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Towards an Improved Hierarchical Control Strategy for a Solar Thermal Power Plant

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Abstract— **This paper improves a recently proposed two-layer hierarchical control strategy for the ACUREX plant at the Plataforma Solar de Almería. Improvements target the lower layer of the two-layer hierarchical control strategy. Two alternative systematic approaches are proposed and evaluated. The two approaches take explicit account of the measured disturbances. Improvements are illustrated by way of some simulation scenarios and measured data from the ACUREX plant.**

I. Introduction

ACUREX is a parabolic trough-based solar thermal power plant. It is one of the research facilities at the Plataforma Solar de Almería (PSA) owned and operated by the Spanish research centre for energy, environmental studies and technology (CIEMAT). The PSA is located in south-east Spain and is considered the largest research centre in Europe for concentrating solar technologies.

ACUREX has served as a benchmark for many researchers across academia and industry working in process modelling and control. The plant is mainly composed of a distributed solar collector field, a thermal storage tank and a power unit; solar radiation is the main source of energy, however, ironically it acts as a disturbance to the plant due to the daily cycle of radiation and passing clouds. Due to the stratified tank technology used for storing the thermal energy of the plant, the field inlet temperature is also a dominant disturbance to the plant. Hence, designing an effective control strategy that can handle the constant changes in solar radiation and the field inlet temperature while maintaining the field outlet temperature at a desired level will enable longer plant operating hours and cost reductions [1].

Recent work proposed, an effective two-layer hierarchical control strategy [2] to automatically operate the ACUREX plant without intervention from the plant operator and without adding cost. Taking into account the status of solar radiation and the field inlet temperature (measured disturbances), an adequate reachable reference temperature (set point) is generated from an upper layer while satisfying the plant safety constraints. Due to the nature of hierarchy, a gain scheduling (GS) predictive control strategy is adopted in a lower layer. It was shown [2] that the generated reference temperature works indirectly as feedforward to the lower layer and hence the role of the GS predictive control strategy at the lower layer was merely for set point tracking and coping with the plant nonlinear dynamics. Therefore, the main objective of this paper is to improve the feedback control performance at the lower layer by taking explicit account of the measured disturbances. This is achieved here through two alternative approaches:

- The first approach utilises a recently proposed GS feedforward predictive control strategy [3] that assumes the availability of the current measurements of solar radiation and the field inlet temperature.
- The second approach utilises a variant of the GS feedforward predictive control strategy that assumes the availability of the expected future behaviour of solar radiation and the field inlet temperature. This approach is developed here as such an assumption has received little attention in the literature.

Apart from the proposed strategies in [4], [5], hierarchical control for the ACUREX plant has received little attention. While no feedforward to account for the measured disturbances has been reported in [5] and a rather simple classical parallel feedforward has been designed for the lower layer in [4] based on steady state energy balance, the two approaches proposed here for the lower layer incorporate feedforward more systematically into a predictive control strategy by including the dynamic effects of the measured disturbances of the ACUREX plant into the predictions of future outputs.

The efficacy of both approaches within a two-layer hierarchical control structure will be illustrated by way of some simulation scenarios and measured data from the ACUREX plant. The plant description is outlined in Section II, Section III discusses briefly a nonlinear simulation model of the Plant, Section IV gives an overview of the to be improved two-layer hierarchical control strategy. Section V introduces the proposed approaches to improve the two-layer hierarchical control strategy given in Section IV. Section VI illustrates the efficacy of both approaches within a two-layer hierarchical control structure for two common scenarios and finally conclusions are given in section VII.

II. Plant Description

Collectors of the ACUREX plant are parabolic in shape and concentrate the incident solar radiation onto a receiver tube that is placed at its focal line; see Fig. 1. The distributed solar collector field consists of 480 east-west single axis collectors arranged in 10 parallel loops with 48 collectors in each loop. Electricity is generated through the following process. A heat transfer fluid (HTF) is heated as it flows through

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the receiver tube and circulates through the distributed solar collector field. The heated HTF then passes through a series of heat exchangers to produce steam which in turn is used to drive a steam turbine to generate electricity.

Fig. 1: ACUREX distributed solar collector field.

The control problem at the ACUREX plant is to maintain the field outlet temperature at a desired level despite changes, mainly in solar radiation and the field inlet temperature. The approach to this is by efficiently manipulating the volumetric flow rate of the HTF within a certain range (0.002-0.012 m^3/s). For a detailed description of the plant, see [1].

III. Nonlinear Simulation Model of the Plant

The ACUREX plant is represented in this paper by a nonlinear simulation model. The model is constructed based on a nonlinear distributed parameter model of the plant and has been recently validated in [3]. The dominant dynamics of the ACUREX plant are captured by the following set of energy balance partial differential equations (PDEs):

$$\begin{aligned} &\rho_m C_m A_m \frac{\partial T_m}{\partial t} = n_o G I - D_o \pi H_l (T_m - T_a) \\ &-D_i \pi H_t (T_m - T_f) \\ &\rho_f C_f A_f \frac{\partial T_f}{\partial t} + \rho_f C_f q \frac{\partial T_f}{\partial x} = D_i \pi H_t (T_m - T_f) \end{aligned} \tag{1}$$

where the subindex m refers to the metal of the receiver tube and f to the HTF [1]. Table I gives a description of all the variables and parameters and lists their SI units.

A nonlinear simulation model of the plant has been constructed in [6] by dividing the receiver tube into N segments each of length Δx and hence the nonlinear distributed parameter model in (1) has been approximated by the following set of ordinary differential equations (ODEs):

$$\left.\begin{aligned} &\rho_m C_m A_m \frac{dT_{m,n}}{dt} = n_o G I \\ &-D_o \pi H_l (T_{m,n} - T_a) \\ &-D_i \pi H_t (T_{m,n} - T_{f,n}) \\ &\rho_f C_f A_f \frac{dT_{f,n}}{dt} + \rho_f C_f q \frac{T_{f,n} - T_{f,n-1}}{\Delta x} \\ &= D_i \pi H_t (T_{m,n} - T_{f,n}) \end{aligned}\right. , \quad n = 1, ..., N \tag{2}$$

with the boundary condition $T_{f,0} = T_{f,inlet}$ (field inlet temperature) and H_l,H_t,ρ_f and C_f being time−varying.

It has been shown [6] that dividing the receiver tube into 7 segments ($N = 7$) is a reasonable trade-off between the prediction accuracy and computational burden while still adequate enough to capture the resonant modes of the plant.

Remark 1: The set of ODEs (2) is implemented and solved using the MATLAB solver ODE45 (an explicit Runge-Kutta method) where the temperature distribution in the receiver tube and HTF can be accessed at any point in time and for any segment n. The number of ODEs solved at each sample time k for N segments is $2 \times N$.

In summary, the ACUREX plant is represented in this paper by the nonlinear simulation model described in (2).

TABLE I: Variables and Parameters.

Symbol	Description	SI unit
ρ	Density	kg/m^3
C	Specific heat capacity	J/kg°C
A	Cross-sectional area	m^2
T	Temperature	°C
t	Time	s
I	Solar radiation	W/m^2
n_o	Mirror optical efficiency	−
G	Mirror optical aperture	m
D_o	Outer diameter of the receiver tube	m
H_l	Global coefficient of thermal losses	W/m°C
T_a	Ambient temperature	°C
D_i	Inner diameter of the receiver tube	m
H_t	Metal-fluid heat transfer coefficient	W/m^2°C
q	HTF volumetric flow rate	m^3/s
x	Space	m

IV. Two-Layer Hierarchical Control Structure

The main objective of this paper is to improve the feedback control performance at the lower layer of the recently proposed two-layer hierarchical control strategy [2]. More specifically, the aim is to take systematic account of the measured disturbances at the lower layer. Before establishing how this aim is achieved, readers need to be familiar with the basic concepts of this two-layer hierarchical control strategy.

A. Overview

A novel pragmatic approach was proposed in [2] to drive the plant near optimal operating conditions by generating a reference temperature that is adequate, reachable and smoothly adapted to changes in solar radiation and the field inlet temperature while also satisfying the plant safety constraints. Conceptually, the approach has a hierarchical structure, namely upper and lower layers.

B. Upper layer

The approach to generate the reference temperature at the upper layer is intuitive and makes use of system identification. Given the process time constant and taking into account the frequency response of the plant, linear time-invariant (LTI) state space models of solar radiation and the field inlet temperature are estimated around 5 nominal operating points across the whole range of the flow rate (0.002-0.012 m^3/s). The estimated models establish a clear, direct and dynamic relationships with the field outlet temperature (reference temperature). Each LTI state space model takes the form:

$$x_{k+1} = A x_k + B u_k; \quad y_k = C x_k \tag{3}$$

where $x_k \in \mathbb{R}^{n\times 1}$, $u_k \in \mathbb{R}^{m\times 1}$ and $y_k \in \mathbb{R}^{l\times 1}$ are the state vector, input vector and output vector at sample k. $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$ and $C \in \mathbb{R}^{l\times n}$ are the coefficient matrices.

In particular, for each of the 5 operating points, a complete one-step ahead prediction model predicts the *best* reference temperature, given the measurements of solar radiation and the field inlet temperature, as follows:

$$\begin{aligned}
\underbrace{\begin{bmatrix} x^I_{k+1} \\ x^{T_{f,inlet}}_{k+1} \end{bmatrix}}_{x^i{}_{k+1}} &= \underbrace{\begin{bmatrix} A^I & 0 \\ 0 & A^{T_{f,inlet}} \end{bmatrix}}_{A^i} \underbrace{\begin{bmatrix} x^I_k \\ x^{T_{f,inlet}}_k \end{bmatrix}}_{x^i{}_k} \\
&+ \underbrace{\begin{bmatrix} B^I & 0 \\ 0 & B^{T_{f,inlet}} \end{bmatrix}}_{B^i} \underbrace{\begin{bmatrix} I_k \\ T_{f,inlet_k} \end{bmatrix}}_{u_k} \\
T^i{}_{ref\,k} &= \underbrace{\begin{bmatrix} C^I & C^{T_{f,inlet}} \end{bmatrix}}_{C^i} \underbrace{\begin{bmatrix} x^I_k \\ x^{T_{f,inlet}}_k \end{bmatrix}}_{x^i{}_k}
\end{aligned} \tag{4}$$

where $i \in \{1, 2, 3, 4, 5\}$ and T_{ref} is the reference temperature. Due to the nonlinear dynamic behaviour of the plant, a mean value of the generated reference temperatures is considered for the lower layer. It is obvious from (4) how the reference temperature works indirectly as feedforward for the lower layer.

C. Lower layer

A GS predictive control strategy has been adopted at the lower layer for set point tracking and coping with the plant nonlinear dynamics. The GS predictive control strategy has been proposed in [7] and tailored to the ACUREX plant. A notable feature of the control strategy is the design of the scheduling variable. Given a nonlinear lumped parameter model of ACUREX plant reported in [1] and under certain assumptions, the scheduling variable takes the form:

$$Q = \frac{n_o S I}{P_{cp}(T_{ref} - T_{f,inlet})} \tag{5}$$

where Q here is an approximate representation of the flow rate (control signal) q, S is the solar field effective surface and P_{cp} is a factor that takes into account some geometrical and thermal properties.

This draws attention to the point that the control design at the lower layer is consistent with the reference temperature design at the upper layer, i.e. as the generated reference temperature is being smoothly adapted to changes in solar radiation and the field inlet temperature at the upper layer, the scheduling variable at the lower layer is simultaneously being adapted to changes in solar radiation and the field inlet temperature, as well as the generated reference temperature.

The scheduling variable Q switches on-line among 4 local linear model-based predictive controllers as the plant dynamics change with time or operating conditions. For a selected local controller and at each sample time k, an optimisation is performed seeking a future sequence of control moves. Nevertheless, the optimisation takes no direct account of the measured disturbances.

V. Proposals for Improved Algorithms

The feedback control performance at the lower layer of the two-layer hierarchical control strategy [2] is improved here to take explicit and systematic account of the measured disturbances of the ACUREX plant. Two approaches are considered based on two different assumptions. As will be shown later, incorporating a feedforward into the lower layer has the potential benefits of improving the actuator dynamics.

The first approach utilises a recently proposed GS feedforward predictive control strategy [3] that assumes the availability of current measurements of solar radiation and field inlet temperature. The second approach utilises a variant of the GS feedforward predictive control strategy that assumes availability of the expected future behaviour of solar radiation and the field inlet temperature for a given prediction horizon. The second approach is developed here and its efficacy with respect to the first approach is evaluated in a later section. An essential step to ensure that the measured disturbances are accounted for by both approaches at the lower layer is to ensure that, at a given operating point, the local process model includes the disturbance dynamics. This is discussed next.

A. Local process model with measured disturbances

Due to the nonlinearity of the ACUREX plant, local LTI state space models relating the volumetric flow rate of the HTF (q) to the field outlet temperature (T_f) were estimated in [7] directly from input-output data around 4 nominal operating points. Each LTI state space model takes the form of (3). Predictions of these models were improved in [3] by estimating dynamic LTI state space models models of solar radiation (I) and the field inlet temperature ($T_{f,inlet}$) around the same nominal operating points. Hence, at a given operating point, a local process model can be augmented to include the disturbance dynamics, for $j \in \{1, 2, 3, 4\}$, as follows:

$$\begin{aligned}
\underbrace{\begin{bmatrix} x^q_{k+1} \\ x^I_{k+1} \\ x^{T_{f,inlet}}_{k+1} \end{bmatrix}}_{x^j_{k+1}} &= \underbrace{\begin{bmatrix} A^q & 0 & 0 \\ 0 & A^I & 0 \\ 0 & 0 & A^{T_{f,inlet}} \end{bmatrix}}_{A^j} \underbrace{\begin{bmatrix} x^q_k \\ x^I_k \\ x^{T_{f,inlet}}_k \end{bmatrix}}_{x^j_k} \\
&+ \underbrace{\begin{bmatrix} B^q & 0 & 0 \\ 0 & B^I & 0 \\ 0 & 0 & B^{T_{f,inlet}} \end{bmatrix}}_{B^j} \begin{bmatrix} q_k \\ I_k \\ T_{f,inlet_k} \end{bmatrix} \\
y^j_k &= \underbrace{\begin{bmatrix} C^q & C^I & C^{T_{f,inlet}} \end{bmatrix}}_{C^j} \underbrace{\begin{bmatrix} x^q_k \\ x^I_k \\ x^{T_{f,inlet}}_k \end{bmatrix}}_{x^j_k}
\end{aligned} \tag{6}$$

Remark 2: Regardless of the assumptions made about the future of the measured disturbances, the local process model in (6) is a core component of both GS feedforward predictive control strategies discussed next.

B. First approach

This first approach is a GS feedforward model-based predictive control (MPC) and has been proposed in [3]. This approach assumes the following:

- The availability of the current measurements of solar radiation I and the field inlet temperature $T_{f,inlet}$ at sample time k.
- $I_k = I_{k+1} = ... = I_{ss}$ and similarly $T_{f,inlet_k} = T_{f,inlet_{k+1}} = ... = T_{f,inlet_{ss}}$, where I_{ss} and $T_{f,inlet_{ss}}$ are steady-state estimates of solar radiation and the field inlet temperature respectively.

Given these assumptions and the local process model in (6), the optimisation required to find the future sequence of control moves, at a given operating point, takes the form:

$$\min_{\underset{\to}{\bar{q}}} \quad \underset{\to k-1}{\bar{q}^T} S \underset{\to k-1}{\bar{q}} + \underset{\to k-1}{\bar{q}^T} L\bar{x}_k \quad \text{s.t.} \quad \beta \underset{\to}{\bar{q}} \leq \gamma \tag{7}$$

where $\underset{\to k-1}{\bar{q}} = [\bar{q}_k^T \quad \bar{q}_{k+1}^T \quad ... \quad \bar{q}_{k+n_c-1}^T]^T$ and n_c is the number of control moves. S and L depend upon the matrices A, B^q, weighting matrices of appropriate dimensions δ and λ and terminal weight P obtained from an appropriate Lyapunov equation. β is time-invariant and γ depends upon the system past input-output information. Note that $\bar{q}$ and $\bar{x}$ are the deviation from estimated steady-state values q_{ss} and x_{ss} respectively. For detailed treatment of this and full definitions of the various variables and parameters see [3].

Algorithm 1

1: For each of the nominal operating points and given the local process model in (6), define the parameters in (7).
2: For a selected local controller and at each sampling instant, perform the optimization in (7).
3: Solve for the first element of $\underset{\to}{\bar{q}}$ and implement on process.

C. Second approach

A notable contribution of this paper is the development of this second approach. It is a variant of the GS feedforward MPC [3] and assumes the following:

- The availability of n_a-step ahead predictions of solar radiation I and the field inlet temperature $T_{f,inlet}$ at sample time k.
- $I_k \neq I_{k+1} \neq ... \neq I_{ss}$ and similarly $T_{f,inlet_k} \neq T_{f,inlet_{k+1}} \neq ... \neq T_{f,inlet_{ss}}$, where I_{ss} and $T_{f,inlet_{ss}}$ in this case are I_{k+n_a} and $T_{f,inlet_{k+n_a}}$ respectively.

Remark 3: To keep a neat and compact algorithm, the prediction horizon of solar radiation and the field inlet temperature are assumed to be the same.

This second approach builds on the control design in [3], where a single local feedforward MPC was designed around a given operating point with n_a-step ahead predictions of solar radiation. More specifically and within a gain scheduling framework, it extends the control design to cover the whole range of operation and considers n_a-step ahead predictions of both solar radiation and the field inlet temperature. Hence, given the above assumptions and the local process model (6), the optimisation required to find the future sequence of control moves, at a given operating point, takes the form:

$$\min_{\underset{\to}{\bar{q}}} \quad \underset{\to k-1}{\bar{q}^T} S \underset{\to k-1}{\bar{q}} + \underset{\to k-1}{\bar{q}^T} L\bar{x}_k + \underset{\to k-1}{\bar{q}^T} M \underset{\to k-1}{\bar{I}} + \underset{\to k-1}{\bar{q}^T} N \underset{\to k-1}{\bar{T}_{f,inlet}} \quad \text{s.t.} \quad \beta \underset{\to}{\bar{q}} \leq \gamma \tag{8}$$

where M depends upon A, B^q, B^I, δ and P, and similarly N depends upon A, B^q, $B^{T_{f,inlet}}$, δ and P. For detailed definitions of these variables and parameters see [3].

Algorithm 2

1: For each of the nominal operating points and given the local process model in (6), define the parameters in (8).
2: For a selected local controller and at each sampling instant, perform the optimization in (8).
3: Solve for the first element of $\underset{\to}{\bar{q}}$ and implement on process.

Remark 4: Given n_a-step ahead predictions of solar radiation and the field inlet temperature and with slight modifications to the one-step ahead prediction model in (4), one can in fact obtain n_a-step ahead predictions of the reference temperature. It has been shown in [8] that an effective use of advance information on set point changes within an optimum predictive control law can be advantageous and beneficial and yet this has been little studied in the context of solar plant.

D. Summary

This section has proposed two algorithms to improve the feedback control performance at the lower layer of a two-layer hierarchical control strategy [2]. The two algorithms both make explicit use of the measured disturbances, but based on two different assumptions. The schematic diagram in Fig. 2 gives an insight into the overall control design and information flow. To put it succinctly, a notable improvement to the two-layer hierarchical control strategy [2] is achieved by systematic incorporation of feedforward action into the predictive control strategy represented in Fig. 2.

VI. Evaluation

In this section, the efficacy of Algorithm 1 and Algorithm 2 at the lower layer of a two-layer hierarchical control strategy is illustrated by way of some simulation scenarios and, at some point, some measured data from the ACUREX plant. More specifically:

- Using some measured data from the ACUREX plant, the first scenario illustrates that incorporating Algorithm 1 at the lower layer of the two-layer hierarchical control strategy [2] improves the feedback control action. This is illustrated by comparison with the original algorithm, that is, a standard gain scheduling model-based predictive control (GSMPC) strategy.

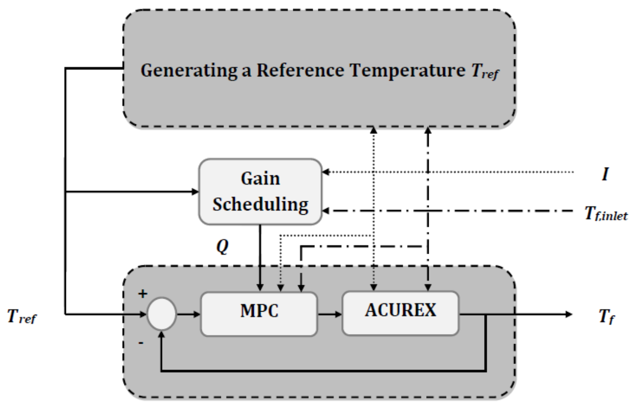


Fig. 2: Two-layer hierarchical control structure.

- The second scenario illustrates by way of comparison between Algorithm 1 and Algorithm 2 the behaviour during drastic changes in solar radiation due to thick and scattered passing clouds. While the field inlet temperature is at steady-state, Algorithm 2 shows a better set point tracking performance and lower cost of regulation provided that the prediction horizon is sufficiently large.

A. First scenario

This scenario compares the feedback control performance of Algorithm 1 with the feedback control performance of the GSMPC algorithm originally used at the lower layer in [2]. The reference temperature shown in Fig. 3 (b) is generated using measurements of solar radiation and the field inlet temperature shown in Fig. 3 (a). These measurements were collected from the ACUREX plant on 15 July 2003.

One can notice from Fig. 3 (b) that both algorithms show very similar set point tracking performance, which is not a surprise because the reference temperature, as mentioned before, is already working indirectly as feedforward for the lower layer. Hence, any improvement is due to the explicit use of the measured disturbance information by Algorithm 1 and this should be apparent in the feedback control action.

The solar radiation is constantly subject to changes due to its daily cycle and passing clouds. The measured solar radiation shown in Fig. 3 (a) is a fine example of both. Yet and despite the transient behaviour of the measured field inlet temperature also shown in Fig. 3 (a), it is fairly obvious from the actuator dynamics in Fig. 3 (c), before 12.5 hr for transients and after 12.5 hr for steady-state, that Algorithm 1 is coping very well with these conditions when compared with the GSMPC algorithm. Fig. 3 (d) shows the switching from one local predictive controller to another across the whole range of operation and one can clearly see that both algorithms have a matching switching performance.

B. Second scenario

The scenario here compares the feedback control performance of Algorithm 1 with the feedback control performance of Algorithm 2 at the lower layer of a two-layer hierarchical

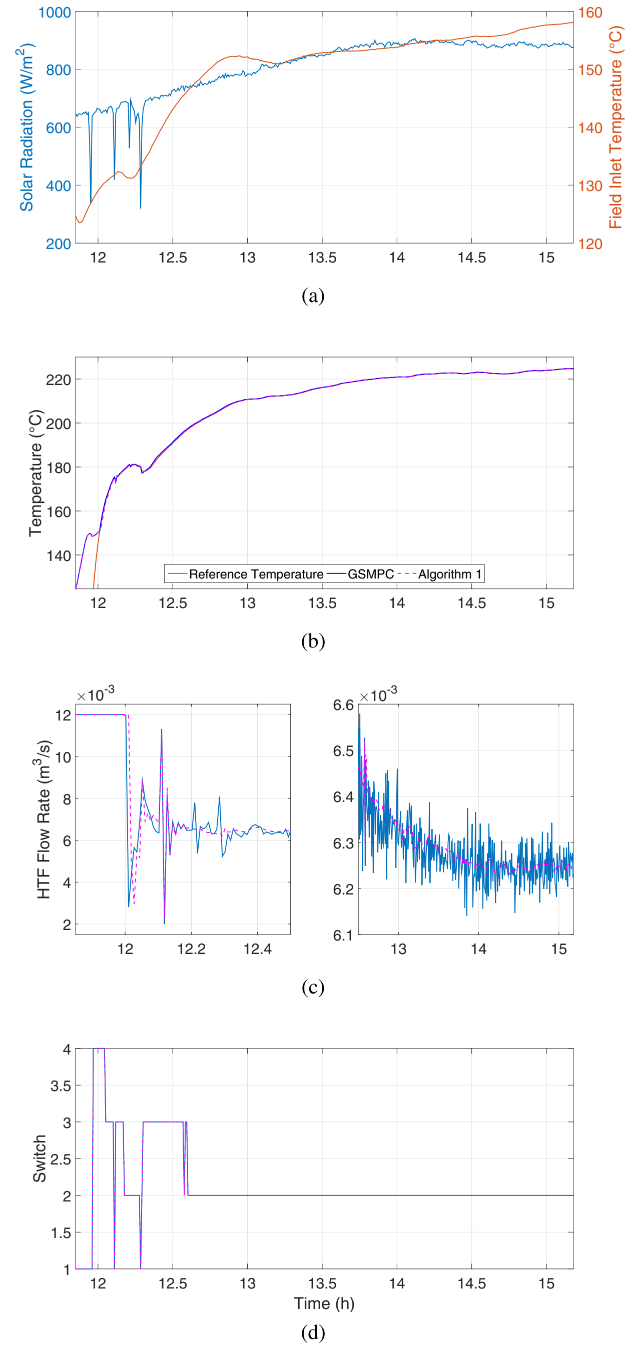


Fig. 3: First scenario: Control performance of GSMPC against Algorithm 1.

control strategy. The scenario is quite extreme. While the field inlet temperature as shown in Fig. 4 (a) is at steady-state, solar radiation as shown in Fig. 4 (a) is experiencing some drastic changes due to thick and passing clouds.

Just before 12.15 hr, the control performance of Algorithm 1 is quite similar to the control performance of Algorithm 2 as shown in Fig. 4 (c). Note that Algorithm 2 has a prediction horizon of 32.5 min. After 12.15 hr and due to the strong changes in solar radiation, some differences in the control performance start to emerge. As a general perception and while both algorithms have a matching switching performance as shown in Fig. 4 (d), one can notice that the sudden, sharp changes in the control actions are more obvious in Algorithm 1. To be more precise, the set point tracking performance has been assessed for both algorithms as well as the cost of regulation during the large changes in solar radiation. It has been found that Algorithm 2 has a lower root mean square error (RMSE) and cost of regulation than Algorithm 1 by about 9.2% and 2.6% respectively. Despite the apparent benefits of Algorithm 2, it is fair to say that the control signal in general has experienced some large changes in response to the relatively large changes in solar radiation which could result in undesired wear in the actuator.

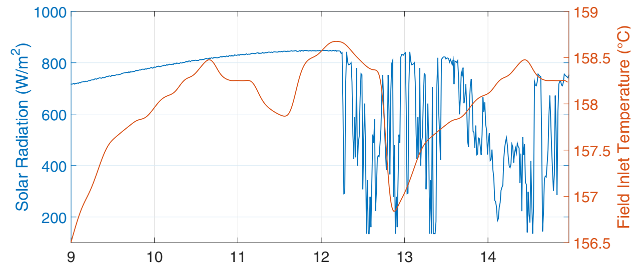
VII. Conclusions

This paper has improved a recently proposed two-layer hierarchical control strategy for the ACUREX plant. Improvements targeted the lower layer of the two-layer hierarchical control strategy by taking explicit account of the measured disturbances systematically through two main approaches.

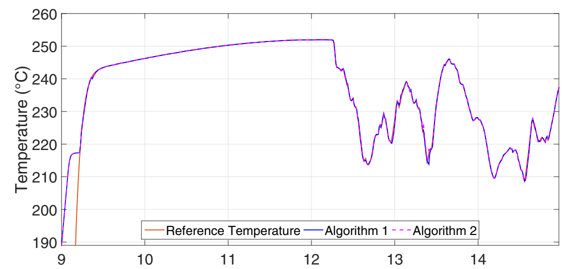
The first approach assumes the availability of the current measurements of solar radiation and the field inlet temperature and when compared to the algorithm that was originally used in [2], it has shown by way of a simulation scenario and measured data from the ACUREX plant that an improvement to the actuator dynamics can indeed be achieved.

A notable contribution of this paper is the development of the second approach that assumes the availability of the expected future behaviour of solar radiation and the field inlet temperature along a given prediction horizon. Although simulation results have shown only small improvements in set point tracking and cost of regulation, when compared with the first approach, it is worth noting that the choice of the prediction horizon was not optimal and hence future research might consider investigating questions like: *How far ahead should one predict?* and accordingly *How significant can the improvements be?* Obviously, this has to be in accordance with the forecasting models available in the existing literature.

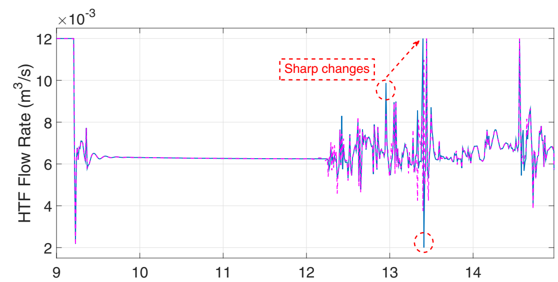
While in [9] it has been shown that accurate forecasting of solar radiation is achievable for short forecast horizon, forecasting the field inlet temperature is indeed an area that has not been looked at. Forecasting the field inlet temperature could be of a particular importance during the transient (start-up) phase of the plant where changes are mostly noticed.



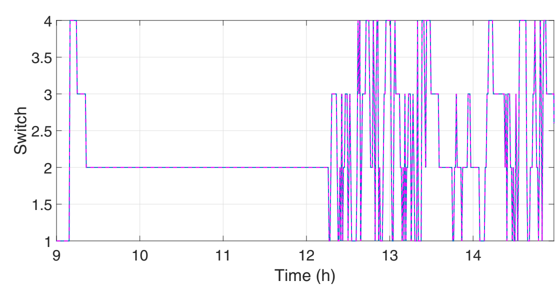
(a)



(b)



(c)



(d)

Fig. 4: Second scenario: Control performance of Algorithm 1 against Algorithm 2.

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