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Multi-Scenario Model Predictive Control for Greenhouse Crop Production Considering Market Price Uncertainty

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***Abstract*— This paper presents a stochastic model predictive control (SMPC) strategy to maximize the economic profit of a greenhouse crop production. The strategy consists of an optimization problem that is solved with a multi-scenario MPC formulation (MS-MPC). It considers the uncertainty of market price by using its historical evolution per year as multiple price scenarios in the cost function. MS-MPC calculates a single set of dates to harvest and sell the crop production that optimizes profits for all the considered scenarios. In addition, MS-MPC determines the optimal temperature references that should be achieved inside the greenhouse for the growth of the crop. A case study for a Mediterranean tomato crop is simulated to analyze the performance of the developed MS-MPC strategy using a hierarchical control architecture with two layers. In the upper layer, MS-MPC calculations are executed following a receding horizon implementation. In the lower layer, regulatory control techniques are applied to reach the optimal temperature references by using natural ventilation and a heating system. Results show that MS-MPC can improve economic profits compared to the use of an average price scenario for the MPC calculations.**

***Note to Practitioners*—This paper was motivated by the need of greenhouse farmers for strategies that maximize profit considering market prices and crop production dynamics. It is not easy for them to make decisions to achieve such long-term objectives while minimizing economic risks, because market prices are very difficult to predict. As a solution, this work presents a novel control strategy to maximize profits by means of automatic selection of the best possible dates to harvest and sell the crop production. This selection is made thanks to considering the uncertainty of market prices in the control strategy by evaluating different *scenarios*, which are recorded evolutions of the prices from previous years. Although the strategy was tested in simulation, results suggest that using multiple scenarios of historical prices is better for the optimization of profits than just considering an average yearly trend of prices. The more scenarios are considered, the more protection against possible evolution of market prices is obtained. In future research, this control strategy could be extended to include other uncertainties of factors affecting decision making, such as weather forecasts.**

***Index Terms*— Agriculture, hierarchical system, multiple scenarios, stochastic control.**

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NOMENCLATURE

Greenhouse climate model

$\boldsymbol{c}$	Vector of constants and parameters.
$c_{\text{area,ss}}$	Soil surface of the greenhouse.
$c_{\text{cnv,p-a}}$	Pipe heating convection coefficient.
$c_{\text{den,a}}$	Air density.
$c_{\text{sph,a}}$	Specific heat of air.
$c_{\text{vol,g}}$	Volume of air inside the greenhouse.
$\boldsymbol{d}$	Vector of measurable disturbances. *Source*: weather forecasts or data of typical local weather when used in MS-MPC optimization.
$d_{\text{T,ext}}$	Air temperature outside the greenhouse.
$d_{\text{wv,ext}}$	Wind velocity outside the greenhouse.
f	Nonlinear functions based on energy transfers and mass balances.
f_{ah}	Function that indicates the activation of the heating system.
Q	Heat exchanges ocurring in the greenhouse.
$Q_{\text{cnv,ss-a}}$	Convective flux between the soil surface and air inside the greenhouse.
$Q_{\text{cnv-cnd,a-e}}$	Convective and conductive flux through the cover of the greenhouse.
$Q_{\text{heat-a}}$	Heat flux provided by the heating system.
Q_{loss}	Heat lost by infiltration losses.
$Q_{\text{sol,a}}$	Solar radiation flux.
Q_{trp}	Latent heat effect due to crop transpiration.
Q_{vent}	Heat lost by natural ventilation.
t	Time.
$\boldsymbol{u}$	Vector of inputs. *Source*: control signals generated by the controllers in the regulatory control layer (see Fig. 1).

$u_{\mathrm{T,h}}$	Temperature of the heating pipes.
$\boldsymbol{x}$	Vector of state variables.
$x_{\mathrm{T,a}}$	Air temperature inside the greenhouse.

Tomato growth model

α_{F}	Maximum partitioning coefficient of new growth to fruit.
κ_{F}	Development time from first fruit appearance until maturity.
ϑ	Transition coefficient between vegetative and full fruit growth.
D_{F}	Function that affects the rate of development of fruit.
f_{F}	Function that affects the partitioning of biomass to fruit.
g	Function that reduces growth.
GR_{net}	Plant photosynthesis and respiration.
N	Number of nodes.
N_{FF}	Number of nodes per plant when the first fruit appears.
PGRED	Function that modifies the rate of photosynthesis.
T_{d}	Daily mean temperature inside the greenhouse. *Source*: calculated from $x^{\mathrm{r}}_{\mathrm{T,a}}$ when used in the MS-MPC optimization.
T_{dt}	Daytime temperature inside the greenhouse. *Source*: calculated from $x^{\mathrm{r}}_{\mathrm{T,a}}$ when used in the MS-MPC optimization.
W	Aboveground biomass accumulation.
W_{F}	Fruit dry matter.
W_{M}	Mature fruit biomass accumulation.
X_{F}	Accumulated fresh weight of mature fruits.
X_{LAI}	Leaf area index.

Generic MPC formulation

$\boldsymbol{b}$	Constraint vector.
f_{c}	Function that calculates the cost to achieve a desired goal.
h	Constraint function.
J	Objective function.
k	Integer variable to indicate discrete-time instants.
N_{p}	Length of the prediction horizon.
s	Function describing the system dynamic.
$\boldsymbol{u}$	Vector of control actions.

MS-MPC optimization problem

c_{res}	Cost of resources.
$\Delta\tau$	Number of hours that the heating is active.
f_{hc}	Cost of using the heating system.
i	Integer variable to indicate price scenarios.
I	Income for selling the harvested tomatoes.
j	Integer variable to indicate harvest and sale dates.
$\boldsymbol{n}$	Vector of harvest and sale dates.
n_{days}	Optimal duration of the crop cycle.
$n_{\mathrm{days_{max}}}$	Maximum number of days for the crop cycle.
$n_{\mathrm{days_{min}}}$	Minimum number of days for the crop cycle.
N_{h}	Number of harvests and sales during the crop cycle.
N_{s}	Number of market price scenarios.
P	Tomato price.
W_{hf}	Weight of harvested fruits.
$x^{\mathrm{r}}_{\mathrm{T,a}}$	Greenhouse air temperature reference.

I. INTRODUCTION

GREENHOUSES are ideal systems to control the growth of a crop, for their microclimate can be regulated for optimal plant cultivation. The controlled variables are those affecting the growth of the crop, e.g., air temperature, solar radiation and CO_2 concentration, as well as fertilization and irrigation aspects. The manipulated variables are related to the actuators, such as ventilation or heating, which are devices that perform actions to compensate the effect of disturbances, which are caused by the lack of complete isolation against external weather conditions [1].

Optimization of crop production in greenhouses can be achieved with automatic control techniques [2], [3], which employ different criteria and actuators to calculate the required control actions, e.g., to maximize fruit production or its quality, the economic profit, or to save resources as water, energy, and fertilizers [4], [5], [6], [7], [8]. Although this should be ideally addressed as a multiobjective control problem [9], [10], most research works consider only one objective to optimize, for the sake of simplicity. Even so, several factors (e.g., weather conditions, market and energy prices, agricultural policies, etc.) influence the control actions and make the optimization of one objective still a challenge [1].

Fulfilling such long-term objectives requires weather forecasts as well as models of greenhouse climate and crop to predict the growth of the plants and fruits. For this reason, it is natural to apply optimal [11], [12] and model predictive control (MPC) strategies [13]. In particular, MPC can take into account dynamics, constraints, and prediction data in the optimization of control actions [14]. There are varied examples of MPC strategies applied to greenhouses in the literature [15], [16], [17], [18]. However, classical MPC formulations have feasibility limitations when dealing with uncertainties, such as unmodeled dynamics (i.e., lack of information on model structure and/or parameters) or inaccurate disturbances prediction. These sources of uncertainty can cause the violation of constraints or result in deviations from optimal operating points. As a consequence, robust model predictive control (RMPC) has been applied to greenhouses in the recent years [19], [20], [21], [22], [23]. Despite the suitability of RMPC in this context, it requires uncertainties to be bounded, leading to conservative results that ignore their probabilistic nature [24], e.g., the case of market price for fruits.

When maximization of profits is pursued for greenhouse crop production, it is necessary to know in advance the ideal time to sell the produced fruits. The time of sale is strongly conditioned by the market price, that is, the money that farmers receive for selling their production on a particular day of the year. This price is typically set during auctions, based on the quality of the fruits, and their supply and demand, which also depend on factors as the season and even political situations. Therefore, the market price is an exogenous

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variable that confers significant uncertainty to the problem of optimal control of greenhouse cultivation because its evolution throughout a year is stochastic, with sudden fluctuations and difficult to predict. To the best of our knowledge, there are not accurate models for long-term prediction of market price for greenhouse crops, although some works have been published in this regard [25], [26]. Due to this fact, market price is not treated in optimization problems or it is commonly simplified to a fixed mean value when considered in cost functions. In this context, market price uncertainty has been addressed only in [27], where a receding horizon optimal control (RHOC) method with an economic objective function was studied. It considered the price of tomato by using artificial forecasts generated from historical price data of five years and the average yearly trend of prices to calculate the income through crop yield.

This article also deals with the maximization of profits for greenhouse crop production. Yet, instead of considering an artificial price forecast or an average yearly trend, the market price is directly treated as a stochastic variable. To this end, a stochastic model predictive control (SMPC) method was selected [24], [28]. Specifically, a multi-scenario MPC strategy (MS-MPC) has been developed, which takes into account different possible evolutions of disturbances affecting a system. In this work, the scenarios are evolutions of market price for tomato from different previous growing seasons (i.e., scenarios based on historical prices). MS-MPC calculates a single control sequence considering all the scenarios, so it offers some robustness against potential realizations of the uncertainty. This approach differs from the method reported in [27], where a RHOC problem was solved but only a single market price realization was considered each time that the optimization was performed (i.e, either one artificial price forecast or an average yearly trend was used). The disadvantage of the cited approach compared to MS-MPC is discussed in Section III-B.

The MS-MPC method was selected due to its successful application to other complex systems with stochastic disturbances, such as the level regulation of open water systems [29], [30], [31], [32]. As described in [24], the use of MS-MPC over classical MPC or RMPC allows to explicitly account for the uncertainty in the mathematical formulation of the control problem, and to provide a tradeoff between constraint violation probability and control performance.

The novel aspect of this work is to incorporate the stochasticity of market price to the problem of maximization of profits for greenhouse crop production, and determine in an automatic manner the optimal dates to harvest and sell a crop production, which in previous studies was not addressed or the dates were assumed to be manually selected based on the experience of farmers [33]. The developed MS-MPC strategy is integrated into a hierarchical control architecture and it also calculates the optimal temperature references for the growth of the crop.

In summary, the main contributions of this work are as follows:

- Implementation of a stochastic model predictive control strategy specifically formulated for greenhouse crops.
- To incorporate the stochasticity of market price to the problem of maximization of profits in greenhouses.
- Automatic selection of the optimal dates to harvest and sell the crop production, and the simultaneous calculation of the temperature set points to advance or delay those dates. In this manner, the probability of maximizing profits is increased for any possible evolution of market prices.

The manuscript is organized as follows. Section II presents the problem formulation. In Section III, the results of a case study are discussed, and the performance of MS-MPC compared to other variants of MPC is evaluated. Finally, the conclusions of the work are summarized in Section IV.

II. Problem Formulation

The considered greenhouse control problem focuses on the maximization of the economic profit for a Mediterranean tomato crop, defined as the difference between the income that farmers receive and the cost of the resources employed. To this end, farmers desire to produce as many fruits as possible and to sell their production when market prices are higher. Also, farmers want to regulate the greenhouse microclimate to increase the growth of the crop while minimizing the use of resources, such as electricity, fuel, water, and fertilizers.

Regarding the sale of the crop production, certain crops as tomatoes require multiple harvests during a season depending on their maturity and the daily market prices. For this reason, most farmers perform harvests once every week or two weeks, when the fruits present an optimal maturity. Nonetheless, when they expect higher market prices, they commonly change the climatic conditions inside the greenhouse to modify the crop growth rate, so that the next harvest is delayed or advanced to match the desired date of sale.

As for the regulation of the microclimate, it depends on the geographical location and the actuators available. In general, assuming that an optimal irrigation is performed, farmers in Mediterranean regions focus on controlling the air temperature inside the greenhouse. For example, during the daytime, natural ventilation is used to decrease the very high temperatures due to the sun. During the nighttime, heating systems may be needed to maintain adequate conditions. Two different temperature control set points are required per day because the physiological needs of the plants are different with and without sunlight [1]. For this reason, higher temperatures are required for photosynthesis during the daytime, while it is not necessary to maintain such high temperatures at night because the plants are not active [9], [33]. Although the crop does not grow during the nighttime, very low temperatures should be avoided to protect the fruits, which justifies the use of heating systems. In addition, heating systems can operate at a lower energy-consuming operating point because a lower temperature set point is used during the nighttime.

The overall problem can be solved with a strategy that optimizes the calculation of the temperature set points and the selection of the dates to harvest and sell the crop production from an economic perspective, with market prices considered as a disturbance. Thus, protection against market price uncertainty is required to minimize the risk of selling the crop production when prices are not convenient for farmers. To this end, different formulations could be adopted:

- The simplest method is to consider an average value of prices as a nominal scenario for the optimization. However, if the disturbance affecting the real system is not well described by a normal distribution, this method is not recommended.
- A more robust but conservative option is to implement a min-max MPC strategy [34]. With this method, protection against any possible realization of the disturbance is guaranteed (e.g., very low market prices), but at the expense of losing control performance and increasing the computational cost.
- A stochastic approach is less conservative and offers a compromise between control performance and robustness against uncertainties. It allows for an admissible level of constraint violation probability while aiming for a significantly better control performance than when using min-max MPC. With a multi-scenario MPC, the more price scenarios are considered, the more protection against uncertainty is obtained.

A. Hierarchical Control Architecture

The MS-MPC strategy has been formulated according to the hierarchical control architecture presented in Fig. 1. Multilayer hierarchical control architectures are widely applied for greenhouse control to deal with the presence of different dynamics and timescales, since the evolution of the greenhouse microclimate (in seconds or minutes) is much faster than the crop growth (in days or weeks) [9], [11], [33], [35]. The proposed architecture has two layers:

1) The upper layer is devoted to solve the optimization problem using MS-MPC, as detailed in Section II-E. This layer takes into account the long-term aspects to calculate the optimal harvest and sale dates, and the temperature references by evaluating their impact on a cost function. To predict the future growth of the crop and the expected economic profit, models of greenhouse climate and crop growth are used, as explained in Section II-B and Section II-C, respectively.
2) The lower layer of regulatory control is in charge of generating the corresponding control signals for the actuators to regulate the greenhouse microclimate to achieve the optimal temperature references received from the upper layer. For the case study presented in this paper, proportional-integral-derivative (PID) controllers were selected. Although different PID-based control schemes have been tested in previous works [1], including natural ventilation [36] and heating [37], in this case, PI controllers with antiwindup are used to simplify the lower layer and focus on analyzing the performance of the upper layer with the proposed MS-MPC strategy.

Thanks to this architecture, optimization and control actions are connected according to the timescales of the dynamics occurring in the greenhouse. On the one hand, MS-MPC in

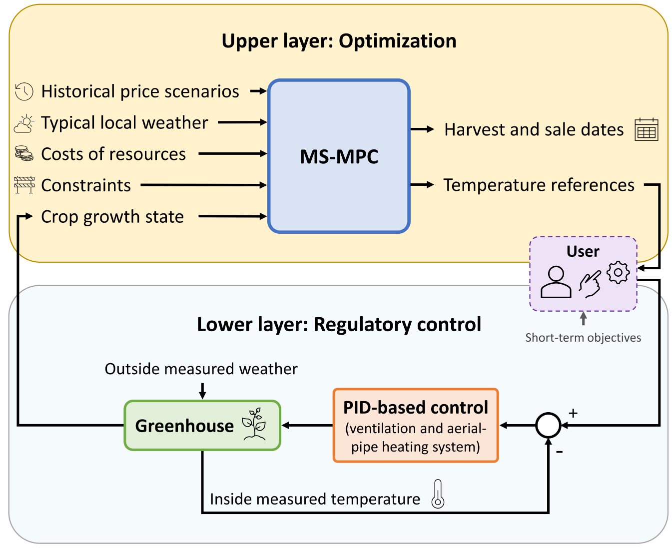

Fig. 1. Hierarchical control architecture integrating MS-MPC.

the optimization layer is executed once every 24 h with a receding horizon approach, receiving a feedback of the crop growth state from the lower layer. On the other hand, control actions in the lower layer are executed with a sampling time of 30 s to precisely track the optimal set points and avoid undesired effects of other disturbances, caused by the outside weather variations, for example.

Furthermore, the proposed architecture can be easily integrated into a cloud-based decision support system (DSS), as the approach described in [38]. The cloud platform hosting the DSS would receive climate records from the data acquisition devices installed in a greenhouse, and information regarding the state of the crops from soft sensors and manual measurements [39]. The results of the developed MS-MPC strategy in the upper layer of the architecture could be presented to farmers, e.g., through a mobile app, to inform them of the optimal harvest and sale dates. Farmers could decide to trust the calculations of the optimization layer but they would have also the possibility to interact with the hierarchical architecture. Thus, the calculated harvest and sales dates, as well as the instructions that are sent to the lower layer for climate control, can be modified depending on short-term objectives determined by the farmers, for example, due to the appearance of pests and diseases affecting the crop, a sudden change of weather conditions, or a significant variation in market prices. These short-term aspects are not considered in the upper layer since they are usually tackled more effectively by the farmers during daily operation, based on their own experience. By means of the feedback of the crop growth state every 24 h, the proposed architecture can take into account the changes caused by the possible interaction of farmers and farm supervisors who manage the greenhouse, being a clear example of a Human-in-the-loop system [40], [41].

B. Greenhouse Climate Model

A pseudophysical model has been used to describe the microclimate inside the greenhouse. The model reproduces

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the evolution in time of the air temperature, air humidity, and soil surface temperature inside the greenhouse according to a system of differential equations expressed as follows:

$$\frac{d\boldsymbol{x}}{dt} = f(\boldsymbol{x}, X_{\text{LAI}}, \boldsymbol{u}, \boldsymbol{d}, \boldsymbol{c}, t) \quad (1)$$

where $\boldsymbol{x}$ is a vector of the state variables, X_{LAI} is the leaf area index (indicates the state of growth of the crop), $\boldsymbol{u}$ is a vector of inputs (control signals for the actuators), $\boldsymbol{d}$ is a vector of measurable disturbances (mainly the weather outside the greenhouse), $\boldsymbol{c}$ is a vector of constants and parameters of the system, t is the time, and f represents the nonlinear functions based on energy transfers and mass balances. For reasons of limited space, the complete description of the model is not presented here, but it can be found in [1]. Also, it is important to remark that the model has been validated in other previous works [39], [42]. The model is used in discrete-time form with a sampling time of 30 s to simulate the greenhouse climate dynamics for the lower layer of the architecture presented in Fig. 1. On the other hand, a steady-state expression is selected for the optimization problem of MS-MPC to predict the use of the heating system and calculate the associated costs. The decision variable in the optimization problem is the air temperature reference $x^{\text{r}}_{\text{T,a}}$, which affects crop growth and heating activation. Therefore, in the following paragraphs it is explained how an expression has been deduced to determine when the heating is activated depending on the value of the temperature reference.

The evolution of the air temperature inside the greenhouse is calculated with the following differential equation:

$$\begin{aligned} c_{\text{sph,a}}\, c_{\text{den,a}}\, \frac{c_{\text{vol,g}}}{c_{\text{area,ss}}}\, \frac{dx_{\text{T,a}}}{dt} &= Q_{\text{sol,a}} + Q_{\text{cnv,ss-a}} + Q_{\text{heat-a}} \\ &\quad - Q_{\text{cnv-cnd,a-e}} - Q_{\text{vent}} \\ &\quad - Q_{\text{loss}} - Q_{\text{trp}} \end{aligned} \quad (2)$$

where $x_{\text{T,a}}$ is the inside air temperature (in kelvin), $c_{\text{sph,a}}$ is the specific heat of air (in joule per kilogram kelvin), $c_{\text{den,a}}$ is the air density (in kilogram per cubic meter), $c_{\text{vol,g}}$ is the volume of air (in cubic meter) inside the greenhouse, and $c_{\text{area,ss}}$ is the soil surface (in square meter) of the greenhouse. Q denotes the different heat exchanges (in watt per square meter) occurring in the greenhouse: $Q_{\text{sol,a}}$ is the solar radiation flux assumed to be absorbed by the air (despite it is inert to radiation), $Q_{\text{cnv,ss-a}}$ is the convective flux between the soil surface and inside air, $Q_{\text{heat-a}}$ is the heat flux provided by the heating system, $Q_{\text{cnv-cnd,a-e}}$ is the convective and conductive flux through the cover due to the difference between the inside and outside air temperatures, Q_{trp} is the latent heat effect due to crop transpiration, Q_{vent} is the heat lost by natural ventilation, and Q_{loss} is the heat lost by infiltration losses.

Considering steady-state and supposing that the heating system is only used during the night, when the vents of the greenhouse are closed ($Q_{\text{sol,a}} = 0$, $Q_{\text{trp}} \approx 0$, and $Q_{\text{vent}} = 0$), the expression in (2) becomes:

$$Q_{\text{heat-a}} = Q_{\text{cnv-cnd,a-e}} + Q_{\text{loss}} - Q_{\text{cnv,ss-a}} \quad (3)$$

with $Q_{\text{heat-a}} = c_{\text{cnv,p-a}}\,(u_{\text{T,h}} - x_{\text{T,a}})$ where $c_{\text{cnv,p-a}}$ is a convection coefficient (in watt per square meter kelvin) for the difference of temperature between the heating pipes $u_{\text{T,h}}$ and the air inside the greenhouse. The expression is solved for that difference:

$$u_{\text{T,h}} - x_{\text{T,a}} = \frac{Q_{\text{cnv-cnd,a-e}} + Q_{\text{loss}} - Q_{\text{cnv,ss-a}}}{c_{\text{cnv,p-a}}} \quad (4)$$

where all the terms in the right-hand side can be expressed to exclusively depend on the temperature reference, the external air temperature $d_{\text{T,ext}}$, and the external wind velocity $d_{\text{wv,ext}}$. Since the values of these three variables are known during optimization, the value of $u_{\text{T,h}} - x_{\text{T,a}}$ can be calculated with (4). If the difference is positive, the function f_{ah} in (5) indicates in the optimization that the heating system should be activated and the temperature of the heating pipes has to be greater than the air temperature inside the greenhouse (so that the temperature reference can be reached). Each activation of the heating system affects the cost calculation, as later shown in (13).

$$f_{\text{ah}}\left(x^{\text{r}}_{\text{T,a}}, d_{\text{T,ext}}, d_{\text{wv,ext}}\right) = \begin{cases} 1 & \text{if } u_{\text{T,h}} - x_{\text{T,a}} > 0, \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

C. Tomato Growth Model

The reduced TOMGRO model is used in this work to reproduce the tomato crop growth. This model was originally published in [43] and it has been adapted to Mediterranean crops, according to the modifications and calibrations presented in [1], [39], and [44]. It has five state variables: the number of nodes N (in nodes), the leaf area index X_{LAI} (in square meter of leaves per square meter of soil), the fruit dry matter W_{F} (in grams per square meter), the mature fruit biomass accumulation W_{M} (in grams per square meter), and the aboveground biomass accumulation W (in grams per square meter). All these state variables are calculated based on a set of nonlinear differential equations. The reader is again referred to the previously mentioned publications for the complete explanation of the model [1], [39], [43], [44].

For the simulation of the crop growth in the lower layer of the proposed architecture, the model is used in discrete-time form, with a sampling time of 30 s. For the optimization problem of MS-MPC, the model is also used in discrete-time form, but with a sampling time of hours, which is a valid simplification due to the slow dynamics of the crop growth. In this case, the sampling time is variable and depends on the duration of nighttime and daytime periods per day, as explained later in Section II-E.

The most important state variable of the model for the optimization problem is the mature fruit biomass accumulation since it represents the growth of mature tomatoes. It is calculated with the following expression:

$$\frac{dW_{\text{M}}}{dt} = D_{\text{F}}(T_{\text{d}})\,(W_{\text{F}} - W_{\text{M}}), \qquad \text{if } N > N_{\text{FF}} + \kappa_{\text{F}} \quad (6)$$

where $D_{\text{F}}(T_{\text{d}})$ is a function that affects the rate of development of fruit depending on the daily mean temperature inside the greenhouse T_{d}, N_{FF} is the number of nodes per plant when the first fruit appears, and κ_{F} is the development time (in nodes) from the first fruit appearance until its maturity. The growth of mature tomatoes is also affected by other climatic variables through the following expression for the evolution of fruit dry matter:

$$\frac{dW_{\mathrm{F}}}{dt} = GR_{\mathrm{net}}\,\alpha_{\mathrm{F}}\, f_{\mathrm{F}}(T_{\mathrm{d}})\left[1 - e^{-\vartheta(N - N_{\mathrm{FF}})}\right] g(T_{\mathrm{dt}}) \qquad (7)$$

where GR_{net} comprises plant photosynthesis and respiration, which depend on CO_2 concentration in air and solar radiation, α_{F} is the maximum partitioning coefficient of new growth to fruit, $f_{\mathrm{F}}(T_{\mathrm{d}})$ is a function that affects the partitioning of biomass to fruit, ϑ is a transition coefficient between vegetative and full fruit growth, and $g(T_{\mathrm{dt}})$ is a function that reduces growth when high daytime temperatures T_{dt} occur.

Table I summarizes the different functions of the model that take into account the effect of the air temperature inside the greenhouse on the crop growth. Notice that, for the optimization problem, $T = x^{\mathrm{r}}_{\mathrm{T,a}}$ as the temperature reference is the decision variable, so T_{d} and T_{dt} are also calculated depending on the value of $x^{\mathrm{r}}_{\mathrm{T,a}}$. In the tomato growth model, all temperatures variables are expressed in Celsius.

Additionally, since the market price used in this work is referred to fresh tomatoes, the dry weight of mature fruits is converted to fresh weight (in grams per square meter). It is assumed that the 6% of the fruit weight corresponds to dry matter [1]. Hence, the accumulated fresh weight of mature fruits X_{F} is calculated as $X_{\mathrm{F}} = (0.06)^{-1}\, W_{\mathrm{M}}$.

D. Example of Generic MPC Formulation

MPC is a control technique that calculates a sequence of control actions $\boldsymbol{u} = \{u(1), \ldots, u(N_{\mathrm{p}})\}$ to optimize an objective function J over a prediction horizon [45]. Thus, it consists of an optimization problem that can be solved at every time instant k. For instance, considering the greenhouse climate control problem, a generic MPC formulation is given by:

$$\min_{\boldsymbol{u}} J(k) = \sum_{k=1}^{N_{\mathrm{p}}} f_{\mathrm{c}}(x(k+1), u(k)) \qquad (8)$$

subject to:

for $k = 1, \ldots, N_{\mathrm{p}}$

$$x(k+1) = s(x(k), u(k), d(k)) \qquad (9)$$

$$h(x(k+1), u(k)) \leq b(k) \qquad (10)$$

where N_{p} is the length of the prediction horizon, $x(k)$ are the values of the state variables at time instant k (e.g., air temperature and humidity), $u(k)$ are the control actions at time instant k (e.g., control signals for the natural ventilation system and the heating system), $d(k)$ are the disturbances at time instant k (non-controllable variables, e.g., the weather outside the greenhouse), f_{c} is a function that calculates the cost to achieve a desired goal (e.g., the cost of using the actuators for temperature control), s is the function describing the system dynamics [see (1) for the greenhouse climate], h is a constraint function, and $\boldsymbol{b}$ is the constraint vector. An example of constraints imposed in (10) can be the operating limits of the actuators, so that the control signals calculated in $\boldsymbol{u}$ are implementable.

TABLE I

IMPACT OF NONOPTIMAL AIR TEMPERATURE ON CROP GROWTH

Function	Description	Affects
$f_N(T)$	Reduces vegetative development	N
$\mathrm{PGRED}(T)$	Modifies the rate of photosynthesis	GR_{net}
$f_{\mathrm{F}}(T_{\mathrm{d}})$	Modifies partitioning to fruit	W_{F}
$g(T_{\mathrm{dt}})$	Reduces fruit growth when $T_{\mathrm{dt}} > 24\,^{\circ}\mathrm{C}$	W_{F}
$D_{\mathrm{F}}(T_{\mathrm{d}})$	Modifies the rate of fruit development	W_{M}

The optimal solution (if there exists a feasible solution) is found by solving the constrained optimization problem in (8)-(10). Since MPC works in a receding-horizon way, the optimization problem is repeatedly solved at every time instant (i.e., control sample time), and only the first control action of $\boldsymbol{u}$ is sent to the actuators. Although the example presented in (8)-(10) correspond to the minimization of an objective function, MPC can also be used to maximize a desired objective and to calculate optimal set points including other variables affecting the system under study, as it is explained in the following section.

E. Optimization Using MS-MPC

The composition of the cost function for the optimization problem using MS-MPC starts with the formulation of the income due to the multiple harvests and sales of the crop production. Let n_j denote the jth harvest and sale date for $j = 1, 2, \ldots, N_{\mathrm{h}}$, where N_{h} is the total number of harvests and sales during the crop cycle. Thus, the vector $\boldsymbol{n} = [n_1\ n_2\ \ldots\ n_{N_{\mathrm{h}}}]$ contains the dates when the production has to be harvested and sold. The last date $n_{N_{\mathrm{h}}}$ limits the duration of the crop cycle, which means that the remaining amount of mature fruits is harvested and sold, and the crop is removed afterward. Therefore, the optimal duration of the crop cycle can be expressed as $n_{\mathrm{days}} = n_{N_{\mathrm{h}}}$. For every harvest, the income from selling the mature fruits can be calculated as:

$$I(j) = c_{\mathrm{area,ss}}\, P_i(n_j)\, W_{\mathrm{hf}}(n_j) \qquad (11)$$

where $I(j)$ is the income (in euros) for selling the jth harvest, $P_i(n_j)$ is the tomato price (in euro per kilogram) for the date n_j and for the ith price scenario, and $W_{\mathrm{hf}}(n_j)$ is the weight of harvested fruits (in kilograms per square meter). This weight is manually measured by the farmers, but for the optimization problem is calculated based on the tomato growth model as:

$$W_{\mathrm{hf}}(n_j) = X_{\mathrm{F}}(n_j) - X_{\mathrm{F}}(n_{j-1}) \qquad (12)$$

where $X_{\mathrm{F}}(n_j)$ is the accumulated fresh weight of mature fruits on the date n_j (converted to kilograms per square meter), and $X_{\mathrm{F}}(n_{j-1})$ is the accumulated fresh weight of mature fruits that was determined on the previous date of harvest n_{j-1}.

For the calculation of the economic costs, it is assumed that they are associated to the heating system because the operating costs of a heating system are much greater than those of natural ventilation. Hence, the following expression is used:

$$f_{\mathrm{hc}}(k) = c_{\mathrm{res}}\ \Delta\tau(k)\ f_{\mathrm{ah}}\big(x^{\mathrm{r}}_{\mathrm{T,a}}, d_{\mathrm{T,ext}}, d_{\mathrm{wv,ext}}\big) \qquad (13)$$

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where $f_{\mathrm{hc}}(k)$ is the cost of using the heating system (in euros), c_{res} is the cost of resources (in euro per hour), which were assumed as fixed mean values, and $\Delta\tau(k)$ is the number of hours that the heating is active, which depends on the duration of the nighttime periods and it can be calculated based on the day of the year and the location of the greenhouse, or with solar radiation data. Notice that, if the cost of using natural ventilation increases, it can easily be added to (13), as well as the cost of other actuators with high electrical consumption, such as humidification or dehumidification systems.

As it can be noticed in (13), the optimization is solved in discrete-time instants for $k = 1, 2, \ldots, 2\,n_{\mathrm{days}} + 1$, where every k value corresponds to a nighttime or daytime period and $2\,n_{\mathrm{days}} + 1$ is the length of the optimization horizon. In this sense, considering just two samples per day is necessary to reduce the computational cost of the problem. Hence, the calculation of the optimal temperature reference $\boldsymbol{x}^{\boldsymbol{r}}_{\mathrm{T,a}} = [x^{\mathrm{r}}_{\mathrm{T,a}}(k) \;\ldots\; x^{\mathrm{r}}_{\mathrm{T,a}}(2\;n_{\mathrm{days}} + 1)]$ is performed by distinguishing between the daytime and nighttime periods. If the nighttime and daytime averages of the typical external weather are given as inputs to the optimization problem (see Fig. 1), temperature set points $x^{\mathrm{r}}_{\mathrm{T,a}}(k)$ are calculated as the average value of the optimal temperature that the crop needs in each k instant.

The cost function of the optimization problem is the economic profit but it is expressed to take into account multiple price scenarios as follows:

$$\max_{\{n_{\mathrm{days}};\, \boldsymbol{n};\, \boldsymbol{x}^{\mathrm{r}}_{\mathrm{T,a}}\}} \sum_{i=1}^{N_{\mathrm{s}}} \left(\sum_{j=1}^{N_{\mathrm{h}}} I_i(j) - \sum_{k=1}^{2\,n_{\mathrm{days}}+1} f_{\mathrm{hc}}(k) \right) \tag{14}$$

subject to:

$$n_{\mathrm{days}} \in \mathbb{Z} : n_{\mathrm{days_{min}}} \le n_{\mathrm{days}} \le n_{\mathrm{days_{max}}} \tag{15}$$

$$n_1 \in \mathbb{Z} : n_{\mathrm{days_{min}}} \le n_1 \le n_{\mathrm{days_{min}}} + 7 \tag{16}$$

$$n_j \in \mathbb{Z} : n_{j-1} + 7 \le n_j \le n_{j-1} + 14, \qquad \text{for } j > 1 \tag{17}$$

$$x^{\mathrm{r}}_{\mathrm{T,a}}(k) \in \mathbb{R} : x^{\mathrm{r}}_{\mathrm{T,a_{min}}}(k) \le x^{\mathrm{r}}_{\mathrm{T,a}}(k) \le x^{\mathrm{r}}_{\mathrm{T,a_{max}}}(k) \tag{18}$$

where N_{s} is the number of market price scenarios, and the income $I_i(j)$ is calculated in particular for each scenario for $i = 1, 2, \ldots, N_{\mathrm{s}}$. The optimal solution of the developed MS-MPC strategy contains the duration of the crop cycle, the harvest and sale dates and the temperature reference for the crop. Notice that it is a single solution which is compatible with all the price scenarios considered in the optimization.

Regarding the constraints, (15) imposes that the duration of the crop cycle must be between a minimum and a maximum number of days. The maximum number of days $n_{\mathrm{days_{max}}}$ determines if a short or long crop cycle is preferred. The minimum number of days $n_{\mathrm{days_{min}}}$ corresponds to the time that farmers need to wait for the formation of the first fruits, which mainly depends on crop variety. In this regard, (16) imposes that the first harvest and sale date have to occur during the first week after the formation of the first fruits. For the rest of the dates, linear inequality constraints are imposed in (17) so that there is a minimum of 7 days and a maximum of 14 days of difference between the harvests. This policy is flexible to perform delay and advance actions over the crop growth, but also strict to guarantee that the fruits are harvested with an adequate level of ripeness. The last restriction in (18) ensures that the optimized temperature set points are achievable on nighttime and daytime (depending on k instants), based on the weather that typically occurs in the location of the greenhouse.

The problem described in (14)-(18) is a mixed-integer nonlinear programming (MINLP) problem, since the harvest and sale dates must be integer numbers. It has been solved by using the genetic algorithm of the Global Optimization Toolbox of MATLAB (MathWorks, Massachusetts, USA), which was selected due to the good compromise that it offers in terms of optimality and computational time, considering the imposed constraints. Some options of the genetic algorithm were set by following the recommendations from MathWorks for solving mixed integer optimization problems. The population size was increased to 300, the mutation rate was decreased by increasing the crossover fraction to 0.9, and the elite count was increased to 30.

Fig. 2 shows the operational flowchart of the optimization problem integrated in the hierarchical control architecture. For the receding horizon implementation, a new optimization problem is solved every 24 h. Thus, an additional set of functions were coded in MATLAB to execute a series of adjustments. For instance, every time that a harvest and sale date is passed, N_{h} is decreased in one unit. Also, before any new optimization, the previous optimal solution is adapted to be included in the initial population matrix of the genetic algorithm, so that the computational cost can be reduced in case the next optimal solution is close to the previous one.

III. Results and Discussion

A traditional Almería-type greenhouse has been considered for the case study. The greenhouse is located at "Las Palmerillas" Experimental Station of the Cajamar Foundation, in El Ejido, Almería, Spain. It has a total area of 877 m^2 and a plant density of 1.4 plants/m^2. Natural ventilation of the greenhouse is performed by regulating the openings of two lateral windows (32.75 × 1.90 m) and five roof windows (8.36 × 0.73 m). The aerial-pipe heating system consists of a boiler that consumes 16 kg/h of biomass, and a water circulation pump with an electrical power of 1.5 kW. Hot water circulates through pipes and the air temperature inside the greenhouse is increased by convection. Although the greenhouse and its actuators are part of an experimental facility, the results of the case study can be extrapolated to commercial-type greenhouses.

An autumn/winter crop cycle was selected, starting in September, and assuming $N_{\mathrm{h}} = 7$ harvests. During these seasons of the year, the greenhouse heating system is more likely to be used in the nighttime, when cold outside temperatures occur. To calculate the cost of using the heating system, resource prices were considered constant throughout the cycle, with a cost of 0.255 €/kg for biomass, and 0.135 €/kWh for electricity.

In the upper control layer, climate data recorded in the location of the greenhouse were used for the prediction of the local weather. The standard climatic data were daytime and nighttime average values of the external air temperature

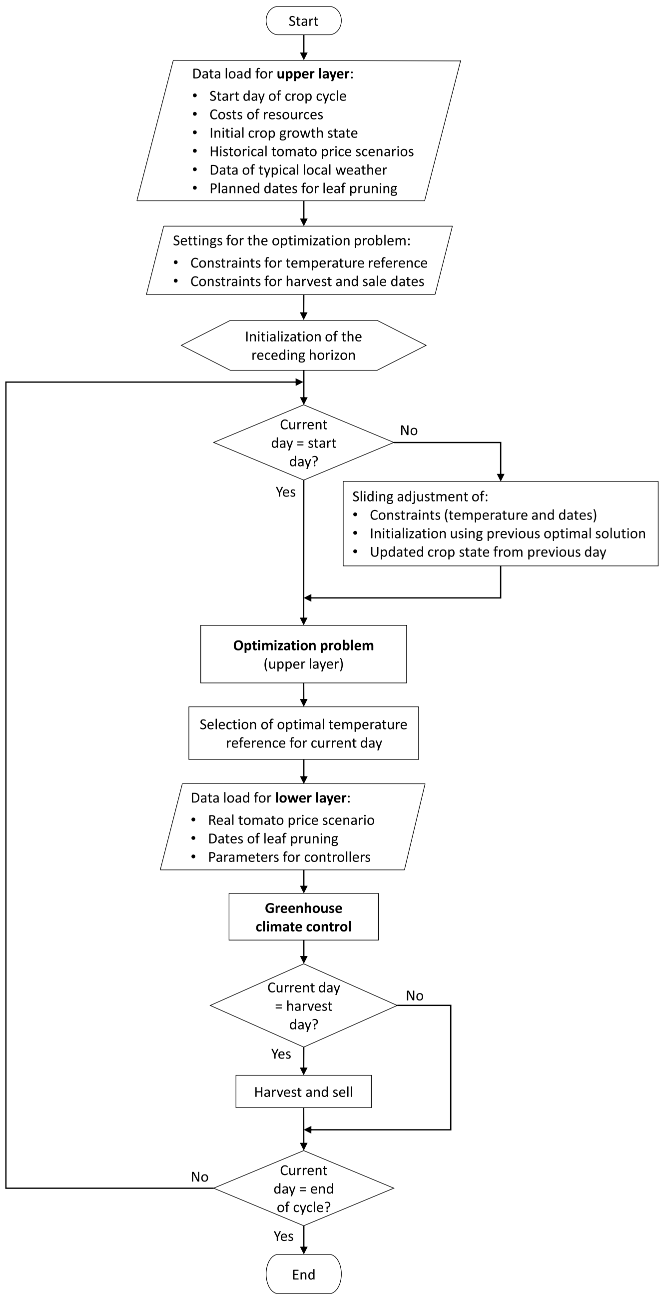

Fig. 2. Operational flowchart of the architecture exposed in Fig. 1.

and solar radiation, as required for the optimization problem. In addition, historical data measured inside the greenhouse were studied to impose the constraints for the optimization of the temperature reference. Restrictions were set for nighttime and daytime periods depending on the months of the year, as presented in Fig. 3.

In the lower control layer, data for the outside weather variables measured every 30 s during the 2019-20 season were used as inputs into the *Greenhouse* block of Fig. 1, in which the nonlinear models are used to simulate the real greenhouse microclimate and the crop growth. In the case of the greenhouse climate model, five sets of values for some time-varying parameters of the model were used to reproduce the change of dynamics in the real greenhouse depending on the months of the year [42]. The use of periodically calibrated

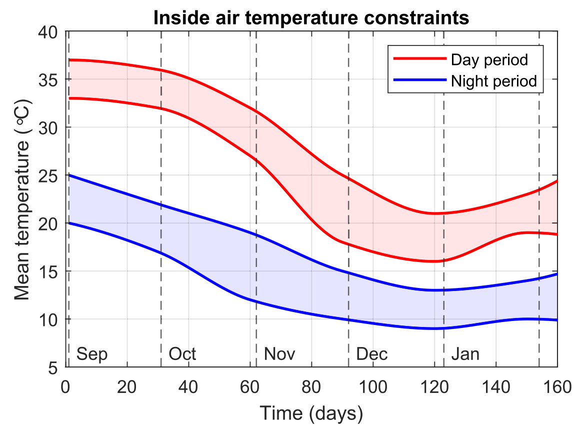

Fig. 3. Constraints bands imposed for temperature reference optimization.

values for time-varying parameters, such as those related with convection and conduction processes [recall (2)], is required by this type of greenhouse climate models, to ensure that the simulation of its state variables is accurate for any time of the year, with different operating conditions. For the tomato growth simulation, an optimal fertigation of the crop and an average CO_2 concentration of 400 ppm in the air inside the greenhouse were assumed, since greenhouses of the region are not usually equipped with carbon dioxide enrichment systems. Regarding the regulatory control methods, PI controllers with antiwindup were used to regulate the opening of the windows for the natural ventilation, and the water temperature for the aerial-pipe heating system (limited to 60 °C). The parameters of the controllers were tuned with different values for adaptation to the change of dynamics of the greenhouse through the year.

Cultural practices that affect crop growth were also taken into account. For example, farmers perform periodical prunings (defoliation) to remove leaves from the plants and favor the ripening of the fruits. It was assumed that the prunings occur every 15-20 days during the cycle and that a 10% of leaf area index is reduced in each pruning. In the upper layer, pruning dates were assumed to be planned by the farmers, so they were considered in the optimization problem as fixed dates. Thus, in the lower layer, the prunings were performed in the planned days.

To compose the scenarios for the optimization problem, historical data of market prices for tomato were used. Fig. 4 presents the scenarios and the restrictions imposed for the optimization to calculate the duration of the crop cycle, with a minimum duration of 77 days and a maximum of 160 days. For the optimization in the upper layer, 14 scenarios of the mean daily price paid to the farmers in Andalusia, Spain, were used [see Fig. 4(a)]. These multiple scenarios correspond to the seasons from 2002-03 to 2014-15, and 2020-21. For the performance assessment explained in Section III-B, five scenarios of the mean daily price registered specifically in the province of Almería were used [see Fig. 4(b)], which are considered as real occurrence scenarios (i.e., not included before for optimization), corresponding to the seasons from 2015-16 to 2019-20.

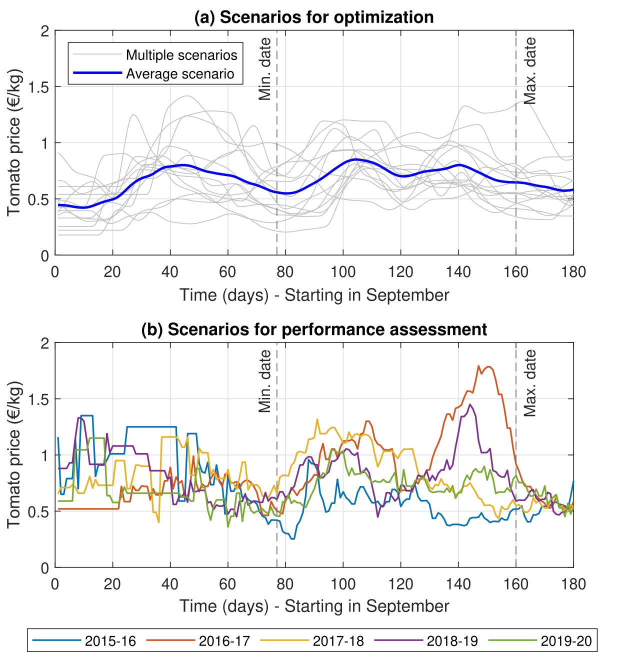

Fig. 4. Price scenarios: (a) for optimization and (b) for performance assessment.

A. Simulation Results

Simulation of MS-MPC for the described case study lasted 3 h and 5 min, using an Intel Core i7-7700 processor up to 4.20 GHz. The optimal length of the crop cycle resulted in 160 days, with 682.59 h of heating use, and achieving a crop yield of 9.77 kg/m^2. Fig. 5 presents the optimal harvest and sale dates of the crop production, and Fig. 6 shows the optimal temperature reference.

As observed in Fig. 5, the optimal harvest and sale dates $\boldsymbol{n}$ = [84 98 112 126 140 148 160] are mostly spaced every 14 days between the limits of duration of the crop cycle. For the last three dates, from day 140 to 160, the harvests and sales should be performed in a shorter period of time since in the majority of the scenarios the price starts to decrease after presenting a last peak value. These results are, in terms of probability, the optimal dates to minimize the risk of obtaining low economic profits despite the remarkable price uncertainty.

Regarding the results in Fig. 6, the upper values for the temperature references, corresponding to the average temperature for daytime periods, are usually equal to the limits of the imposed constraints. This was an expected result, due to the strong restrictions presented in Fig. 3. If wider constraints bands were imposed, temperature references would be optimized to be closer to 24 °C, which are ideal for the tomato crop growth but not reachable in greenhouses of the southeast of Spain during daytime in September and October, or in December and January.

To evaluate if the temperature references were reached in the lower layer, Fig. 7 shows the daily mean temperature inside the greenhouse compared against the daily mean temperature according to the optimal references. As it can be noticed, the trajectories are similar, which confirms that the constraints for the temperature references were correctly imposed. For instance, Fig. 8 shows that the controllers in

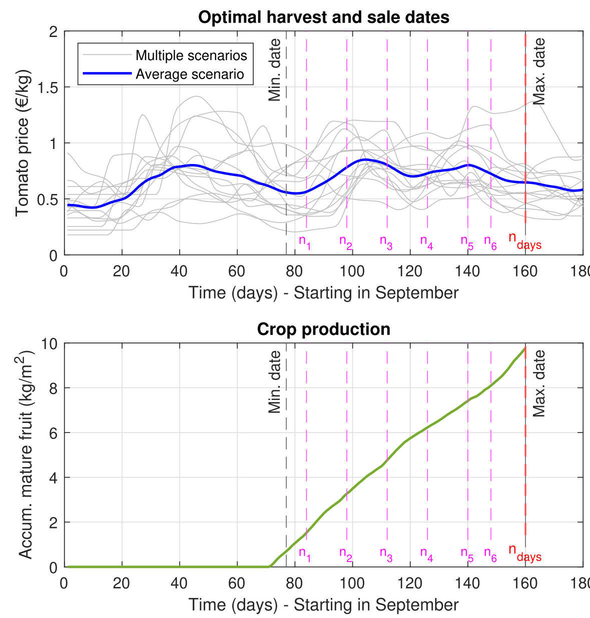

Fig. 5. Optimal harvest and sale dates obtained with MS-MPC.

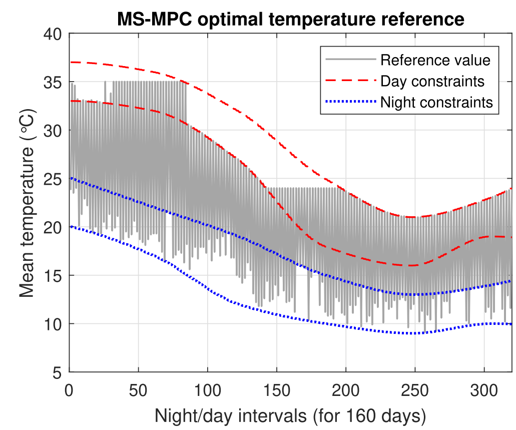

Fig. 6. Optimal temperature reference (mean values) calculated with MS-MPC. The reference is plotted for night/day intervals in 160 days of total crop cycle.

the lower layer work properly on days when the set points can be reached. However, the unforeseen variations of the external climatic conditions affect the temperature inside the greenhouse and make it difficult to track the optimal trajectory (see the occasional differences in Fig. 7). In this sense, the receding horizon implementation helps to partially compensate for control errors when the temperature set points are not reached in the greenhouse on certain days. The mean absolute error (MAE) computed for the lines plotted in Fig. 7 results in 1.16 °C, which is an acceptable value of deviation for the mean daily temperature control. Nonetheless, improvements for optimal temperature tracking could be made, as discussed in [46], by taking into account short-term weather forecasts and by converting night and day temperature set points into a dynamic reference curve, instead of using directly the mean optimal values calculated in an upper layer.

As for the computation time of the optimization problem, Fig. 9 shows that the developed strategy is suitable for daily execution. On the first day, a computation time of 29 minutes is needed to find an optimal solution for a horizon of 160 days.

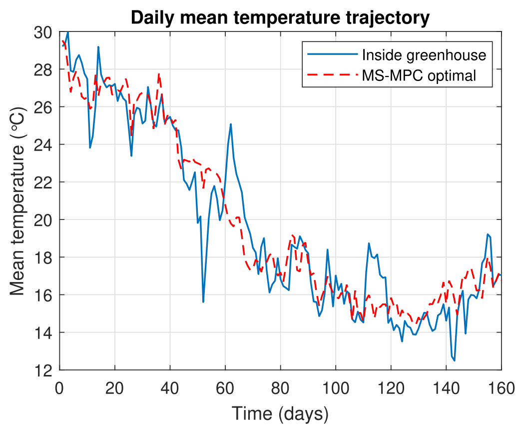

Fig. 7. Comparison of daily mean temperature that occurred inside the greenhouse versus the desired optimal trajectory calculated with MS-MPC.

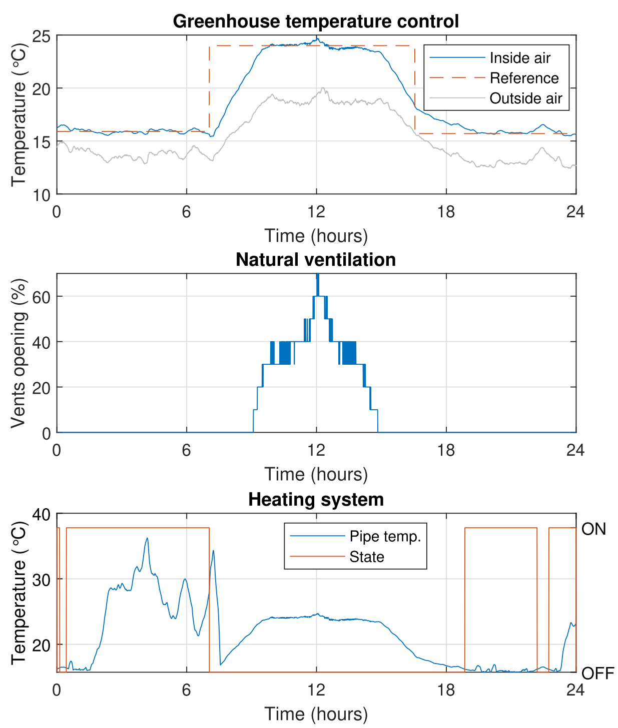

Fig. 8. Results of regulatory control in the lower layer to track the temperature reference in day 84.

For the remaining days, the computation time presents a decreasing trend because the horizon is shortened and the optimization is initialized each day using the previous optimal solution.

B. Performance Assessment

MS-MPC calculations take into account only a specific number of market price scenarios provided in the optimization layer. When following the optimal temperature reference and the optimal harvest and sale dates during a crop cycle, the resulting economic profit for the farmer will depend on the real price scenario, which might differ from the scenarios explicitly considered in the optimization problem. Hence, in this section, the robustness of the developed MS-MPC strategy is evaluated by considering that new price scenarios occur in reality.

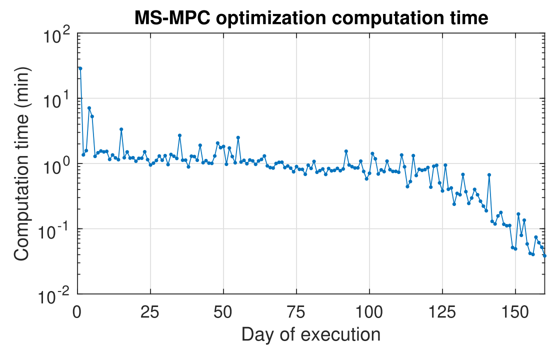

Fig. 9. Computation time of the optimization problem for MS-MPC.

Five real price scenarios that were not provided to the MS-MPC have been used for performance assessment [see Fig. 4(b)]. The results of the MS-MPC strategy are compared against four variants of MPC to separately assess the impact of different sources of uncertainty in terms of performance:

- Average scenario MPC (AS-MPC). A new simulation was executed by modifying the cost function of the optimization problem to consider only the average of the 14 scenarios shown in Fig. 4(a). This is a similar approach as studied in [27].
- Perfect forecast MPC for price (PF-MPC-P). With this method, the cost function uses the same price scenario that is considered to occur in reality. Thus, five individual simulations were performed, one for each scenario, assuming a perfect "prediction" of prices.
- Perfect forecast MPC for weather (PF-MPC-W). In this case, the market price in the cost function has a fixed value of 0.6 €/kg, but the optimization is solved by using the same external weather that is considered to occur in reality. Only one simulation was executed using the real weather measured in the experimental greenhouse during 2019-20.
- Perfect forecast MPC for price and weather (PF-MPC-P&W). This case exhibits the ideal MPC behavior. Again, only one simulation was executed using price and weather data from 2019-20 to provide a bound as the best achievable performance (considering the imposed constraints) to evaluate the developed MS-MPC strategy.

For a proper comparison, all these variants of MPC were simulated according to the hypotheses presented in Section III, except for the particular considerations described above for each case.

Table II presents the optimal harvest and sale dates calculated by each strategy after their simulation with receding horizon. MS-MPC and AS-MPC determined the same optimal dates, which indicates that MS-MPC is conservative in this aspect to guarantee the feasibility in all the scenarios considered for optimization. Regarding the *real* scenarios, the dates calculated by PF-MPC-P are completely different for each case because individual optimizations were executed. In this sense, the differences can be explained attending to the evolution of price in each scenario [see Fig. 4(b)]. Some scenarios present two peaks of price, like 2016-17 and 2018-19, while others are more similar to the historical average scenario, such as 2017-18 and 2019-20. In general, PF-MPC-P tries to calculate

TABLE II
OPTIMAL HARVEST AND SALE DATES (IN DAYS AFTER TRANSPLANTING) CALCULATED BY EACH CONTROL STRATEGY

Strategy	n_1	n_2	n_3	n_4	n_5	n_6	n_{days}
AS-MPC	84	98	112	126	140	148	160
MS-MPC	84	98	112	126	140	148	160
PF-MPC-P: 15-16	77	88	98	107	117	125	139
PF-MPC-P: 16-17	82	96	109	122	136	150	158
PF-MPC-P: 17-18	84	97	109	123	134	145	159
PF-MPC-P: 18-19	78	88	102	115	129	143	157
PF-MPC-P: 19-20	82	96	107	121	132	146	160
PF-MPC-W: 19-20	84	94	108	122	136	146	160
PF-MPC-P&W: 19-20	83	97	107	121	132	146	160

TABLE III
COMPARISON OF PROFITS (IN EURO PER SQUARE METER) CONSIDERING REAL SCENARIOS OCCURRING IN THE PROVINCE OF ALMERÍA

Strategy	2015-16	2016-17	2017-18	2018-19	2019-20
PF-MPC-P&W	–	–	–	–	5.31
PF-MPC-P	2.48	7.54	5.90	5.31	4.80
PF-MPC-W	–	–	–	–	4.54
MS-MPC	2.05	6.47	4.99	4.56	4.34
AS-MPC	1.95	6.38	4.89	4.47	4.23

the optimal dates to be close to peak price days, as it could be expected. This is especially noticeable with the 2015-16 scenario, in which harvests n_1, n_2, and n_3 should be performed sooner in comparison to the rest of scenarios because the peak price of this season occurred between days 77 and 100. As a consequence, due to the imposed constraints for dates and the fixed number of harvests, the crop cycle length n_{days} would be 139 days compared to 160 days calculated for other seasons. Lastly, regarding PF-MPC-W: 19-20 and PF-MPC-P: 19-20, the differences in the optimal days are small, but the impact on the profit is considerable. In this sense, for PF-MPC-P&W: 19-20 compared to PF-MPC-P: 19-20, differences only appear for n_1 and n_2, since using an additional perfect weather forecast has less impact on the profit optimization than a perfect prediction of prices.

The comparison of profits obtained with each strategy is presented in Table III. As can be noticed, profits with MS-MPC are slightly greater than with AS-MPC in all the scenarios. Although the sale dates are the same with both strategies, the profits are different because AS-MPC requires more use of the heating system (see Table IV), thus increasing the costs. To contextualize the superiority of MS-MPC over AS-MPC in profit results, in the province of Almería, the average number of greenhouses per farm is 2.7, with a mean area of 7700 m^2 per greenhouse. For an average-size farm, MS-MPC could offer a mean increase of 2037 € in profit per crop cycle, for the analyzed price scenarios.

In terms of achievable profits, according to Table III, MS-MPC is conservative but not excessively, losing between 9.6% and 17.4% of potential economic profit depending on the *real* price scenario when compared to PF-MPC-P; and 18.3%

TABLE IV
COMPARISON OF CONTROL RESULTS OBTAINED WITH EACH STRATEGY

Strategy	Heating (h)	Yield (kg/m^2)	MAE (°C)
AS-MPC	706.24	9.79	1.13
MS-MPC	682.59	9.77	1.16
PF-MPC-P: 15-16	524.53	7.33	1.19
PF-MPC-P: 16-17	683.03	9.50	1.18
PF-MPC-P: 17-18	665.23	9.60	1.16
PF-MPC-P: 18-19	687.94	9.35	1.18
PF-MPC-P: 19-20	679.32	9.75	1.14
PF-MPC-W: 19-20	574.51	9.68	1.01
PF-MPC-P&W: 19-20	572.51	9.71	1.04

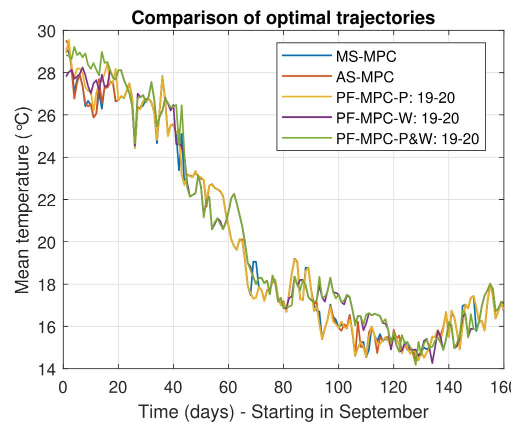

Fig. 10. Comparison of the optimal temperature trajectory calculated by the different control strategies.

if compared against the ideal PF-MPC-P&W. Besides, if MS-MPC is compared to PF-MPC-W, the performance loss due to weather prediction uncertainty is of 4.4%, which is a similar result to the one reported in [47], so this suggests that there might be some room for improvement of MS-MPC if better weather forecasts are used.

Table IV shows a summary of control results obtained with each strategy. A very interesting outcome is that AS-MPC provides the greatest crop yield but the least economic profits. Optimization using an average price scenario uses more heating, which increases costs and reduces profit. It is also interesting to compare PF-MPC-P: 19-20 and PF-MPC-W: 19-20 to understand the impact of weather and price forecasts. With PF-MPC-W, less use of heating is needed since perfect weather forecast allows to calculate the best temperature reference for the climate that is going to happen in reality, obtaining a reduced control error as shown in MAE column of Table IV. In contrast, with PF-MPC-P, MAE for temperature control is worse but greater profits are obtained due to better selection of harvest and sale dates.

Regarding the optimal temperature references calculated by each strategy, a brief comparison is shown in Fig. 10. During the first 20 days of crop cycle, greater differences are noticeable. However, for the rest of the cycle, the temperature references are more similar due to the effect of the receding horizon and the restrictions imposed, but still the small differences have a positive impact on the profit optimization if less heating is required, for example.

IV. Conclusion

The maximization of profits for greenhouse crop production has been considered including the stochastic evolution of market price in the cost function. The main finding of this study is that greater economic profits can be obtained if MS-MPC is used instead of AS-MPC, due to a reduction in the use of heating. This result reinforces the idea that using multiple scenarios of historical market price is convenient and can outperform the use of just an average yearly trend of prices.

Increasing the number of scenarios brings robustness because more possible realizations of the uncertainty are included in the optimization problem. However, two inconveniences may arise. On the one hand, the results could become overconservative. On the other hand, the computational burden could increase, but this can be a minor issue if the optimization is executed only once a day, as proposed. Although the MS-MPC approach is conservative to guarantee the compatibility of the optimal solution for all the scenarios, it may be attractive for real implementation considering that farmers would like to minimize economic risks.

It is important to highlight that only market prices have been treated as a stochastic disturbance in this work, but the problem can be formulated to include also the uncertainty of weather forecasts. This might be studied to analyze if a very conservative solution is obtained when taking into account combined scenarios of uncertainties.

In future works, other stochastic control techniques could be applied to the same problem for an extensive performance analysis. In this regard, tree-based formulations and the weighting of scenarios by its probability of occurrence might be appropriate options for the problem discussed. Also, the optimal number of harvests and sales could be automatically determined, but this would require the use of other type of crop growth models, presumably to estimate the quantity of mature fruits per plant and the time needed to achieve optimal ripeness. In addition, other variables of interest for crop growth could be taken into account for automatic control, in order to effectively advance or delay the ripeness of fruits.

Acknowledgment

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