2024 European Control Conference (ECC)
June 25-28, 2024. Stockholm, Sweden

Stochastic Model Predictive Control for Irrigation: addressing solar and rain uncertainties to enhance sustainable productivity

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***Abstract*—This work addresses a challenging agricultural control problem: to take into account environmental uncertainties (precipitation and solar radiance) in irrigation policies. To tackle these uncertainties, a stochastic model predictive control approach is designed, wherein each type of uncertainty is addressed using two different techniques tailored to effectively counteract them. Simulation experiments were conducted using real-world data spanning various types of days to validate the efficacy of the proposed approach. The results were benchmarked against other methods, showcasing the significant advantages of the proposed approach in terms of accuracy and robustness in agricultural irrigation control in the face of uncertainties. Therefore, this probabilistic approach also offers an effective solution to manage uncertainties and water resources, enhancing the productivity and sustainability of the sector.**

***Keywords*—smart agriculture, irrigation control, model predictive control, stochastic MPC**

I. INTRODUCTION

Many farmers worldwide are introducing automatic irrigation control in their plots. However, the most common practice is to use open-loop control policies. This is, the irrigation is scheduled using a timer so that it typically waters a fixed amount of time each day or week. The amount of water employed is, at best, chosen as a result of an agronomic analysis of the crop needs, the soil in use, and other agronomic specifications.

However, as in most control frameworks, closed-loop control structures are more desirable, especially against uncertainties. In agriculture, rain, which is a disturbance, may provide the same desirable effect on the plant as the control input (the irrigation), so the automatic irrigation controller could save valuable amounts of water on rainy days. This could only happen if such a controller was aware of this effect and could have access to information regarding either the rain or the state of the system. This is what we refer to as *feedback* control.

Similarly, varying solar radiation, different stages of the crop, seasons, soils, and many other aspects have an influence on the amount of water the plant needs, which varies throughout days, weeks, and months. Hence, a decision maker (automatic irrigation controller in this case) should be as informed as possible of these factors in order to optimize the amount of water employed. In smart agriculture, this is of extreme importance, as droughts are severely affecting many regions of the world. Optimal irrigation policies could be of great help towards sustainability, thanks to the savings they may imply against traditional open-loop irrigation control policies.

This being said, there are many ways the aforementioned controllers could be aware of the necessary information. The most common approach is monitoring soil moisture. Soil moisture sensors measure the amount of water available at the root level from which the plant can drink. A closed-loop irrigation control policy could then be to apply water where there is not enough moisture [1].

More advanced control techniques could be able to take into account different disturbances, like rain or solar radiation. Robust approaches in control offer a way to counteract disturbances. Within the many techniques available, model predictive controllers (MPCs) have the advantage of performing in an optimal way while satisfying operation constraints [2]. They are widely used in agriculture too, see e.g. the review in [3], although not necessarily applied to irrigation control.

In particular, stochastic approaches are used to ensure stability and convergence of the system under the presence of uncertain disturbances [4], [5]. However, stochastic formulations employed to deal with uncertainty in irrigation are still an open problem for the smart agriculture community. Taking into account the probabilistic characteristics of the uncertainties in irrigation may be of great help when modeling undesired or uncontrollable features, like the authors in [6] review.

Considering the stochastic model, the authors in [7] generate reasonable irrigation allocation strategies by considering water flows among various factors like crop evapotranspiration, precipitation, and soil water content. Similarly, the authors in [8] improve the optimal stochastic water allocation considering the presence of uncertainty. In the context of MPC for agriculture, Stochastic MPCs (SMPC) have been used to control robots or for strategic decision-making, see, e.g., [3], [9]. In this paper, we propose to apply an SMPC formulation to the irrigation control problem in real-time, in contrast to the daily allocations previously mentioned.

The uncertainties stemming from rainfall and solar radiance are considered disturbances. To effectively manage these uncertainties associated with disturbances, our approach combines two distinct stochastic methods within a single

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MPC framework. Specifically, solar irradiance is treated as a disturbance with a known probability distribution, and chance constraints are applied accordingly. Conversely, rainfall is addressed by employing multiple scenarios based on historical data.

The primary contribution of our work lies in the integration of two types of MPC: Chance-Constrained MPC (CC-MPC) [10], [11] and Multi-Scenario MPC (MS-MPC) [12], [13], all within a unified SMPC formulation. This unique approach allows for managing uncertainties through two well-established SMPC paradigms.

Furthermore, we have benchmarked the performance of our proposed SMPC against other well-known MPC-based techniques, ensuring a reliable and accurate basis for comparison. These are an ideal MPC (aware of the exact model and future disturbances), an standard MPC and a min-max MPC. The comparison is performed on a simulated case study, although the system model is obtained from a real-world strawberry field. Besides, uncertainty data is also obtained from real-world measurements.

The remainder of this document is structured as follows. Section II presents a general irrigation model utilized in this study. Section III describes the stochastic formation of the MPC controller. The description of the case study and its results are presented and discussed in Section IV. Finally, Section V draws some conclusions and future directions.

II. IRRIGATION MODEL

We aim to control soil moisture, measured as the volumetric water content, which will be denoted $x(t)$, measured as a percentage. The dynamics of soil moisture at different depths can be modeled using Richards equation [14]. In this model, soil is divided into different layers, in which water is assumed to flow downwards. For the sake of conciseness, the reader is kindly referred to Section II in [15] for further details on how this model is derived.

In this paper, we will consider a linearized, discrete-time model of soil moisture x at each of the L layers. This soil moisture evolves according to different inputs and disturbances. In [15], these are the irrigation water flow applied at the top layer, $u(t)$, measured in m^3/s; the plant's transpiration $E_{\mathrm{tr}}(t)$ and water evaporation $E_g(t)$. Here, we assume that the latter two depend at the same time on external variables: rain $r(t)$, measured in mm and solar radiation $s(t)$, measured in W/m^2. Hence, the dynamics are given by:

$$x(k+1) = Ax(k) + Bu(k) + B_w w(k), \tag{1}$$

where w encompasses the disturbances: $w = (s, r)$.

Besides, it is desired that the closed-loop system satisfies certain operation constraints. Certainly, it is agronomically desirable to maintain volumetric water content between two key values. Water should be available above the so-called permanent wilting point, denoted $\underline{x}$. Below this threshold, the plant is no longer able to extract water and therefore dies. Opposite, water can be kept below the so-called field capacity point. This indicates the moisture value retained by the soil after it is saturated and naturally drained. Above this value, water is not kept by the soil, and therefore further irrigation is a direct waste. According to [16], up to 20% below the field capacity, the crop still maintains its productivity. Hence, we will limit volumetric water content below such value, which will be denoted $\overline{x}$.

In addition, the control action must also be kept within the feasible amount, that is, the maximum water flow that the irrigation system can provide, which will be denoted $\overline{u}$. Correspondingly, the following constraints must be satisfied during the operation:

$$x(k) \in \mathcal{X} = \{x : \underline{x} \le x \le \overline{x}\}, \quad \forall k, \tag{2a}$$

$$u(k) \in \mathcal{U} = \{u : 0 \le u \le \overline{u}\}, \quad \forall k. \tag{2b}$$

A reference point is defined, denoted x_{ref}, to which the controller will aim to drive the volumetric water content.

Finally, uncertainty must be modeled and used as will be described in Sections III and IV. We propose two different techniques to do so, according to historical real-world data. On the one hand, solar radiance is known to behave similarly through consecutive days in a quasi-periodic fashion. In this context, the stochastic variable used to model s is assumed to follow a normal distribution with mean μ and standard deviation σ, represented as $\mathcal{N}(\mu, \sigma^2)$. On the other hand, rain is not that constant, and neither does it follow Gaussian patterns. Hence, we propose considering a different approach to model precipitation uncertainty. This will consist of accounting for different possible scenarios according to past observations of actual precipitation periods.

III. STOCHASTIC MPC

In this section, the stochastic formulation applied to an irrigation system is proposed. Before that, a brief introduction to the standard model predictive control is provided.

A. MPC formulation

MPC is a control technique widely used in industrial processes due to its ability to deal with non-linearities, delays, and constraints on both input and output variables, among others [17]. The main idea behind this approach is to optimize an objective function over a prediction horizon (N_{p}) subject to the dynamic model and the constraints on input and output variables. The solution of the optimization problem results in a sequence of control along N_{p}, i.e., $U = \{u(k), u(k+1), \cdots, u(k+N_{\mathrm{p}}-1)\}$, where only the first element of the sequence is applied to the system at current time k. Then, the states are updated, and the problem is solved again at the next time step, $k+1$, in a receding horizon fashion.

The optimization problem is therefore defined as follows:

$$\min_{U} \sum_{i=k}^{k+N_{\mathrm{p}}-1} J(x(i), u(i)), \tag{3}$$

subject to

$$x(i+1) = Ax(i) + Bu(i) + B_w w(i), \tag{4a}$$
$$x(i+1) \in \mathcal{X},\ \forall i \in [k, k+N_\mathrm{p}-1], \tag{4b}$$
$$u(i) \in \mathcal{U},\ \forall i \in [k, k+N_\mathrm{p}-1]. \tag{4c}$$

Here, the objective cost function is defined as a quadratic function expressed by

$$J(x(k),\, u(k)) = (x_\mathrm{ref} - x(k))^\top Q(x_\mathrm{ref} - x(k)) + u(k)^\top R\, u(k), \tag{5}$$

where Q and R are semi-positive definite matrices. These matrices serve as weighting factors: Q is responsible for regulating the states to track a reference (x_ref), while R tunes the control effort applied to the inputs.

However, standard MPC (ST-MPC) does not consider uncertainties, necessitating the formulation of an MPC based on robust or stochastic techniques.

B. SMPC formulation

In stochastic MPC approaches, there are several ways of modeling and dealing with uncertainty. In this Section, we propose two different methods to cope with typical disturbances present in agriculture: precipitation and solar radiance. Namely, multi-scenario MPC will be considered for the former, and chance constraint MPC for the latter.

Multi-scenario MPC involves calculating a single control action that satisfies all evaluated scenarios, taking into account their respective probabilities of occurrence, as discussed in [18]. This approach has gained widespread popularity due to its versatility in implementation and its intuitiveness, as noted in [13], [19]. An advantageous aspect of MS-MPC is its ability to bypass the need for an initial characterization of uncertainty through a probability distribution function. Consequently, the optimization problem can be reformulated as an equivalent deterministic problem. Moreover, this approach guarantees a convex solution to the optimization problem, ensuring robustness against all probable disturbance evolutions.

The optimization problem to be solved at each time instant k consists in considering a given number of disturbance scenarios (N_s) and computing a single control sequence. The MS-MPC is formulated as follows.

$$\min_U \sum_{j=1}^{N_s} \rho_j \left(\sum_{i=k}^{k+N_\mathrm{p}-1} J(x_j(i), u(i)) \right), \tag{6}$$

subject to

$$x_j(i+1) = Ax_j(i) + Bu(i) + B_w w_j(i), \tag{7a}$$
$$x_j(i+1) \in \mathcal{X}, \tag{7b}$$
$$u(i) \in \mathcal{U}, \tag{7c}$$
$$w_j(k) = w(k), \tag{7d}$$

applied $\forall i \in [k, k+N_\mathrm{p}-1]$, and $\forall j \in [1, N_\mathrm{s}]$. Moreover, N_s represents a finite number of scenarios, and ρ_j signifies the probability associated with the occurrence of scenario j. The uncertainty w_j is the same for all scenarios at the initial time k but diverges along the prediction horizon, according to the scenario. It is important to note that the set of scenarios is updated at each time step, considering the known disturbance. Therefore,

$$\sum_{j=1}^{N_\mathrm{s}} \rho_j = 1.$$

As solar irradiance inherently exhibits stochastic behavior, ensuring compliance with constraints can be addressed using chance constraints. CC-MPC, an approach within this context, necessitates the characterization of uncertainty through a probability distribution function. It reformulates probabilistic constraints by considering their cumulative distribution function (cdf). This approach involves relaxing the initial constraints, which implies accepting a certain level of risk violation. The stochastic nature that affects constraint (2a), which involves the rain in the irrigation system, can be written in a probabilistic fashion as

$$\mathbb{P}\left[\underline{x} \leq x(k) \leq \overline{x}\right] \geq 1 - \delta_x. \tag{8}$$

Here, $\mathbb{P}[\cdot]$ represents the probability operator, and δ_x quantifies the risk of constraint violation. In this context, the probabilistic constraint, often referred to as a *chance constraint*, can be formulated in two ways: as joint or individual chance constraints, as discussed in [20]. For this study, we focus on the development of joint chance constraints. It is worth noting that solar irradiance can be modeled as a known cdf as follows.

$$\begin{aligned} &\mathbb{P}\left[x(i) \geq \underline{x}\right] \geq 1 - \delta_x \Leftrightarrow \phi_i\left(x(i) \geq \underline{x}\right) \geq 1 - \delta_x \Leftrightarrow \\ &\underline{x} - x(i) \geq \phi_i^{-1}\left(1 - \delta_x\right) \Leftrightarrow x(i) \leq \underline{x} - \phi_i^{-1}\left(1 - \delta_x\right), \\ &\forall i \in [k, k+N_\mathrm{p}-1]. \end{aligned}$$

In this context, ϕ_i represents the cdf corresponding to the random variable associated with the states over N_p time steps. Similarly, this procedure can be replicated to establish the equivalent deterministic chance constraint for the upper limit, resulting in

$$\begin{aligned} &\mathbb{P}\left[x(i) \leq \overline{x}\right] \geq 1 - \delta_x \Leftrightarrow \phi_i\left(-\overline{x} + x(i)\right) \geq 1 - \delta_x \Leftrightarrow \\ &-\overline{x} + x(i) \geq \phi_i^{-1}\left(1 - \delta_x\right) \Leftrightarrow x(i) \geq \overline{x} + \phi_i^{-1}\left(1 - \delta_x\right), \\ &\forall i \in [k, k+N_\mathrm{p}-1]. \end{aligned}$$

The cumulative distribution function can be derived from either a known stochastic cdf or constructed based on historical data. As explained in Section II, solar radiance is assumed to follow a normal distribution, whose cdf is tuned based on real-world measurements.

By considering both stochastic variables, the SMPC formulated using the best features of both approaches, MS-MPC and CC-MPC, can be expressed as

$$\min_{U} \sum_{j=1}^{N_s} \rho_j \left(\sum_{i=k}^{k+N_\mathrm{p}-1} \mathbb{E}\left[J(x_j(i), u(i)) \right] \right), \tag{9}$$

subject to

$$x_j(i+1) = Ax_j(i) + Bu(i) + B_w w_j(i), \tag{10a}$$
$$x_j(i+1) \geq \underline{x} - \phi_i^{-1}(1-\delta_x), \tag{10b}$$
$$x_j(i+1) \leq \overline{x} + \phi_i^{-1}(1-\delta_x), \tag{10c}$$
$$u(i) \in \mathcal{U}, \tag{10d}$$
$$w_j(k) = w(k), \tag{10e}$$
$$\forall i \in [k, k+N_\mathrm{p}-1] \text{ and } \forall j \in [1, N_\mathrm{s}].$$

Here, $\mathbb{E}[\cdot]$ represents the expected value of the objective function given by Equation (5).

IV. Case study

This section provides a description of the case study, presents the key findings, and offers a discussion leading to the formulation of conclusions.

A. Experimental setup

We propose a simulation case study based on a linearized discrete-time model of a real strawberry field located in Almonte, Spain. This model was first derived in [15]. The root zone is divided into $L = 4$ layers, whose volumetric water content evolve according to (1), being

$$A = \begin{bmatrix} 0.4153 & 0.6227 & -0.2378 & 0.1073 \\ 0.1353 & 0.7985 & 0.0905 & -0.0166 \\ 0.0053 & 0.0613 & 0.8894 & 0.0474 \\ 0.0012 & -0.0017 & 0.0518 & 0.9562 \end{bmatrix} \tag{11a}$$

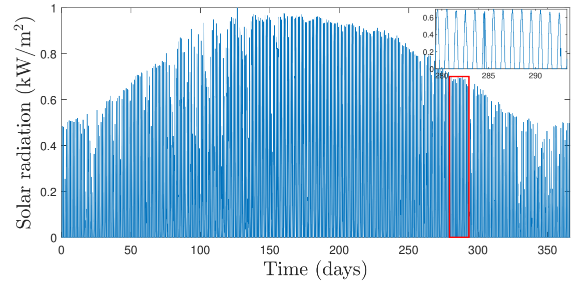
$$B = 1 \times 10^{-2} \times \begin{bmatrix} 3.57 & 0.33 & 0 & 0.01 \end{bmatrix}^\top, \tag{11b}$$

$$B_w = \begin{bmatrix} -0.6279 & 0.0357 \\ -1.2636 & 0.0033 \\ -1.3483 & 0.0000 \\ -1.1122 & 0.0001 \end{bmatrix} \otimes [1 \times 10^{-3} \quad 1]. \tag{11c}$$

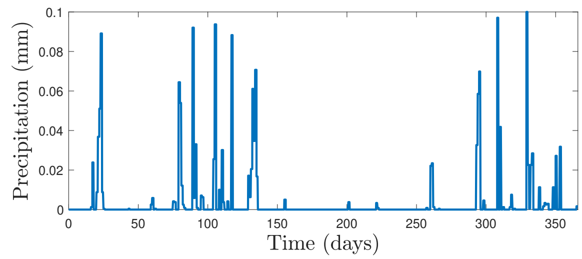
Here, input signals are normalized to match the identification procedure presented in [15].

The sampling time for the discrete-time model is set to $15\,\mathrm{min}$, while the prediction horizon is set to $N = 96$ samples (24 hours). The reference is given by $x_\mathrm{ref} = [0.1434, 0.1679, 0.2006, 0.2346]^\top$, and the constraints are given by $\underline{x} = 0.85 \cdot x_\mathrm{ref}$, $\overline{x} = 1.15 \cdot x_\mathrm{ref}$ and $\overline{u} = 1$.

Uncertainty is modeled based on data collected from real-world measurements, as explained next. Both precipitation and solar radiance data are obtained for the whole year 2020 at Seville's airport weather station in southern Spain. Data is provided by the Spanish State Meteorological Agency (AEMET) and can be accessed at [21]. They are shown in Figure 1. Notice that solar radiance exhibits two frequencies: an annual one and a daily one. Rain is more frequent during



(a) Solar radiance.



(b) Precipitation

Fig. 1: Solar radiance ($\mathrm{kW/m^2}$) and precipitation (mm) data obtained at Seville's airport during 2020. Sampling time of $15\,\mathrm{min}$. Data available at [21].

spring and fall, while pretty scarce in the Andalusia region of Spain.

Precipitation measurements are only available on a daily basis. In order to down-sample the values to match our sampling period of 15 minutes, we processed the data employing a zero-order holder, assuming a uniform distribution of the rain throughout the day. Similarly, solar radiance data is obtained hourly and then divided into equal periods of 15 minutes.

Next, the uncertainty models presented in Section II are obtained based on real observations. We adjust the solar radiation profile such that it follows $s \sim \mathcal{N}(2.0825, 2.8746) \times 10^{-7}$. On the other hand, precipitation is considered using $N_\mathrm{s} = 30$ different scenarios chosen from the observations mentioned before, with the same occurrence probability ρ.

The cost in the optimization problem is defined as per (5), using

$$Q = \mathrm{diag}([1, 10, 10, 1])/100,$$
$$R = 1.$$

Note that with such small values of Q over R, we aim to minimize the control effort, that is, the amount of water employed, while following a specific reference is not important, as long as moisture is kept within the constraints, given by the permanent wilting point and field capacity.

TABLE I: Comparison among MPC controllers by using PIs.

Controller	PI_1	PI_2	$\mathrm{PI}_3 \times 10^2$
SMPC	36.08	80.10	[13.16, 15.20, 17.81, 20.65]
ST-MPC	38.13	80.22	[13.16, 15.20, 17.81, 20.65]
Min-max MPC	37.42	80.19	[13.16, 15.20, 17.82, 20.65]
ID-MPC	30.99	79.98	[13.19, 15.24, 17.86, 20.71]

B. Results and discussion

Based on this framework, the stochastic model predictive control proposed in this paper is applied to the crop field. The risk of constraint violation is set to $\delta_x = 0.1$. The simulation is also applied to three other benchmark controllers in order to compare the performance of the proposed approach during a 15-day-long simulation. These are (i) a standard MPC (ST-MPC), as described in Section III, (ii) a min-max MPC, which is known for handling uncertainties by solving a twofold optimization problem, minimizing the objective cost while considering the worst-case scenario [22], and (iii) an ideal MPC (ID-MPC), in which future disturbances are known and accessible to the controller. Note that the latter is not feasible in practice, although it will be used to gain a sense of the best possible performance.

The results are shown in Figure 2, in which the four layers are depicted. The constraints are indicated with the dashed-dotted line, and the dashed line signals the reference. The decided irrigation command, and the actual realization of the disturbances are shown in the lower plots. To facilitate a trustworthy comparison among the controllers mentioned above, we have defined specific performance indicators (PI) during the simulation time.

- PI_1: Final cumulative cost, computed as

$$\mathrm{PI}_1 = \sum_{k=1}^{1440} J(x(k), u(k)). \tag{12}$$

- PI_2: The amount of irrigation water applied to the crop.
- PI_3: The mean value of each estate x_i for $i = \{1, 2, 3, 4\}$.

Table I displays the results obtained by evaluating the defined PIs through the application of the aforementioned MPC controllers.

When considering PI_1, which reflects cost efficiency, it can be seen that SMPC achieves the lowest cost efficiency at 36.08, while ST-MPC and Min-max MPC have higher values of 38.13 and 37.42, respectively. This discrepancy in PI_1 suggests that SMPC may be the most cost-efficient option among the three, approaching the performance of the ID-MPC. It is worth noting that the ID-MPC offers the minimum cost value due to its ideal nature, but it is physically unrealizable in practice. As can be seen, the Min-max MPC shows an over-conservatism due to its formulation based on the realization of the worst-case scenario. Regarding PI_2, it is important to highlight that SMPC stands out by offering the lowest value in terms of irrigation efficiency, closely approaching the ID-MPC. Finally, all controllers have successfully achieved values closely aligned with the desired references in terms of PI_3. Although there exist minor deviations in the precise values, it is evident that all controllers exhibit effectiveness in attaining the specified reference objectives. However, it is important to note that this achievement comes at the expense of incurring a higher final cumulative cost. In this comprehensive evaluation of various MPC strategies, it becomes evident that all controllers, including SMPC, ST-MPC, Min-max MPC, and the ideal but unrealizable ID-MPC, exhibit noteworthy performance in their respective domains. Overall, the proposed SMPC showcases cost-efficiency in agricultural operations, making it a potential cost-saving choice.

V. Conclusion

In this study, we have presented a novel approach in the field of MPC by integrating two prominent paradigms, CC-MPC and MS-MPC, into a unified SMPC formulation. This integration has enabled us to comprehensively manage uncertainties, providing new insights and opportunities in agriculture control systems.

Our proposed SMPC showed promising results in the performance evaluation. The controllers, including SMPC, ST-MPC, and Min-max MPC, demonstrated comparable performance in terms of cost efficiency and water irrigation resource management. All controllers performed well in tracking reference objectives, although this led to higher cumulative costs, indicating the inherent trade-off between reference tracking and cost optimization. Above all, the proposed approach outperforms others standard in expert literature.

Future directions will be focused on practically implementing the proposed SMPC approach in agricultural control systems. Validating the effectiveness of this approach under actual operating conditions requires addressing real-world uncertainties and disturbances.

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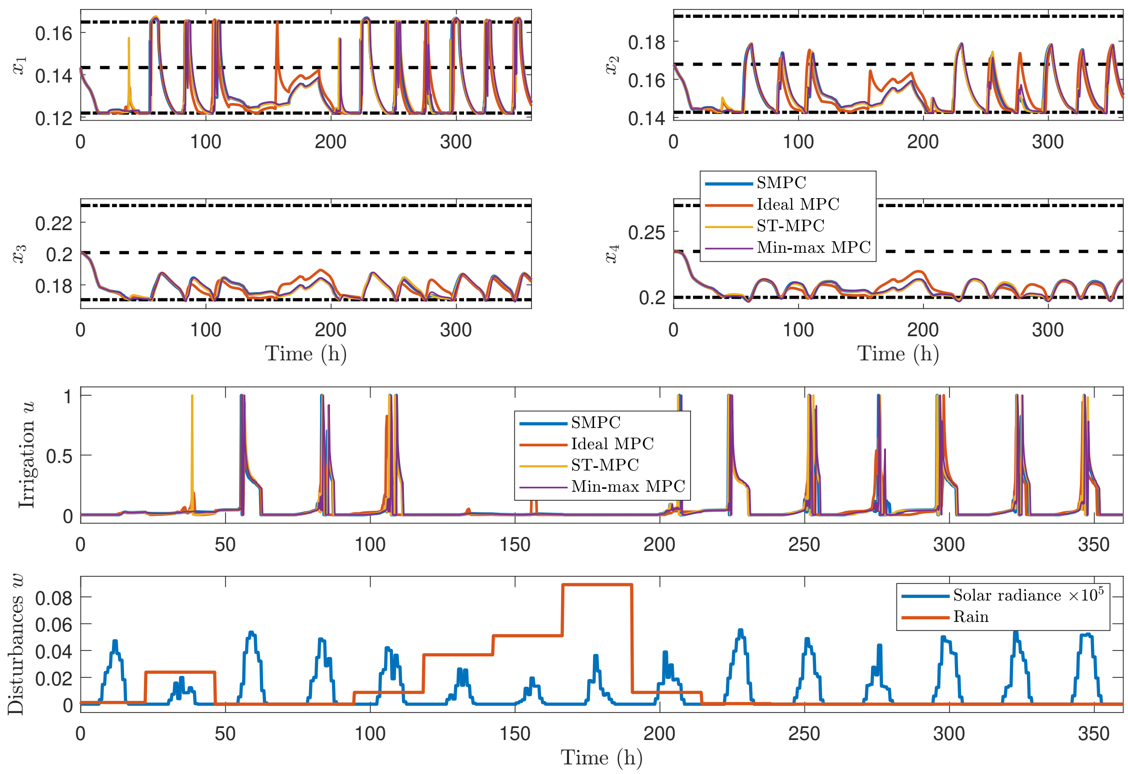

Fig. 2: Performance comparison of the different MPCs tested

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