k)$, and the forgetting factor δ. The next step is to update $\hat{\theta}(k)$ using its previous value and the weighted output error, that is $K(k)\,(y(k) - \hat{y}(k))$, as can be observed in Equation 8. Finally, in Equation 9 the matrix $P(k)$ is updated.

The forgetting factor δ is a constant between 0 and 1. To estimate static parameters, it is set to $\delta = 1$ and $\delta < 1$ for parameters that vary with time. Tipically δ is chosen between 0.985 and 0.995 [20].

2) MPC: this block represent the predictive controller. Note that the time-varying model is provided by the parameter estimator block, thus both toguether constitute the Adaptative MPC. The optimization problem to be iteratively solved by the controller in a receding horizon manner is:

$$\begin{aligned} \min_{u} \quad & \sum_{j=0}^{N-1} J(u,\epsilon) \\ \text{s.t.} \quad & x(j+1) = A(k)x(j) + B(k)u(j), \\ & x(0) = x(k), \\ & u(-1) = u(k-1), \\ & \epsilon(j) \geq 0, \\ & x_{min} - \epsilon(j) \leq x(k) \leq x_{max} + \epsilon(j), \end{aligned} \tag{10}$$

where $J(u,\epsilon)$ is the cost function, x_{min} and x_{max} are the minimum and maximum moinsture constraints respectively, $\epsilon(j)$ are the soft-constraint variables and N is the prediction horizon. The simulation time k (time of day in case of a real application) is constant for the optimization problem.

IV. Technical Description of Bioalverde

The data used in the simulations come from a working farm located in the city of Dos Hermanas, Sevilla, Andalusia, Spain. Geographically, the coordinates of the farm are 37º19'51.065" North latitude and 5º56'14.166" East longitude.

On this farm, a real-time measurement and control system based on the Internet of Things has been installed. The measurement system consists of low-cost devices equipped with capacitive-type soil moisture, ambient temperature and humidity sensors. These sensors are connected to a microcontroller that transmits the data wirelessly to a gateway. Additionally, flow meters have been installed in the pipes to quantify the water consumption used during irrigation.

The data sets used to infer models were obtained from two measuring devices, named node 4 and node 6. These devices measure the soil moisture in two layers, that is $n_x = 2$, with x_1 being the moisture measurement of an upper layer and x_2 the moisture measurement of a lower layer. Furthermore, the binary control action affects to the solenoid valve, thus $n_u = 1$. The water pump is automtically activated when a pressure drop is detected in the irrigation pipes. Two data sets have been collected in periods of approximately one month delay. The dates are May 12th and June 30th of the year 2023.

A comparative analysis using a dataset collected for node 4 and the open-loop predictions of the models is proposed. For the sake of clarity, we will focus our partial comparison on the output variable, specifically the humidity of the lower layer x_2. Figure 2 provides a visual representation of this dataset, which has been partitioned into two distinct segments.

In the graph at the top of the Figure 2 it can be seen that both models provide humidity predictions with negligible errors. Furthermore, as expected, the predictions from the nonlinear model fit the data set better compared to those

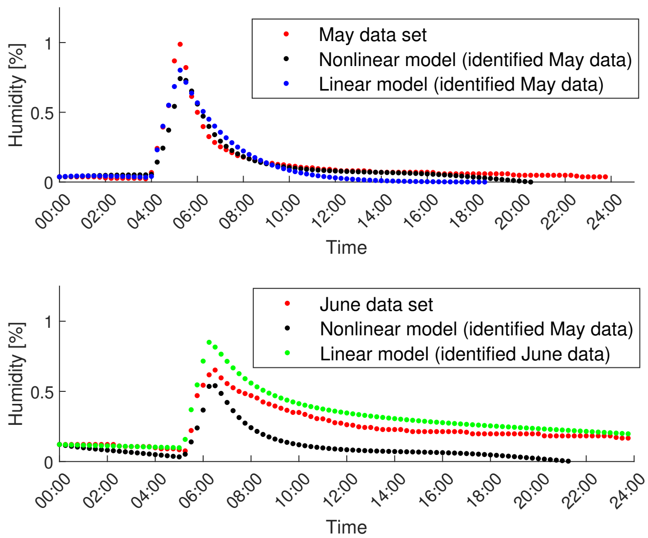

Fig. 2. In the upper part of the graph, the humidity data collected during the month of May are presented, together with the linear and nonlinear models generated from the data set of this period. In the lower part, the humidity data collected in June are shown, together with the nonlinear model identified from the data set of this particular month and the nonlinear model identified from the May data set.

from the linear model. On the other hand, at the bottom of the graph, as anticipated, given the dynamic nature of the system, the model obtained from May fails at accurately predicting the behavior of the June data.

Reference [21] provides details regarding the coefficients of the nonlinear and linear models are found, and details about the implementation, data processing, and acquisition of these models have also been documented.

In this irrigation system, the output vector is equal to the state vector, that is:

$$y(k) = [x_1(k) \quad x_2(k)]^T, \tag{11}$$

where $x_1(k)$ and $x_2(k)$ are the scaled and calibrated soil moistures of the upper and lower layer, respectively. For this farm, matrix $\Phi(k)$ in Equation 6 can be written as:

$$\Phi(k)^T = \begin{bmatrix} x_1(k-1) & 0 \\ x_2(k-1) & 0 \\ 0 & x_1(k-1) \\ 0 & x_2(k-1) \\ u(k-1) & 0 \\ 0 & u(k-1) \end{bmatrix} \tag{12}$$

The value of the forgetting factor δ has been chosen at 0.9999 to get a slow variation of the model parameters, as mentioned in section II.

In this paper, the following cost function has been considered:

$$J(u,\epsilon) = \lambda(u(j)-u(j-1))^2+\beta(k+j)\cdot u(j)+0.5\cdot\sigma\cdot\epsilon_(j+1)^2,$$

where λ is the cost that penalizes the variation of the controller output, β is the weight associated with the use of the water pump and σ is the weight of the soft-constraints. Note that λ determines how frequently the pump and the valve are activated, preventing deterioration. In addition, manipulating β value over the prediction horizon, irrigation can be avoided during specific times, as specified by the farmer or by increasing the cost according to the energy plan implemented on the farm. For the simulation, a time period has been restricted where the cost of driving the pump is very high.

V. Simulation

Simulations have been designed to compare the performance of an Adaptive Model Predictive Controller against a conventional Model Predictive Controller that relies on a constant linear model. Each simulation is executed over a span of 4 days, resulting in a total of 384 simulation steps ($N = 96$ steps per day). The weights assigned to λ, σ and β are $1, 10000$ and 10 respectively. The scenarios proposed are detailed below:

1) Scenario 1: The first scenario starts with a linear model based on the data from node 6 gathered during the May period. This linear model serves as the foundation for both the Adaptive MPC and the conventional MPC.

The nonlinear model of node 6 obtained during the June period acts as the real plant in this scenario. The aim is to evaluate the adaptability of the Adaptive MPC when facing model variations and to analyze the impact of these changes on the performance of the conventional MPC.

2) Scenario 2: In this scenario, the linear model from node 4 (collected during the June period) and the nonlinear model of node 6 from the same period are employed. This setup aims to investigate the feasibility of using a standard linear model for all measurement devices while simultaneously evaluating the adaptability of the Adaptive MPC to a distinct original model.

For a detailed evaluation of the performance of the controller, humidity predictions and control actions at two specific simulation moments are analyzed: day 1 and day 3, equivalent to iterations $k = 1$ and $k = 289$, respectively. These predictions overlay the real plant in an open-loop scheme. The purpose is to observe the adaptability of the Adaptive MPC and compare it with the conventional MPC. Specifically, the agreement between predictions made from the linear model and those from the nonlinear model is sought.

With these scenarios, insights into the robustness of the Adaptive MPC against model variations and the advisability of using a standard linear model for different measurement devices are expected to be gained.

VI. Results

This section will present the results of the simulations described in section V.

1) Scenario 1: In Figures 3 and 4 the behavior of the MPC and Adaptive MPC controllers can be observed, respectively at $k = 289$. The curves resulting from these predictions for layer 1 and 2 humidities are x_1p and x_2p respectively (painted red). The predicted control actions along the prediction horizon are denoted by $valvestatus$. The result of applying the predicted control actions on the actual plant can be seen with the curves painted in blue, with x_1r being the humidity of layer 1 and x_2r to the humidity of layer 2. The moisture and time constraints are represented in black. It is important to note that the color criteria and nomenclature will be maintained in the other graphs that present results associated with simulation times, that is, for different values of k.

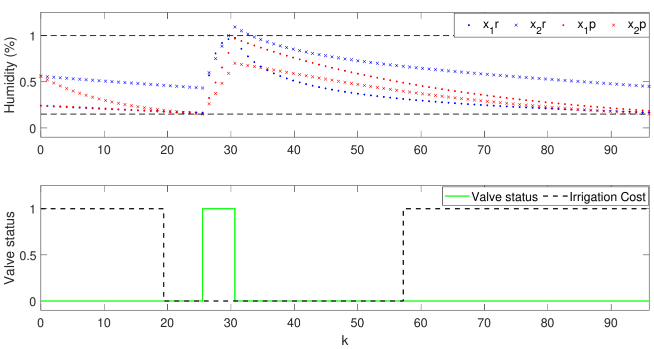

Fig. 3. Humidities and control actions predicted for the MPC at K = 289

In the case of the MPC, significant differences can be observed between the control applied to the non-linear and linear plant, which was expected when using a constant linear model. On the other hand, for the Adaptive MPC there is a clear reduction of this error, which is quantified with the calculation of the mean square error (MSE) presented in the table I. It should be noted that the behavior of both controllers at $k = 1$ is the same (also reflected in this table).

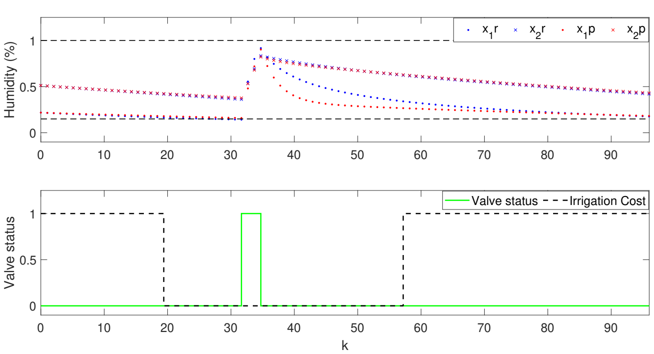

Fig. 4. Humidities and control actions predicted for the AMPC at K = 289.

TABLE I

MSE OF THE CONTROLLERS IN SCENARIO 1

k=1		
Controller	MSE (x_1)	MSE (x_2)
AMPC	0.02734	0.06089
MPC	0.02734	0.06089
k=289		
AMPC	0.00553	0.00007
MPC	0.01884	0.07621

Finally, the closed-loop curves throughout the 4-day simulation are presented in Figure 5, in blue you can observe the humidities and control actions resulting from the MPC and in red the humidities and control actions of the Adaptive MPC.

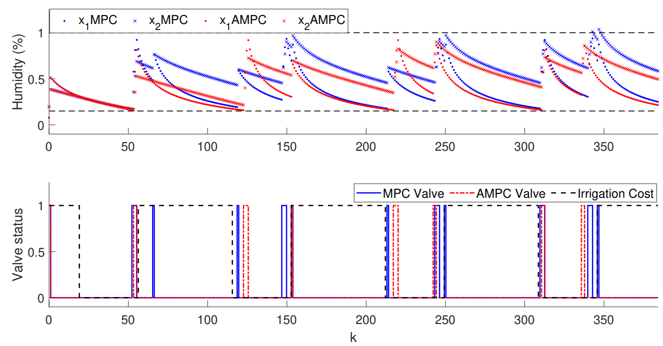

Fig. 5. Closed-loop curves throughout the 4-day simulation (MPC vs AMPC).

Table II shows the differences between both controllers, in the first column the number of outputs in one (Valve status=1) that the controller had throughout the simulation horizon is quantified, taking into account the nominal flow rate of the water pump (8 liters per minute) the volume of water used throughout the simulation is calculated and finally the last column shows the number of starts of the water pump, this value is important because a higher number of starts of the pump favors its deterioration.

TABLE II

COMPARISON OF WATER CONSUMPTION AND NUMBER OF PUMP STARTS BETWEEN MPC AND AMPC IN SCENARIO 1

Controller	Total Water consumption (L)	Daily average (L)	Number of water pump starts
AMPC	1920	480	7
MPC	2880	720	11

2) Scenario 2: The resulting graphs of scenario 2 have been similar to those of scenario 1. The closed-loop curves of the 4 days of simulation for this scenario are presented in Figure 6. The quantitative results in tables III and IV support this affirmation.

TABLE III

MSE OF THE CONTROLLERS IN SCENARIO 2

k=1		
Controller	MSE (x_1)	MSE (x_2)
AMPC	0.01336	0.04176
MPC	0.01336	0.04176
k=289		
AMPC	0.00499	0.01120
MPC	0.00622	0.05084

In both scenarios, there are considerable savings in water consumption (although this is not the main objective of the controller), there is also a significant reduction in the number

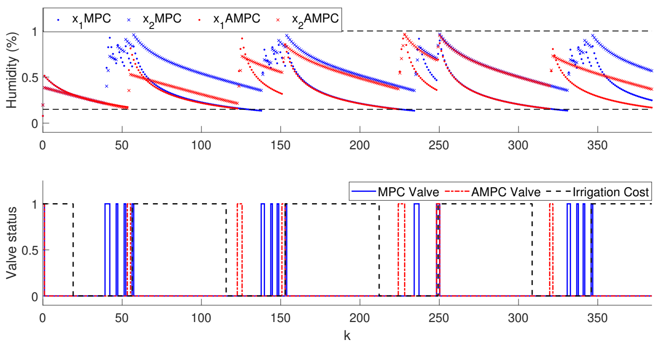

Fig. 6. Closed-loop curves throughout the 4-day simulation (MPC vs AMPC).

TABLE IV
COMPARISON OF WATER CONSUMPTION AND NUMBER OF PUMP STARTS BETWEEN MPC AND AMPC IN SCENARIO 2

Controller	Total Water consumption (L)	Daily average (L)	Number of water pump starts
AMPC	1920	480	6
MPC	2640	660	14

of starts of the water pump which not only helps to delay the deterioration of the pump, but can also save electricity consumption due to the current peaks that an electric motor consumes at starts.

VII. CONCLUSIONS

This comparative study between model-based predictive control and model-based adaptive predictive control has yielded significant results in the proposed simulation scenarios. The robustness of Adaptive MPC to adapt to models whose parameters vary over time and its ability to adjust from an initial model obtained from another measurement device has been observed. This opens the possibility of employing a single controller for all devices that have been deployed in the field, which is one of the objectives of this study.

The considerable savings in water consumption and the reduction in the number of water pump starts, although not the primary objectives of the controller, underline the benefits of having an adaptive model in a model-based predictive control strategy. These benefits not only translate into more efficient operation and reduced operating costs, but also promote sustainability by minimizing the environmental impact of water and electrical energy use.

Analysis of the results has shown that the proposed controller, by adapting and correcting its control parameters in real time, can compensate for process deviations and respond more effectively to system changes compared to a traditional MPC.

In conclusion, the findings of this work highlight the feasibility and advantages of using Adaptive MPC in irrigation automation in agriculture.

For future work, it is proposed to evaluate other recursive estimation methods (such as the Kalman filter) and their implementation in the field, in order to validate and refine the performance in a real production environment.

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