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RESEARCH ARTICLE

Model Predictive Control Structures for Periodic ON–OFF Irrigation

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ABSTRACT Agriculture accounts for approximately 70% of the world's freshwater consumption. Furthermore, traditional irrigation practices, which rely on empirical methods, result in excessive water usage. This, in turn, leads to increased working hours for irrigation pumps and higher electricity consumption. The main objective of this study is to develop and evaluate periodic model predictive control structures that explicitly account for on-off irrigation, a characteristic of drip irrigation systems where watering can be turned on and off, but flow cannot be regulated. While both proposed control structures incorporate an economic upper layer (Real Time Optimizer, RTO), they differ in the costs associated with the lower layer. The first structure, called Model Predictive Control for Tracking (MPCT), focuses on tracking effectiveness, while the second structure, called Economic Model Predictive Control for Tracking (EMPCT), incorporates the economic cost into the tracking term. These proposed structures are tested in a realistic case study, specifically in a strawberry greenhouse, and both show satisfactory performance. The choice of the best option will depend on specific conditions.

INDEX TERMS Economic model predictive control, non-linear equations, on-off irrigation, periodic MPC, transient regime.

NOMENCLATURE

A. ABBREVIATIONS

FC	Field Capacity.
EMPCT	Economic Model Predictive Control for Tracking.
MPC	Model Predictive Control.
MPCT	Model Predictive Control for Tracking.
NEMPC	Non-linear Economic Model Predictive Control.
ODE	Ordinary Differential Equation.
PEM	Prediction Error Minimization.
PWP	Permanent Wilting Point.
RTO	Real-Time Optimizer.
VWC	Volumetric Water Content.
WDN	Water Distribution Networks.

B. SYMBOLS

θ_i	Volumetric Water Content of each layer.
$\theta_{max}, \theta_{min}$	Maximum and minimum Volumetric Water Content.
D_i	Soil thickness.
P_t	Precipitation.
I	Irrigation flow.
I_{max}, I_{min}	Maximum and minimum irrigation flow.
E_g	Soil evaporation.
E_{tr}	Crop transpiration.
$Q_{i,i+1}$	Water flow between consecutive layers.

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ψi	Matrix potential of each layer.
K_i	Hydraulic conductivity of each layer.
K_{sat}	Hydraulic conductivity at saturation.
θ_{sat}	Volumetric Water Content at saturation.
B	Empirical parameter related to soil texture.
x^{ref}, u^{ref}	Optimal states and control action, given by RTO.
x^r, u^r	States and control action, given by planner.
$\hat{x}$, $\hat{u}$	States and control action, given by tracking MPC.
x, u	States and control action, given by real system.
N	Prediction horizon of the second stage.
N_r	Prediction horizon of the first stage.
m	Number of states.
n	Number of control actions.
d	Number of disturbances.
q	Valve's water flow.
z_{ee}	Weight of the economic term in the lower layer.

I. INTRODUCTION

AGRICULTURE plays a crucial role in a nation's economy as it provides the population's basic needs and serves as the foundation for trade in industries, particularly in rural areas where the population depends on it [1]. Irrigation also plays a critical role in agriculture, especially in arid regions or areas with inadequate precipitation patterns [2].

Water is essential for human survival and for the health of natural ecosystems. Since irrigation uses around 70% of the world's freshwater resources to irrigate 25% of the world's croplands, agriculture has been recognized as the primary water user sector [3]. Moreover, since the surface of land dedicated to growing food is limited and climate change is reducing available fresh water, agricultural cropping systems must make optimal use of the available land and water resources to feed the world's population in the future [4].

Over the last decade, a significant effort has been made to study effective irrigation management protocols for vegetable production and horticulture worldwide [5], [6]. The scientific community has invested considerable time and resources to improve irrigation water management. One practical way of dealing with this overwhelming issue is to properly manage water resources using different approaches and technologies to fulfill water application at the right time, in the right amounts, and at the right spot in the field [7].

Some advanced control strategies in agriculture have proposed algorithms to save water [8], [9], [10], [11], and to minimize electricity consumption [12]. However, these algorithms assume analog/continuous flow irrigation commands, which do not represent the real situation with irrigation tapes, where irrigation control is executed by on-off irrigation. In other words, it is impossible to modulate the irrigation flow in real implementations with irrigation tapes (much more efficient than sprinklers).

A suboptimal, approximated approach for this problem has been employed in Water Distribution Networks (WDN) to consider on-off pump behavior. In [13], a two-layer Nonlinear Economic Model Predictive Control (NEMPC) is proposed. The upper layer of the NEMPC obtains analog flow set points. Then, the lower layer translates these to binary commands that approximate the water volume resulting from the upper layer. Furthermore, [14] presents a sensor-based model-driven control strategy with on-off output applied to a farm irrigation system in Mexico. The objective is to keep the soil moisture in a range and reduce water consumption compared to farmers' traditional irrigation. However, the MPC applied does not use the system model in the problem optimization. Besides, it does not have a guarantee that the closed-loop system converges asymptotically and does not include terminal constraints. A comparison table of the published research about advanced control applied in agriculture and in WDN in which binary control action was used are presented in Table 1.

The main contribution of this work is the development and testing of periodic model predictive control structures that explicitly consider binary irrigation signals in conjunction with an accurate agro-hydrological model that describes the evolution of the Volumetric Water Content (VWC) per soil layer in the crop field. Each controller has a two-layer optimal control strategy, with the upper layer consisting of the Real Time Optimizer (RTO) and the lower layer composed of two stages. The two different proposed controllers differ in the costs associated with the last layer. On the one hand, the first version is a pure Model Predictive Control for Tracking (MPCT). On the other hand, the second version incorporates a combination of tracking economic costs in the last layer, resulting in an Economic Model Predictive Control for Tracking (EMPCT).

The proposed controllers with different structures are tested in a strawberry greenhouse, considering the economic cost associated with the water and electricity consumption. Both structures show adequate performance, and the best option can be selected depending on specific conditions.

The manuscript is organized as follows: Section II explains the agro-hydrological model and the respective physical constraints used in the control strategy. Section III presents the general scheme of the proposed control structures and details it with their respective cost functions of the control strategy lower layer. Also, this section presents the controller's feasibility and stability proof. Section IV explains the case study with the results of the proposed control structures, and finally, Section V comments on the manuscript's findings.

II. PRELIMINARIES

This section introduces the simulation model for the crop field system used in the manuscript, detailing the system's agronomic concepts and physical constraints.

A. MODEL DESCRIPTION

The main variable to take into account in irrigation control is the so-called volumetric water content (VWC), i.e., the

TABLE 1. Comparison table of the previous published research.

Research	Application	Water save	Energy save	Pump flow	Control technique	Feasibility and stability
[8]	Agriculture	Yes	No	Analog	MPC	No
[9]	Agriculture	Yes	No	Analog	Robust MPC	Yes
[10]	Agriculture	Yes	No	Analog	Zone MPC	No
[11]	Agriculture	Yes	No	Analog	Fuzzy Decision Support	-
[12]	Agriculture	Yes	Yes	Analog	Economic MPC	No
[13]	WDN	No	Yes	Binary	NEMPC	No
[14]	Agriculture	Yes	No	Binary	DDMPC	No

soil moisture measured as the volume of water per volume of soil, which can be monitored at different locations and depths of the crop field.[1] This parameter is determinant due to its profound impacts on crop growth and water resource management, and its adequate control enables high irrigation efficiencies [15].

The dynamic model used here is based on the non-linear Ordinary Differential Equations (ODEs) tested in [12] and [16], which characterize the agro-hydrological interactions between soil, crops, and the atmosphere. The soil is divided into $L + 1$ layers that work as water buffers, with inflows and outflows in every layer, where L is the soil layer from the first down to the last layer of the crop root. The first is the surface layer, the last is the drainage zone, and finally, the intermediate layers correspond to the zone where the crops have their roots. The dynamical model, whose variables and parameters are summarized in the nomenclature section -B, is described as follows:

$$\begin{aligned}
\dot{\theta}_1 &:= \frac{1}{D_1}\left(P_t(t) + I(t) - Q_{1,2}\left(\theta_1, \theta_2\right) - E_g(t)\right), \\
\dot{\theta}_j &:= \frac{1}{D_j}\Big(Q_{j-1,j}\left(\theta_{j-1}, \theta_j\right) - Q_{j,j+1}\left(\theta_j, \theta_{j+1}\right) \\
&\qquad -E_{\mathrm{tr}}(t)\Big), j \in \{2, \ldots, L\} \\
\dot{\theta}_{L+1} &:= \frac{1}{D_{L+1}}\left(Q_{L,L+1}\left(\theta_L, \theta_{L+1}\right) - K_{L+1}\left(\theta_{L+1}\right)\right). \qquad (1)
\end{aligned}$$

The water flows between layers, $Q_{j,j+1}$, are characterized as follows:

$$Q_{j,j+1} := \left(\frac{\psi_{j+1} - \psi_i}{\overline{D}_j} + 1\right)\left(\frac{H_j - H_{j+1}}{\psi_{j+1} - \psi_j}\right)\frac{B}{B+3}, \qquad (2)$$

where:

$$\begin{aligned}
K_j\left(\theta_i\right) &:= K_{\mathrm{sat}}\left(\frac{\theta_j}{\theta_{\mathrm{sat}}}\right)^{2B+3}, \\
\psi_j\left(\theta_j\right) &:= \psi_{\mathrm{sat}}\left(\frac{\theta_j}{\theta_{\mathrm{sat}}}\right)^{-B}, \\
H_j\left(\theta_i\right) &:= K_j\left(\theta_j\right)\psi_j\left(\theta_j\right) = K_{\mathrm{sat}}\psi_{\mathrm{sat}}\left(\frac{\theta_i}{\theta_{\mathrm{sat}}}\right)^{B+3}, \\
\overline{D}_j &:= \frac{D_j + D_{j+1}}{2},
\end{aligned}$$

[1]There are also alternative variables to characterize soil moisture, for example, the matrix potential of the soil, usually referred as Ψ.

B. PHYSICAL/MODEL CONSTRAINTS

Furthermore, to characterize the physics of this agro-hydrological model, two parameters need to be considered: the Field Capacity (FC) and the Wilting Point (WP). The FC, which depends on the soil composition and compaction, is the VWC level that is held in soil after the excess of water has drained away by gravitational effects [17]. Below this point, and depending on the nature of the crops, the roots encounter water scarcity and start to absorb (transpire) an amount of water that compromises the crop growth. Finally, the Wilting Point is the VWC level at which the crop cannot absorb enough water to live [18]. An excessive VWC can also compromise crop growth.

With this in mind, the following constraint should be taken into account in the controller design:

- VWC constraints: The VWC level in the root zone must remain within certain limits to prevent crop yield decline. These constraints can be expressed as:

$$\theta_{max} \geq \theta_j(t) \geq \theta_{min}, \qquad j \in 2..L \qquad (3)$$

where j represents the jth soil layer and θ_{max} and θ_{min} define the VWC range in which crop yield is not compromised.

- Irrigation flow constraints: on efficient drip irrigation systems, irrigation is controlled through an ON/OFF valve, and thus the irrigation flow can take only two values:

$$\begin{aligned}
I_{max} &= q \\
I_{min} &= 0 \qquad (4)
\end{aligned}$$

where $I_{max} = q$ is the nominal irrigation flow with the irrigation valve open (ON), whereas $I_{min} = 0$ corresponds to the OFF state of the valve.

TABLE 2. Control considerations.

		Model	Time	Inputs signals
Plant		Non-linear	Continuous	-
MPC	RTO	Non-linear	Discrete	Analog
	Planner	Linearized	Discrete	Analog
	Tracking	Linearized	Discrete	Digital / Binary

III. MODEL PREDITIVE CONTROL STRUCTURES

This section introduces the general two-layer control strategy used in the study and describes the proposed control structures, including the MPCT and EMPCT, along with their respective cost functionals for the lower layer of the control strategy. Additionally, the stability proof for the proposed controller is provided.

A. GENERAL SCHEME OF THE PROPOSED CONTROL STRUCTURES

The irrigation control problem consists of computing and applying optimal irrigation commands based on the measurements of the VWC of each layer of the cultivated soil. This problem presents specific features that make it highly complex. First, optimality entails minimizing the use of resources, mainly water and energy, due to irrigation. Secondly, the non-linear nature of the system dynamics (see equations (1)-(2)) challenges the control design. Furthermore, the on-off operation of the irrigation system (4) forces the design of a control strategy with binary control inputs. Lastly, constraints in (3) should be considered to maintain crop yield.

Model Predictive Control (MPC) [19] is a family of advanced controllers that, among other features, makes it possible to deal with constraints and optimal considerations. The control strategy formulated in this paper is based on an economic, periodic MPC. Economic MPC allows introducing economic considerations in the cost function(s) [20]. Moreover, periodic MPC appears naturally in significant control problems [21], [22] and, in the context of irrigation control, it is possible to take advantage of the quasi-periodic behavior of the agro-hydrological variables, such as the crops' transpiration, the soil's evaporation, or the electricity prices, which are related to the pumping of water for irrigation.

However, the complexities introduced above would lead to a complex optimization problem. To avoid this, we resort to a two-layer MPC control strategy [23], which structure is shown in Figure 1. Table 2 shows the author's considerations for the proposed control strategy.

Next, the different variables involved in the control structure are defined and linked to the physical system. First of all, in the crop field, x is a state vector containing the VWC of each layer of the crop field (1), and the control action u is the applied irrigation (Irrigation, I). Furthermore, in Figure 2, the upper layer is in charge of producing optimal, periodic reference trajectories for the VWC of each soil layer

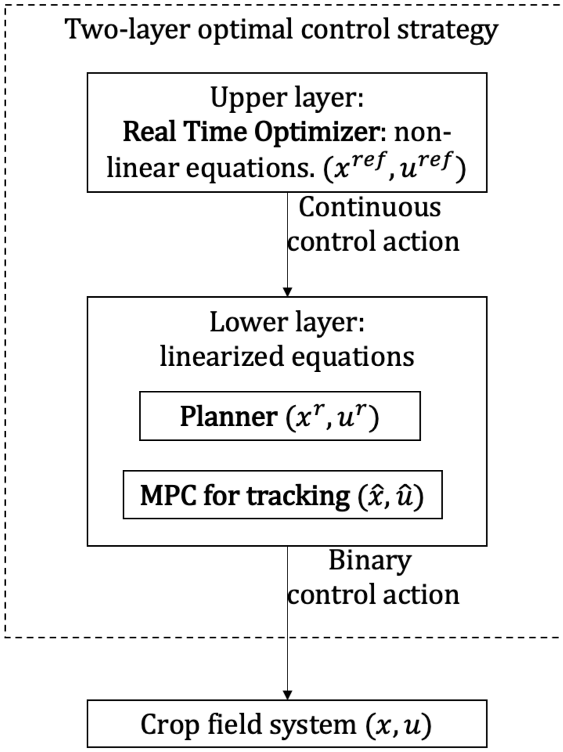

FIGURE 1. Two-layer optimal control strategy for irrigation.

and the irrigation, i.e. the decision variable (x^{ref}, u^{ref}), using a Real-Time Optimizer (RTO) that considers the non-linear dynamics in (1). In this layer, irrigation is regarded as a constrained analog decision variable.

Besides, the lower layer goal is to steer the real VWC of each soil layer to the optimal trajectory given by the RTO. This lower layer is further divided into two stages or sub-layers. The first one is called Planner, and its function is to compute optimal, periodic trajectories (x^r, u^r) that are reachable for the last sub-layer, the MPC for tracking. This last sub-layer has to compute the real irrigation commands to be applied $(\hat{x}, \hat{u})$. The system dynamic is linearized in both sub-layers, but in the last sub-layer the irrigation is assumed to be an on-off (binary signal).

The separation of the optimization problem into two layers presents two essential advantages. First, it allows working with a non-linear system and economic functions while guaranteeing recursive feasibility (constraint satisfaction as the system evolves, see [23]). Furthermore, the optimization problem to be solved is divided into two different problems: the first with non-linear dynamics but analog decision variables and the second with a linear model and binary decision variables. This makes it possible to use different, specific solvers for each problem and reduces the computational burden.

1) UPPER LAYER DESCRIPTION

The objective of the RTO is to provide the best economic trajectory, considering analog control actions, economic costs, and constraints. To this aim, it must use the best approximation of the crop field system, so a discrete-time version of the agro-hydrological equations (1) is used. The ODE model F can be written as follows [2]:

$$x^{ref}(k+1) = F(x^{ref}(k), u^{ref}(k), w(k)), \quad (5)$$

where $x^{ref} \in \mathbb{R}^m$ is a state vector with the VWC of each soil layer, $u^{ref} \in \mathbb{R}^n$ represents the control action vector (the manipulated irrigation flow), $w \in \mathbb{R}^d$ denotes the vector of the non-manipulated input, such that the evaporation and transpiration.

Note that units of all the variables need to be consistent. In this paper, the unit of the soil VWC is $\frac{cm^3}{cm^3}$ that means a given cm^3 of water contained in a given cm^3 of soil, and the irrigation flow is selected as $\frac{cm}{min}$, centimeter per minute, per unit area. The evaporation and transpiration units are $\frac{kg}{min \cdot cm^2}$.

The economic criteria are the operational goals which can be separated into two terms:

- Electricity consumption: This term penalizes the electricity consumption according to a possibly time-varying electricity cost $C_{elec}(k)$.

$$f_1(u^{ref}) = \sum_{k=0}^{N_r-1} C_{elec}(k)u^{ref}(k) \quad (6)$$

  where N_r is the periodic horizon, C_{elec} is the electricity tariff that changes per hour.
- Water consumption: This term penalizes the water consumption, which unitary cost C_{water} is typically constant.

$$f_2(u^{ref}) = \sum_{k=0}^{N_r-1} C_{water}u^{ref}(k) \quad (7)$$

  where C_{water} is the water cost and always is the same price.

Therefore, considering the equations (6) and (7) the economic cost function is:

$$V_p^*(u^{ref}) = f_1(u^{ref}) + f_2(u^{ref}) \quad (8)$$

The RTO problem is solved once a day, providing the best economic trajectory. The constraints in irrigation or VWC are typically constant, while other variables, such as water/electricity costs or crop needs, can be slightly different from one day to the next.

The optimal solution can be obtained from the solution of the following optimization problem:

$$\min_{x^{ref}(0),u^{ref}} \sum_{k=0}^{N_r-1} V_p^*(u^{ref}) \quad (9a)$$

$$s.t.\ x^{ref}(k+1) = F(x^{ref}(0), u^{ref}(k), w(k)) \quad (9b)$$

$$x_{max} \geq x_j^{ref}(k) \geq x_{min}, \quad j \in \{1, \ldots, L+1\}, \quad (9c)$$

$$u_{max} \geq u^{ref}(k) \geq u_{min}, \quad (9d)$$

$$x^{ref}(0) = x^{ref}(N_r) \quad (9e)$$

[2]The ref superscript letter denotes trajectories of signals of the RTO.

The equation (9a) represents the discretized version of the non-linear equation (1), where the initial state is a free variable $x^{ref}(0)$. The equations (9c)-(9d) are the constraints presented in equations (3) and (4) corresponding to the VWC and irrigation physical constraints of the system. The equation (9e) is the terminal constraint, where N_r is a fixed period with which a periodic trajectory is obtained. The quasi-periodic of the crop transpiration and electricity tariff allows us to use a periodic upper layer and lower layer. This helps the controller reach stability since the system does not have to stabilize at an operation point but at a periodic trajectory.

Remark 1: The RTO obtains the best trajectory with the best approximation of the real system, which is discretized of the non-linear ODE model (1). To solve the optimization problem (9a)-(9e), it can be used a variety of optimizers for non-linear equations, to name a few: fmincon, CasADi, and GAMS.

2) LOWER LAYER DESCRIPTION

The optimal trajectory computed by the RTO is sent to the lower layer presented in Figure 1. The goal of this layer is twofold: to compute a feasible trajectory from the current VWC of the soil to the optimal trajectory (Planner stage) and to track this feasible trajectory considering binary control actions, that is, on/off irrigation signals (MPC for tracking stage).

This part of the control strategy is executed each sampling time, receiving feedback of the states x from the crop field system and using a linearized version of the non-linear model (1) around an operation point x_0, which can be chosen around the FC values. The linearized discrete-time state-space model is expressed as:

$$x(k+1) = Ax(k) + Bqu(k) + B_d w(k) \quad (10a)$$

$$y(k) = Cx(k) \quad (10b)$$

where A, B, B_d, C are the system, control, disturbance, and output matrices, respectively. The $x(k) \in \mathbb{R}^{m-1}$ denotes the model's states (VWC at each soil layer), where $y(k)$ is the output system, the $u(k) \in \mathbb{R}^n$ is the control action, q is the valve's flow and the $w(k) \in \mathbb{R}^d$ disturbances associated with this model.

The control objective of this layer is to steer the state x and control action u as close as possible to a periodic reference (x^{ref}, u^{ref}) given by the RTO with the periodic horizon N_r.

Standard tracking schemes are usually based on a hierarchical architecture because, if the reference is unreachable, the controller cannot steer the output signal to the (x^{ref}, u^{ref}).

Considering this, the soal of the Planner stage is to compute a reachable periodic trajectory (x^r, u^r) that is as close as possible to the optimal trajectory (x^{ref}, u^{ref}) (see [24]). The MPC for tracking stage $(\hat{x}, \hat{u})$, follows a reachable periodic trajectory (x^r, u^r) considering a possibly different prediction horizon N [25].

The Planner stage cost function, also known as the offset cost function, is chosen to minimize the sum of the weighted squared error concerning the trajectory computed by the RTO:

$$V_T^t(x^{ref}, u^{ref}; x_0^r, u^r) = \sum_{i=0}^{N_r-1} \|x^r(i) - x^{ref}(i)\|_W^2 + \|u^r(i) - u^{ref}(i)\|_S^2 \tag{11}$$

The term V_T^t penalizes the error between the planned reachable trajectory and the optimal reference to be tracked for one period N_r. Where $(x^{ref}, x^r) \in \mathbb{R}^{m-1}$ and $(u^{ref}, u^r) \in \mathbb{R}^n$, the W, S are the respective cost weights.

The MPC for tracking stage cost function, is chosen to minimize the sum of the weighted squared error of the tracking trajectory $(\hat{x}, \hat{u})$ and the optimal reachable trajectory (x^r, u^r) in a period N, and it is formulated as:

$$V_S^t(x, u; u^r, x^r) = \sum_{i=0}^{N-1} \|\hat{x}(i) - x^r(i)\|_Q^2 + \|\hat{u}(i) - u^r(i)\|_R^2 \tag{12}$$

The term V_S^t penalizes the error between the tracking and the planned reachable reference throughout a prediction horizon $N_r \geq N$, where $(\hat{x}, x^r) \in \mathbb{R}^{m-1}$, $u^r \in \mathbb{R}^n$, $\hat{u} \in \{0, 1\}$ are binary control actions (on/off irrigation commands), and Q, R are the respective weighting matrices.

To evaluate the MPC for tracking stage, the following optimization problem V_N is solved at each sampling time:

$$\min_{x^r, u^r, \hat{x}, \hat{u}} \; V_N(\hat{x}(0), \hat{u}, x^r, u^r)$$
$$s.t. \; x^r(i+1) = Ax^r(i) + qBu^r(i) + B_d w(i) \tag{13a}$$
$$x_{max} \geq x_j^r(i) \geq x_{min}, \quad j \in \{1, \ldots, L+1\}, \tag{13b}$$
$$u_{max} \geq \hat{u}(i) \geq u_{min} \quad i \in \mathbb{Z}_{[0,N-1]} \tag{13c}$$
$$x^r(0) = x^r(N_r) \tag{13d}$$
$$\hat{x}(0) = x \tag{13e}$$
$$\hat{x}(i+1) = A\hat{x}(i) + qB\hat{u}(i) + B_d w(i) \tag{13f}$$
$$x_{max} \geq \hat{x}_j(i) \geq x_{min}, \quad j \in \{1, \ldots, L+1\}, \tag{13g}$$
$$\hat{u}(i) \in \{0, 1\}, \quad i \in \mathbb{Z}_{[0,N-1]} \tag{13h}$$
$$\hat{x}(N) = x^r(N) \tag{13i}$$

The constraints of this optimization problem can be divided into those corresponding to the planner and tracking stages. The constraints of the planner stage are (13a-13d), where (13a) gives the predicted states trajectories; (13b-13c) are the constraints over the state and control input (VWCs and continuous irrigation signal); and (13d) imposes periodicity. Furthermore, the constraints of the tracking sub-layer are (13e-13i), where (13e) imposes that the initial state of the tracking is equal to the current real system state (crop field system); the VWC constraints and the real on/off irrigation are in (13g-13h), and a terminal equality constraint is added in (13i). For more details, see [24].

Remark 2: The separation of the problem into two different layers reduces computational complexity and makes it possible to combine efficient, specialized solvers at each of them. In the lower layer, which runs every sampling time, a linearized model is employed, but control actions are restricted to binary. Thus, solvers such as Gurobi, intended for linear constraints and mixed continuous-binary optimization variables, are a good option. On the contrary, a more approximate non-linear model is used in the upper layer, which runs once a day, translating into an optimization problem with only continuous variables but non-linear constraints. In this case, solvers such as CPLEX can be a suitable alternative.

B. MPCT CONTROL STRUCTURE

Considering the above, we propose two different cost functionals for the lower layer. The MPCT cost functional considers pure tracking, on the one hand, penalizes the difference between the optimal solution of the RTO and the planner, on the other hand, penalizes the difference between the planner and the tracking:

$$V_N^t(\hat{x}(0), x^{ref}, u^{ref}; x^r, u^r, \hat{x}, \hat{u}) = V_T^t(x^{ref}, u^{ref}; x^r, u^r) + V_S^t(x^r, u^r; \hat{x}, \hat{u})$$

where V_T^t and V_S^t are described in (11) and (12), respectively.

C. EMPCT CONTROL STRUCTURE

The EMPCT cost functional also considers economic terms in the second stage of the last layer of the control strategy.

The EMPCT cost functional V_N^f is composed of the same tracking terms mentioned above plus an economic term in the stage cost function V_S^f to consider the electricity and water consumption also in the lower layer. The cost functional V_N^f is expressed as follows:

$$V_N^f(\hat{x}(0), x^{ref}, u^{ref}; x^r, u^r, \hat{x}, \hat{u}) = V_T^f(x^{ref}, u^{ref}; x^r, u^r) + V_S^f(x^r, u^r; \hat{x}, \hat{u})$$

where:

$$V_T^f(x^{ref}, u^{ref}; x^r, u^r) = V_T^t(x^{ref}, u^{ref}; x_0^r, u^r) \tag{14a}$$
$$V_S^f(\hat{x}(0), x^r, u^r; \hat{x}, \hat{u}) = V_S^t(x, u; u^r, x^r) + z_{ee}\hat{u}(i)(C_{elec}(i) + C_{water}) \tag{14b}$$

where z_{ee} weighs the economic term in the stage cost function.

D. FEASIBILITY AND STABILITY PROOF

In this section, we study the closed-loop properties of the proposed control laws. In particular, we prove stability and that the controller maintains recursively feasibility. To this end, we use three assumptions and the following slightly modified lemmas from [24]. Previous proofs that support this demonstration are [24], [26].

Some specified notation aspects in this section: letters in bold are trajectories, sequences of control actions or states with N elements in the case of $(\hat{u}, \hat{x})$ and T elements in the case of the planner $(\mathbf{u^r}, \mathbf{u^r})$; the notation $a(k)$ and a_k is considered equivalent. $x|_i^k$ is the state predicted at time i applying $\hat{u_k}$ from the initial state x_k; $x^r|_i^k$ is the state of the reachable trajectory (planner) at time i applying $\mathbf{u^r}_k$ from the initial state x_k^r; $x^\circ|_i^k$ is the state of the optimal reachable trajectory at time i applying $\mathbf{u_k^\circ}$ from the initial state x_k°. $z(k)$ or z_k is the error between the state of the reachable optimal trajectory and the closed-loop trajectory of the system, that is,

$$z(k) = z_k = \hat{x}_k - x_k^\circ$$

Assumption 3.1: The pair $(A, [B, B_d])$ of the linear system is assumed to be controllable. Following assumption 2.23 from [27] (weak controllability), it is assumed that there exists a $\mathcal{K}_\infty$ function $\alpha(\cdot)$ such that

$$V_N^*(z(k)) \leq \alpha(|z(k)|) \quad \forall z(k) \in \mathcal{Z}$$

where $\mathcal{Z}$ is a complex convex polyhedron.

The previous assumption 3.1 is weaker because it bounds the cost of moving the state $\hat{x}$ to Ω, a compact and positive invariant set including the origin. It confines attention to those initial states $\hat{x}_0$ that can be steered to Ω in N steps holding the problem constraint, i.e., following a feasible evolution, and the only condition is that the cost is not excessive.

Due to the control actions being quantized $\{0, 1\}$, a finite number of trajectories (2^N) steer the initial state $\hat{x}$ to the invariant set Ω. Considering it, it can be guaranteed that, at least, a bounded trajectory steers the initial state to that invariant set Ω.

The planner's trajectories are considered reachable, following definition 1 in [26]. Remember that the control objective is to steer the state $x(k)$ as close as possible to an exogenous periodic reference $r(k)$ with period Td introducing some economic aspects in any of the cases. T would be the number of discrete elements of reachable trajectories and references (given by RTO) in a period.

Assumption 3.2: The proposed cost function V_S^f is strictly convex.

Theorem 3.1: Assume that system satisfies Assumptions 3.1and 3.2, the weighting matrix Q is positive definite, and the prediction horizon is such that $N \geq n_c$. The system controlled by the proposed control law is recursively feasible.

Proof: This theorem is proved by demonstrating that it always exits a feasible solution for the optimization problem (13). Assuming an optimal solution for the optimization problem (13) at time k, a possible feasible solution in $k+1$ can be obtained from the previous one. A simple way to obtain such a viable solution is to use the periodic constraint (13d) of the achievable solution and the terminal constraint $x(N) = x^r(N)$ to construct it. Bearing that the model is linear and there are no disturbances, the new solution can be built by shifting the terms of the solution obtained at time k. The new solution in $k+1$ must cost less than the initial k.

Consider the following *shifted sequences* ($\bar{\mathbf{u}}_k$, $\bar{\mathbf{x}}_k^r$ and $\bar{\mathbf{u}}_k^r$) at time $k+1$ obtained from the solution in k:

$$\bar{\mathbf{u}}_{k+1} = \{\hat{u}^*|_1^k, \cdots, \hat{u}^*|_{N-1}^k, u^{r*}|_N^k\} \tag{15a}$$
$$\bar{\mathbf{x}}_{k+1}^r = \{x^{r*}|_1^k, \cdots, x^{r*}|_{T-1}^k, x^{r*}|_0^k\} \tag{15b}$$
$$\bar{\mathbf{u}}_{k+1}^r = \{u^{r*}|_1^k, \cdots, u^{r*}|_{T-1}^k, u^{r*}|_0^k\} \tag{15c}$$

where $\hat{u}^*|_j^k \quad \forall j = 1, \cdots, N-1$ is the second element of the previous shifted optimal solution obtained in k, $u^{r*}|_N^k$ is the reachable control input at time N. This control action can be taken thanks to the constraint (13i), that is, $\hat{x}(N) = x^r(N)$. $x^{r*}|_0^k$ and $u^{r*}|_0^k$ can be taken thanks to the periodic constraint (13d), that is $x^r(0) = x^r(T)$. And hence, if the solution is feasible at time k, the shifted sequences are also feasible at time $k+1$, and this process can be repeated from $k+1$ to the infinite. Summing up, if $\hat{x}_k$ is feasible $(\hat{x}_k \in \mathcal{X}_N)$ then $\hat{x}_{k+1}$ will also be feasible $(\hat{x}_{k+1} \in \mathcal{X}_N)$. Hence, $\mathcal{X}_N$ is a positive invariant set.

The stability of the optimal trajectory will be proved from Theorem 2 and 3 in [26], and by demonstrating that even when control actions are binary, the error z_k is bounded in the worst case and converges to zero if it is possible to achieve the reachable trajectory with these type of control actions.

From lemma 1 in [26] we propose the following modified lemma

Lemma 3.2: Let x_k be such that the solution of the optimization problem 13 satisfies $\hat{x}_0 = x_0^r$ solved at time k, then

$$\hat{\mathbf{x}} = \mathbf{x}^r + e_x$$

and

$$\hat{\mathbf{u}} = \mathbf{u}^r + e_u$$

.

The error between control actions in the reachable trajectory can be easily bounded by 1 $(|e_u| \leq 1)$, considering the maximum values of the control actions in both stages. Therefore, this error (e_u) can be considered a bounded disturbance in the nominal system. Hence, if the nominal system proposed in [26] is stable, this new optimization problem (13) holds this property.

Remember that even when the control actions $(\hat{\mathbf{u}})$ are binary, the cost hold

$$V_N^*(k+1) - V_N^*(k) \leq -\|\hat{x}_k - x^r|_0^k\|_Q - \|\hat{u}_k - u^r|_0^k\|_R$$

TABLE 3. Soil hydraulic parameters.

Parameter	Value	Units
θ_{sat}	0.395	$\frac{\text{cm}^3}{\text{cm}^3}$
K_{sat}	1.056	$\frac{\text{cm}}{\text{min}}$
ψ_{sat}	12	cm
B	4.05	-

TABLE 4. Electricity tariff and crop transpiration values each time.

Time (h)	C_{elec} (€$\frac{1}{\text{kWh}}$)	$E_{\text{tr}}(\frac{\text{kg}}{\text{min}\cdot\text{cm}^2})\ 10^{-7}$
00	0.28772	0
01h	0.27897	0
02h	0.26661	0
03h	0.26441	0
04h	0.26481	0
05h	0.25634	0
06h	0.25154	0.3394
07h	0.2441	1.425
08h	0.24498	2.016
09h	0.22633	2.5453
10h	0.20147	3.031
11h	0.15039	3.258
12h	0.13733	3.349
13h	0.1328	3.243
14h	0.1216	2.871
15h	0.11679	2.545
16h	0.10289	2.199
17h	0.10921	1.663
18h	0.13274	0.6788
19h	0.20618	0
20h	0.25584	0
21h	0.25311	0
22h	0.21898	0
23h	0.21737	0

and the previous error is reduced or held each step. This demonstration is focused on two objectives: first, prove the recursive feasibility, and second, prove that the system outputs are bounded in the worse case and, in the best case, hold the properties of the previous nominal controller [26]. ■

IV. CASE STUDY: APPLICATION TO STRAWBERRY CROPS

In this section, we perform a realistic simulation case study based on a specific farm, using the specific data (soil, crop needs, etc.) of strawberry exploitation in the city of Huelva (Spain), with their respective soil and crop needs. It should be noted that this crop is carried out inside a greenhouse, and the precipitation value is not considered. Table 3 and Table 4 present the soil agro-hydrological parameters explained in the section II. Finally, Table 4 displays the hourly electricity tariff C_{elec} used for the cost function:

TABLE 5. Constraints and weights values.

Parameter	Value	Units
m	5	-
n	1	-
d	2	-
q	0.0098	$\frac{\text{cm}^3}{\text{cm}^3}$
(x_{max}, x_{min})	[0.23 0.11]	$\frac{\text{m}^3}{\text{cm}^3}$
(u_{max}, u_{min})	[0 1]	$\frac{\text{cm}}{\text{min}}$
Z_{ee}	30	-

A. NON-LINEAR OPTIMIZATION FOR THE UPPER LAYER

The RTO problem (upper layer in Figure 1) has been solved with an open-source tool called CasADI [28]. This tool uses a symbolic framework for non-linear optimization and algorithmic differentiation. In this layer, since the non-linear equations (1) are used, we can solve the optimization using the IPOPT (Interior Point Optimizer) for large-scale non-linear optimization.

The number of states m, control actions n, and disturbances d, as well as the constraints' values with the cost function weights used in this layer, are presented in Table 5.

The RTO works once daily, with a sample time $T_m = 15$ min and the horizon $N_r = 96$ steps.

B. LINEARIZED MODEL FOR THE CONTROL STRATEGY LOWER LAYER

A linearized model is needed to implement the lower layer of the proposed economic model predictive structures. The non-linear equations (1) were linearized at the equilibrium point x_{eq}, which are the initials VWC control values of each soil layer $x(0) = x_{eq}$.The equilibrium points are commonly chosen as the operating point, in this case, are the specific soil FC values $x_{eq} = [0.154, 0.153, 0.152, 0.151]\ \frac{\text{cm}^3}{\text{cm}^3}$, the irrigation to reach the FC point $u_{eq} = 0\ \frac{\text{cm}}{\text{min}}$, the crop transpiration and soil evaporation $w_{eq} = [0, 0]\ \frac{\text{kg}}{\text{min}*\text{cm}^2}$.

The cost matrices are chosen as $Q = 5\mathfrak{I}_{m-1}, R = 5\mathfrak{I}_n$, $W = 20\mathfrak{I}_{m-1}$, $S = 20\mathfrak{I}_n$, where $\mathfrak{I}$ is the identity matrix with a dimension of states and control actions.

The model was linearized with the System Identification Toolbox from Matlab using the Prediction Error Minimization (PEM) algorithm. The linearized model presented in the state space equations (10b) used in the control strategy results in the matrices presented in (16a-16c).

$$A = \begin{bmatrix} -0.0875 & 0.0040 & 0.0078 & 0.0197 \\ -0.0039 & 0.0043 & -0.0134 & 2.433e-04 \\ -0.0930 & 0.0161 & -0.0189 & 0.0191 \\ 0.0244 & -0.0177 & 0.0358 & -0.0030 \end{bmatrix} \quad (16a)$$

$$B = \begin{bmatrix} -0.4741 & -421.0621 & -6.4749e-11 \\ -0.0144 & 13.4946 & -2.2406e-11 \\ -0.4202 & 112.5933 & -3.2192e-12 \\ 0.3239 & -1.6388e03 & 5.6790e-14 \end{bmatrix} \quad (16b)$$

$$C = \begin{bmatrix} -0.9916 & -0.1844 & 0.4443 & 0.2994 \\ -0.1997 & -0.2148 & 0.3577 & 0.1282 \\ 0.0517 & 0.0459 & -0.0281 & 0.0403 \\ 0.0673 & 0.1914 & -0.0637 & 0.0247 \end{bmatrix} \tag{16c}$$

The terms' values used in the cost functional of the lower layer are presented in Table 5, the prediction horizon $N = 24$ steps and the prediction horizon $N_r = 96$ steps that are 24 hours.

In this layer, the output $(\hat{u})$ is a binary control action and is presented in Table 5.

C. PERFORMANCE CRITERIA

In order to evaluate the performance of the proposed model predictive control structures, MPCT and EMPCT, two criteria are considered: the economic cost of each control structure and the interlayer error that is the tracking error between the upper layer and lower layer of the optimal control strategy presented in Figure 1. The economic cost is an important criterion to evaluate because it minimizes the cost of electricity and water consumption. The interlayer error corresponds to the difference between the upper layer output (x^{ref}, u^{ref}) and the one obtained by the lower layer $(\hat{x}, \hat{u})$, that is, the convergence to the optimal trajectories computed by the RTO.

Considering the above, it is possible to determine each criterion quantitatively. For that, the MPCT and EMPCT were simulated fifty days. The first criterion, the economic cost average of each model predictive control structure, can be calculated through equation (17a). The summation of the interlayer error over time is considered for the second performance criterion, as shown in equation (17b).

$$C_{eco} = \frac{1}{days} \sum_{t=0}^{N_t-1} C_{elec}(t)\hat{u}(t) + C_{water}\hat{u}(t) \tag{17a}$$

$$E_{layers} = \frac{1}{days} \sum_{t=0}^{N_t-1} \|\hat{x}(t) - x^{ref}(t)\|^2 + \|\hat{u}(t) - u^{ref}(t)\|^2 \tag{17b}$$

In addition to a quantitative comparison, a qualitative one was conducted in the transient regime to observe the different behaviors of the MPCT and EMPCT, considering the VWC per soil layer. Also, for the cost-effectiveness of each control structure, comparisons were made in terms of water and electricity consumption, as well as irrigation efficiency in one hectare (10000 m^2).

D. RESULTS AND DISCUSSION

For the qualitative comparison of the proposed model predictive control structures, in Figure (2) and Figure (3), the variables were scaled to be able to analyze them better. The real values are presented in Table 4 and Table 5.

Figure 2 presents the MPCT and EMPCT states, which are VWC of four soil layers considering the equation (1), in which the first layer corresponds to the surface and the successive layers to the root zone. It should be noted that the last layer of the root zone has the same dynamics as the drainage zone, which is why just four layers are presented here. The RTO (control strategy upper layer) gives the optimal trajectory x^{ref} considering the non-linear model, as explained in previous sections. For the control strategy lower layer, the Planner stage computes a reachable periodic trajectory x^r, and the MPC for tracking stage $\hat{x}$ follows a reachable periodic trajectory but considers binary control actions.

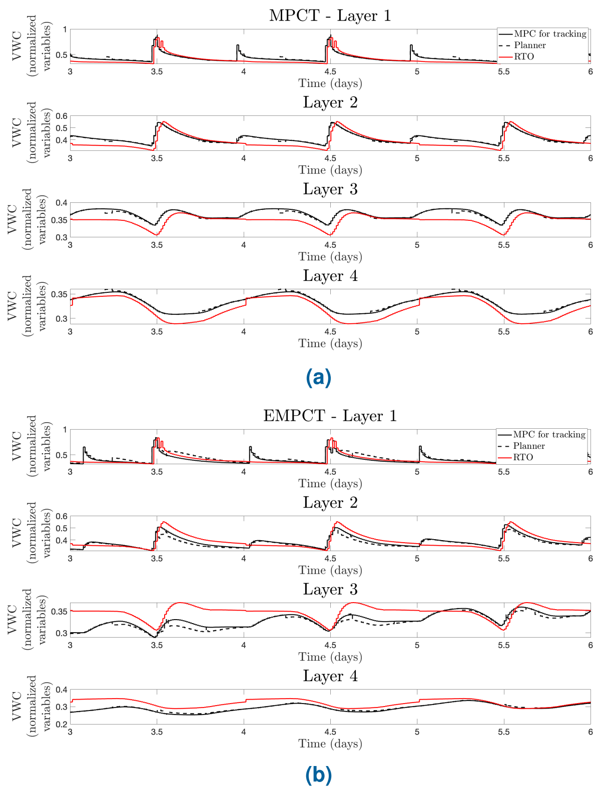

FIGURE 2. Comparison between the VWC of each soil layer of the crop field system using the two economic model predictive structures in the transient regime. (a) MPCT structure with pure tracking cost functional and (b) EMPCT structure with tracking plus economic term in the cost functional.

Figure 3 presents the MPCT and EMPCT control actions, considering the respective characteristics according to control strategy layers. The RTO obtains analog control action u^{ref}, and the MPC for tracking obtains binary control actions $\hat{u}$.

Considering Figure 2(a) for the MPCT structure and Figure 2(b) for the EMPCT structure, both attempt to follow the RTO trajectory, but due to differences in the model in the control strategy upper layer (non-linear equations) and the control strategy lower layer (linearized model), as presented in Figure 1, some differences occur between the RTO and the MPC for tracking; one significant difference can better be seen in the last soil layers (Layer 3 and Layer 4) of the VWC of the MPCT and EMPCT.

Moreover, the differences in the EMPCT are more noticeable because, besides the control actions (analog for the RTO and Planner stage; and binary for the MPC for tracking stage), the controller has to minimize the water and electricity consumption as shown in the equation (14b) and also fulfill the terminal constraints (13d) (13i). Figure 3(a) and Figure 3(b) present the control actions corresponding to each structure.

Regarding Figure 3(a) and 2(a), which correspond to the control actions and states of the MPCT structure, it can be seen that the MPC for tracking also tries to follow the RTO trajectory. However, it must irrigate at an additional time at the optimal trajectory. Since the cost functional of the lower layer penalizes the difference between the planner and RTO trajectories in the Planner stage and the planner and the MPC for tracking trajectories in the MPC for tracking stage, in this last stage, it does not have an economic term. Therefore this extra irrigation command is given without considering the electricity tariff. In this structure, convergence is fast, and periodicity is achieved.

On the other hand, Figure 3(b) and 2(b), which correspond to the EMPCT, the cost functional considers the economic term, so in the transient regime irrigates complying with the constraints and also considering when the electricity tariff is lower. Besides, the VWC of the MPC for tracking stage is different from the RTO trajectory. From this, it can be seen that irrigation occurs when electricity prices are lower, which causes a VWC to deviate from the optimal state trajectory. This difference between the RTO and the last layer occurs because it considers the close loop of the real system every 15 minutes. Despite this, Figure 4 can achieve the same periodicity as the MPCT in a permanent regime after approximately ten days.

For the quantitative comparison between each structure presented in Table 6, the equations 17(a) and 17(b) were used. The RTO average economic cost is $3.3763e - 05$ e per unit crop area. Comparing the two model predictive control structures, the EMPCT is the most economical one. However, as expected, the MPCT has the lower interlayer error since it explicitly minimizes this error without considering the economic cost, whose relevance is more evident in the transitory regime. According to the observations in Figure 2(a) and 2(b), the difference is in the transient regime.

Finally, for the cost effectiveness of each model predictive control structures, Table 7, presents the results of the comparison in terms of water cost, electricity, and irrigation efficiency for each hectare of crop. It can be observed that the EMPCT structure gets more irrigation efficiency by 91% compared to the MPCT, which obtains 88%.

Remark 3: Regarding the simulation results, the difference between the two structures is in the transient regime. The MPCT's convergence is faster (between one or two days) since its goal is only to minimize the tracking cost. In the EMPCT, since it has both tracking and economic term, the use of electricity and water is minimized. However, in terms of economic criteria, the convergence to the optimal RTO trajectory is slower (approximately ten days) but more efficient.

TABLE 6. Performance criteria results.

Controller	MPCT	EMPCT	Units
Economic cost	4.0699×10^{-5}	4.0667×10^{-5}	€
Layers error	0.0020	0.0037	-

TABLE 7. Cost effectiveness of each model predictive control structure.

Controller	MPCT	EMPCT	Units
Water cost	0.2223	0.2167	€
Electricity cost	182.8	182.6	€
Application efficiency	88	91	%

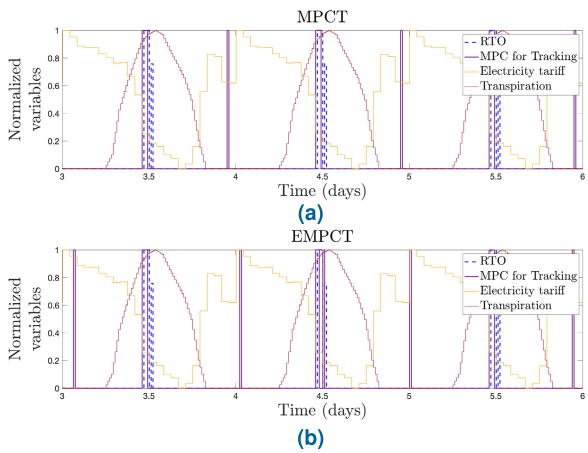

FIGURE 3. Comparison between the two economic model predictive structures in the transient regime in terms of control action considering the disturbances (Electricity tariff and crop transpiration) each time. (a) MPCT and (b) EMPCT.

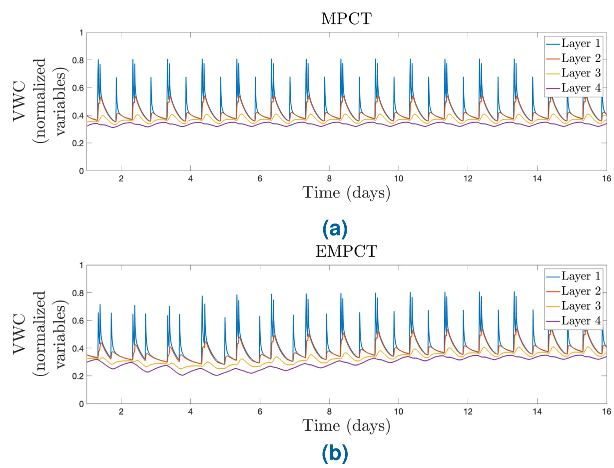

FIGURE 4. VWC at each soil layer of the crop field system using the two economic model predictive structures in the transient and permanent regime. (a) MPCT structure with pure tracking cost functional and (b) EMPCT structure with tracking plus economic term in the cost functional.

The simulations were conducted considering a case where the radiation and, therefore, the E_{tr} are similar daily. The MPCT is the best solution when the transpiration and electricity tariff is similar every day, in summer, for example. In cases where the disturbances change almost every day, such as in the fall, the EMPCT is still the best option because the MPCT will never have time to reach the permanent regime.

V. CONCLUSION

This paper proposed periodic model predictive control structures for on-off irrigation, considering a two-layer control strategy, the upper layer composed of the RTO and the lower layer composed of two stages, the Planner and MPC for tracking. Additionally, it presented the controller's feasibility and stability proof.

The use of a two-layer control is very important in this specific case because the first layer works with non-linear dynamics but analog decision variables, and the second with a linearized model and binary decision variables. This makes it possible to use specific solvers for each problem and reduces the computational burden.

Two cost functions were proposed for the lower layer of the control strategy, resulting in the MPCT and EMPCT structures. Both structures performed well in a simulation scenario with real data from a strawberry farm in Huelva (Spain). Their suitability depends mainly on the farm conditions. Under stable conditions (weather, precipitation, transpiration, electricity costs, etc.), the MPCT converges faster to the optimal (periodic) permanent regime given by the RTO so that it would be the best solution. However, under conditions that vary daily, it is not possible to reach a periodic permanent regimen, and thus the controller will operate in a transient regime. In these situations, the best option is the EMPCT, for economic costs are included in the decision layer (lower layer).

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