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Dual Mode MPC for a Concentrated Solar Thermal Power Plant

A. Alsharkawi * **J. A. Rossiter** **

* *Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield, S1 3JD, UK (e-mail: aalsharkawi1@sheffield.ac.uk*
** *Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield, S1 3JD, UK (e-mail:j.a.rossiter@sheffield.ac.uk*

Abstract: A model predictive control strategy for a concentrated solar thermal power plant is proposed. Design of the proposed controller is based on an estimated linear time-invariant state space model around a nominal operating point. The model is estimated directly from input-output data using the subspace identification method and taking into account the frequency response of the plant. Input-output data are obtained from a nonlinear distributed parameter model of a plant rather than the plant itself. Effectiveness of the proposed control strategy in terms of tracking and disturbance rejection is evaluated through two different scenarios created in a nonlinear simulation environment.

Keywords: Concentrated solar thermal power plant; Parabolic trough; Nonlinear distributed parameter model; Resonant modes; Subspace identification; Model predictive control.

1. INTRODUCTION

It takes only a quick look at the latest world energy statistics IEA (2014) to realise the steady increase in the consumption of fossil fuels (coal, oil and natural gas) and electricity and more importantly the contribution of fossil fuels to the CO_2 emissions over the years. Hence, there is an urgent need to produce marketable electricity from clean and sustainable alternatives to fossil fuels. Solar energy is one of the most promising existing alternatives. It can be converted into electrical energy by two main approaches; a direct approach using photovoltaic (PV) technology and an indirect approach using concentrated solar power (CSP) technology, where electricity is produced by thermal means Goswami et al. (2000). Future scenarios for some of the promising areas for solar energy applications show that CSP plants will play a major role in the long-term energy supply and thus a key element for grid stabilisation and power security while PV plants will be limited to decentralised applications. CSP plants produce electricity by converting the solar energy into stored heat energy and then use this to drive a power cycle, for instance a steam turbine or a heat engine Aringhoff et al. (2005). Parabolic trough, linear Fresnel reflector, solar tower and parabolic dish are the four main CSP technologies. Of these, parabolic trough stands out among these technologies as the most mature and reliable technology and indeed parabolic trough forms the bulk of the current commercial CSP plants Philibert (2010).

From a control point of view, maintaining the thermal variables in a CSP plant close to their desired levels to enable stable power production is far more challenging than in a conventional fossil fuel power plant due to the intermittency of solar energy and therefore efficient and advanced control strategies are required. In addition to Camacho et al. (2012), a comprehensive survey of the modelling and control of parabolic trough CSP plants is presented in Camacho et al. (2007a,b).

The parabolic trough ACUREX plant is considered in this paper. This plant exhibits some important dynamics, namely resonant modes and for a linear control system, high order linear models are required to capture these dynamics and attain a high control performance Camacho et al. (2012). However, obtaining convenient high order linear models analytically is not an easy task due to the nonlinearities and complexities of the plant Álvarez et al. (2009). An empirical approach has been found to be more reasonable as in Camacho et al. (1997); Johansen et al. (2000) where explicit recognition of the plant resonant modes through the estimation of high order linear models for different operating points is reported. High order local linear ARX type models are estimated using experimental data from the plant. These local models formed the basis for the design of gain scheduling control strategies. Both control strategies have a family of local linear controllers that correspond to the different operating points and a scheduling criteria to switch among these controllers as the plant dynamics change with time or operating conditions. As part of their evaluation process, the performance of the scheduling controller is compared to the performance of a single local linear controller over a wide range of operation. Without a doubt, the gain scheduling controller has been shown to be superior to the single controller. However, even though the simulation results and the real implementations on the plant have shown good performance of the control strategies, improvements can still be made. For example, safety constraints on the manipulated and controlled variables of the process have been completely ignored in the control system design in Johansen et al. (2000) and poorly investigated in Camacho et al. (1997) when the controlled variable was only restricted to not exceed a desired reference under any circumstances; this resulted in a severe performance degradation in the presence of disturbances. Moreover, since the linear models have been estimated from experimental data of the plant, an optimal model accuracy will never be achieved due to the slow dynamics of the plant and the fast changes in the operating conditions within a limited time frame. That is evident in Johansen et al. (2000) when the plant was perturbed with Pseudo-Random Binary sequence (PRBS) signals without taking into account the prior knowledge of the process. Three local models were estimated for three different operating points. Gains of the three local models had to be corrected around a nominal solar radiation value due to the changes in the solar radiation during the PRBS tests and one of the local models was unable to capture the resonant modes of the plant accurately which was attributed to the poor PRBS design. The PRBS design in terms of frequency band and amplitude is not reported in Camacho et al. (1997).

This paper takes into account the frequency response of the plant and embeds prior knowledge of the process and then estimates a linear time-invariant (LTI) state space model around a nominal operating point using the subspace identification method. Input-output data are obtained from a nonlinear distributed parameter model of the plant rather than the plant itself. The paper also incorporates the plant safety constraints. A final contribution is to implement and demonstrate the efficacy of a dual mode model-based predictive control (MPC) strategy for tracking and disturbance rejection over a wide range of operation for the nonlinear model. Apart from the plant characteristics that need an advanced control strategy to cope with the changing dynamics, nonlinearities and uncertainties Camacho et al. (2012), the main motivation for implementing the dual mode MPC strategy is due to its ability to do online constraint handling in a systematic fashion. Specifically, the dual mode MPC gives a handle on the predictions over an infinite horizon while still allowing a sensible limit on the number of control degrees of freedom (d.o.f) and constraints.

This paper is organised as follows: section 2 gives a brief description to the plant and control problem; section 3 discusses the mathematical modelling of the plant; section 4 describes the phenomena of resonant modes and the identification process; section 5 outlines the dual mode MPC design. This is then followed by section 6 where the simulation results are presented and finally, the main findings and some concluding remarks are presented in section 7.

2. PLANT DESCRIPTION AND CONTROL PROBLEM

ACUREX is a parabolic trough technology-based concentrated solar thermal power plant. Collectors of this type of technology are parabolic in shape and concentrate the incident solar radiation onto a receiver tube that is placed at its focal line. A heat transfer fluid (HTF) is heated as it flows along the receiver tube and then passes through a series of heat exchangers to produce steam that is used to drive a conventional steam turbine to generate electricity Aringhoff et al. (2005).

The plant is one of the research facilities at the Plataforma Solar de Almera (PSA) in the province of Almeria in south-east Spain and has served as a benchmark for many researchers across academia and industry. ACUREX is mainly composed of a distributed solar collectors field, a thermal storage tank, and a power unit. One of the biggest challenges in such a plant is to maintain the field outlet temperature at a desired level regardless of any changes, mostly in solar radiation, field inlet temperature, or ambient temperature. This is can only be achieved by manipulating the volumetric flow rate of the HTF. A schematic diagram of the plant is shown in Fig. 1 and a more detailed description of the plant can be found in Camacho et al. (2012).

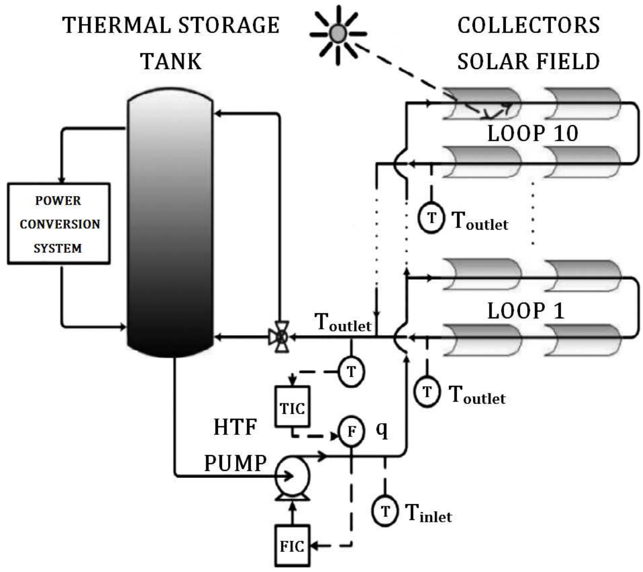

Fig. 1. ACUREX schematic diagram. Figure adapted from Álvarez et al. (2008).

3. MATHEMATICAL MODEL

This section presents a mathematical model of the ACUREX plant. A nonlinear distributed parameter model for simulation purposes is discussed first and this is followed by description of a local LTI state space model to be used for control design purposes.

3.1 Nonlinear Distributed Parameter Model

The distributed solar collector field comprises 480 single axis parabolic trough collectors arranged in 10 parallel loops with 48 collectors in each loop. The dynamic behaviour can be described 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 Camacho et al. (2012). Table 1 gives a description to all the variables and parameters and lists their SI units.

Table 1. 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	Coefficient of metal-fluid heat transmission	$W/m^2°C$
q	HTF volumetric flow rate	m^3/s
x	Space	m

The idea of a distributed parameter model is to divide the receiver tube into a set of an active and a passive series of segments based on the direct contact with the solar radiation Camacho et al. (2012). By considering only the active segments of the tube the energy balance PDEs can be approximated by a set of ordinary differential equations (ODEs) that correspond to n $(n = 1, 2, ...)$ segments each of length Δx (Fig. 2):

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

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. The term $(\rho_f C_f q \frac{T_{f,n} - T_{f,n-1}}{\Delta x})$ in (2) is indeed the main source of nonlinearity of the process.

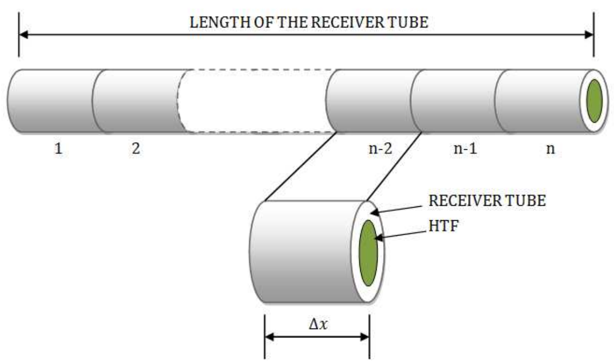

Fig. 2. Nonlinear distributed parameter model schematic diagram.

Experiments have revealed that dividing the receiver tube into n segments is a requirement to capture the main dynamics (resonance characteristics) of the plant. However, it has also been revealed that a lesser number of n (< 3) is unable to capture these dynamics adequately and a greater number of n (> 10) increases the computational burden without adding a significant improvement to the prediction accuracy. Dividing the receiver tube into 7 segments has been found to give a reasonable trade-off as will be demonstrated in a later section.

The system of ODEs in (2) is solved numerically and efficiently using the MATLAB solver ODE45 (an explicit Runge-Kutta method).

3.2 Local LTI State Space Model

Model-based control system design requires suitable mathematical models. Subspace identification is one way of obtaining these models directly from input-output data Favoreel et al. (2000). Algorithms for subspace identification are computationally simple and effective in identifying dynamic state space linear systems and overcome some of the major problems encountered in the classical identification methods, i.e., parametrization, convergence and model reduction. The general form of an estimated discrete-time LTI state space model is given as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + \xi_k \\ y_k &= Cx_k + Du_k + \eta_k \end{aligned} \tag{3}$$

$$E\left[\begin{pmatrix}\xi_p \\ \eta_p\end{pmatrix}\begin{pmatrix}\xi_q{}^T & \eta_q{}^T\end{pmatrix}\right] = \begin{pmatrix} Q & S \\ S^T & R\end{pmatrix}\delta_{pq} \leq 0 \tag{4}$$

where $x_k \in \Re^{n\times 1}$, $u_k \in \Re^{m\times 1}$, $y_k \in \Re^{l\times 1}$, $\xi_k \in \Re^{n\times 1}$ and $\eta_k \in \Re^{l\times 1}$ are the state vector, input vector, output vector, process noise and measurement noise respectively at discrete time instant k. A, B, C and D are the coefficient matrices of appropriate dimensions. ξ_k and η_k are assumed to be white noise sequences. Q, S and R are the covariance matrices of appropriate dimensions. E is the expected value operator and δ_{pq} is the Kronecker delta.

The system in (3) is assumed to be asymptotically stable, the pair (A, B) is controllable and the pair(A, C) is observable Van Overschee and De Moor (1996). A local LTI state space model similar to the one in (3) is estimated from input-output data around a nominal operating point using the N4SID algorithm with the assumptions that there is no direct feedthrough from the input to the output $(D = 0)$ and the system is deterministic $(\xi_k = \eta_k = 0)$. The N4SID subspace identification method is discussed in Favoreel et al. (2000).

4. RESONANT MODES AND SYSTEM IDENTIFICATION

It was mentioned earlier that the plant exhibits some resonance characteristics. The phenomena of these resonance characteristics are described in Meaburn and Hughes (1993) as resonant modes that lie well within the control bandwidth and are a result of the relatively slow flow rate of the HTF. The phenomena are believed to have a significant impact on the control performance. Hence, modelling these resonance characteristics accurately is crucial to ensure a high control performance with adequate robustness. Resonant modes can be accurately accounted for by a nonlinear distributed parameter model or a relatively high order linear models Camacho et al. (2012). Here a LTI state space model is considered which is convenient for the control system design.

Taking into account the prior knowledge of the process, the nonlinear distributed parameter model in (2) is excited with a PRBS signal which is a deterministic binary signal with white noise like properties and ideally suited for linear identification. The signal is generated using MATLAB with an amplitude of 0.0005 m^3/s and a clock period equals to the process sampling time 39 s (the process time constant is around 6 min). The identification process assumes steady state operating conditions around a nominal operating point ($q_{nom} = 0.006\ m^3/s$, $T_{f,nom} = 237$ °C, $I_{nom} = 674.75\ W/m^2$, $T_{f,inlet,nom} = 183$ °C and $T_{a,nom} = 28$ °C). Since only a full-length PRBS captures the white noise like properties and due to the slow dynamics of the plant, the identification process had to be carried out over a large set of data (1209 samples). However, only 1100 samples have been considered as early samples during the transients have been ignored (Fig. 3).

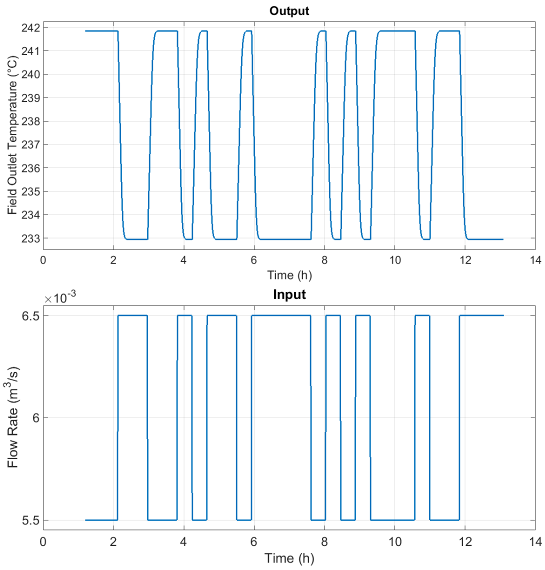

Fig. 3. Input-output data.

Unlike the nonlinear distributed parameter model of the plant, use of a full-length PRBS taking into account the process time constant will be impractical to perform on the plant itself due to the fast changes in the operating conditions and the large data set required and this issue is one for further study. The order of the model is estimated by inspecting the singular values given by the N4SID algorithm. The algorithm suggests a local LTI state space model of the $4^{th}-$order. In terms of model order, the estimated model is less complex than the models presented in Camacho et al. (1997); Johansen et al. (2000) while still adequate enough to capture the phenomena of resonant modes as illustrated in Fig. 4.

Fig. 4 also shows the bode plots of a $3^{rd}-$order and $5^{th}-$order estimated models. Certainly, a model of the $4^{th}-$order is optimal, so to speak, as the $3^{rd}-$order model fails to capture the phenomena of resonant modes accurately and the dynamics of the $5^{th}-$order model are shown to be almost identical to the dynamics of the $4^{th}-$order model.

Since the estimated LTI state space model is mainly used for prediction within the control system design, the simulated model output (infinite-step ahead prediction) is

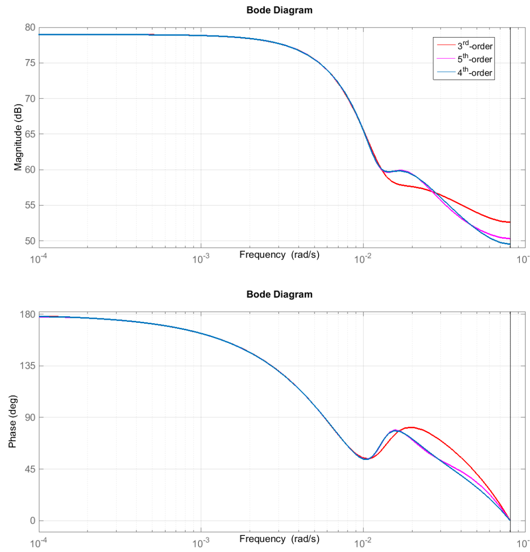

Fig. 4. Bode plots of the estimated LTI state space model.

evaluated through a best fit criterion. The criterion used is given in Ljung (1995) as:

$$Bestfit = \left(1 - \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{\sum_{i=1}^{n} |y_i - \bar{y}|} \right) \times 100 \tag{5}$$

where y, $\hat{y}$ and $\bar{y}$ are the measured output, the simulated model output and the mean of the measured output respectively.

The criterion showed a prediction accuracy of 97.16 % which confirms that the model is able to reproduce the main dynamic characteristics of the plant at a given operating point and time horizon.

5. DUAL MODE MPC

The notation dual mode refers to a separation in the model predictions into transient (mode 1) and asymptotic (mode 2) predictions. The separation gives a handle on the predictions over an infinite horizon, where a standard linear analysis can be applied, while still allowing a reduction in the number of d.o.f. and constraints Rossiter (2003). For a deterministic version of the system in (3) and assuming no direct feedthrough, the deviation from the estimated steady state values x_{ss}, u_{ss} and y_{ss} can be expressed as:

$$\begin{aligned} \hat{x}_{k+1} &= A\hat{x}_k + B\hat{u}_k \\ \hat{y}_k &= C\hat{x}_k \end{aligned} \tag{6}$$

A standard dual mode cost function (online performance measure) J is given as:

$$J = \sum_{i=0}^{n_c-1} \left[\hat{x}_{k+1+i}^T Q \hat{x}_{k+1+i} + \hat{u}_{k+i}^T R \hat{u}_{k+i} \right] + \hat{x}_{k+n_c}^T P \hat{x}_{k+n_c} \tag{7}$$

where n_c is the number of free d.o.f., Q and R are weighting matrices of appropriate dimensions and P is obtained from a Lyapunov equation of appropriate dimension. The cost function in (7) can be simplified to take the form of a standard quadratic programming problem with constraints and solved online as:

$$\underset{\underset{\rightarrow}{\hat{u}}}{min} \quad \underset{\rightarrow k-1}{\hat{u}^T} S \underset{\rightarrow k-1}{\hat{u}} + \underset{\rightarrow k-1}{\hat{u}^T} L\hat{x}_k \quad s.t. \quad M \underset{\rightarrow}{\hat{u}} \leq \gamma \tag{8}$$

where $\underset{\rightarrow k-1}{\hat{u}} = [\hat{u}_k \quad \hat{u}_{k+1} \quad \dots \quad \hat{u}_{k+n_c-1}]^T$, S and L depend upon the matrices A, B, Q, R and P, M is time-invariant and γ depends upon the system past input-output information. Detailed treatment of the control strategy can be found in Rossiter (2003).

6. SIMULATION RESULTS

The proposed control strategy is evaluated through two different simulation scenarios. The first scenario assumes a clear day with a mean solar radiation value of 674.75 W/m^2 while the second scenario considers a sudden change in the solar radiation (e.g. passing cloud). For both scenarios the plant is represented by the nonlinear distributed parameter model in (2) with a slight increase to thermal losses in order to make the scenarios more realistic. Field inlet temperature (T_{in}) and ambient temperature (T_a) are kept fixed at 189 °C and 28 °C respectively even though that may not be the case in the normal operation of the plant. The HTF is assumed to be the synthetic oil Therminol® 55 and constrained to the range 0.002−0.012 m^3/s where the minimum limit is normally for a safety reason. Exceeding a temperature of 305 °C puts the synthetic oil at the risk of being decomposed. The difference between the field outlet temperature and the field inlet temperature is also constrained not to exceed 80 °C in order to avoid the risk of oil leakage Camacho et al. (2012). The latter has been taken care of implicitly when the nominal operating point and the reference temperature were selected. Flow rate constraints are explicitly considered in the control design as will be demonstrated in the following two scenarios.

6.1 First Scenario

Fig. 5 illustrates the simulation results for a clear day where several interesting observations can be made. The time period 12-14 h shows that the dual mode MPC controller works very well (fast transient and no overshoot of the field outlet temperature) near the nominal operating point where the LTI state space model was estimated (0.006 m^3/s) and moreover copes with the slow variation of the daily cycle of solar radiation even though the local model was estimated based on steady state operating conditions. Furthermore, as the system operates slightly farther away from the nominal operating point, the field outlet temperature is able to track the reference temperature with an acceptable transient and an overshoot of less than 1 °C, although this is rather oscillatory. The control action is also somewhat oscillatory during large transients in reference temperature (this moves from 247 °C to 227 °C in the period 11-12hr). Worse control performance is certainly expected at higher (>0.008 m^3/s) and lower (<0.004 m^3/s) flow rates. More importantly however, MPC handles the flow rate constraints efficiently over the whole range of operation.

6.2 Second Scenario

This scenario investigates the effect of a passing cloud on the system. Clouds act as a disturbance to the system and therefore must be properly rejected. Simulation results of a passing cloud near the nominal operating point are illustrated in Fig. 6. The cloud is simulated by a sudden drop in the solar radiation with a relatively high level of noise. Clearly, the controller shows a satisfactory performance by rejecting the disturbance with a fair and sensible recovery time and a deviation from the reference temperature of less than 2 °C. One potentially interesting question for future study is whether performance could be improved further still with a more effective use of the feedforward term; this is an area which has received relatively little attention in the MPC literature.

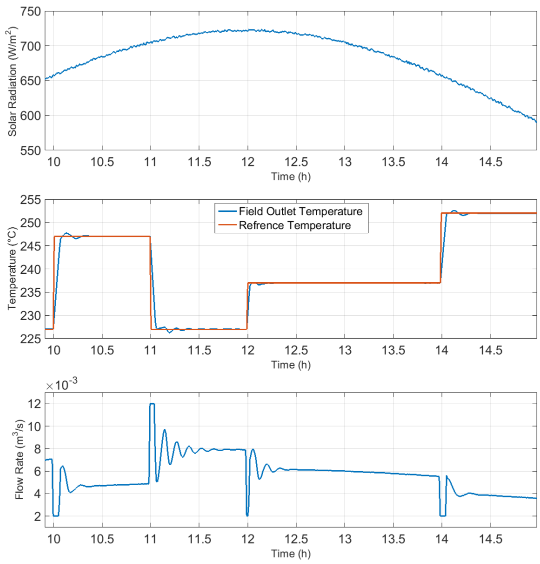

Fig. 5. First scenario: simulation results for a clear day.

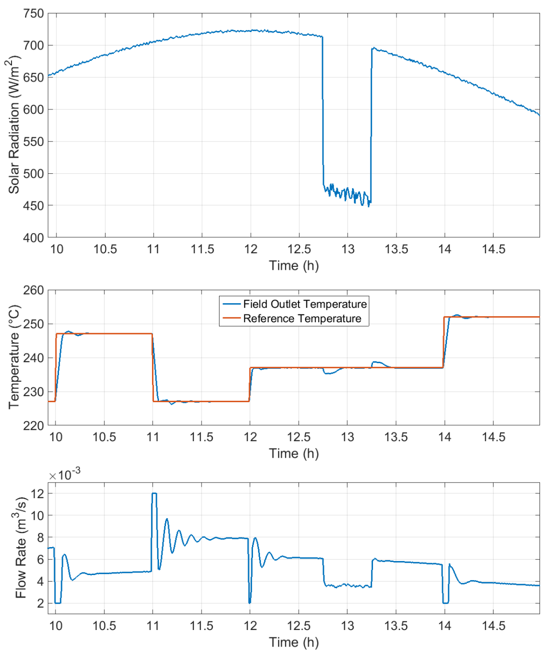

Fig. 6. Second scenario: simulation results for a passing cloud.

7. CONCLUSION

This paper has extended some of the existing control approaches for solar power plant currently in the literature and demonstrated a clear potential benefits as well as identifying areas of obvious future study. First, a LTI state space model was estimated directly from input-output data around a given operating point using a subspace identification method. Due to the slow dynamics of the plant and the fast changes in the operating conditions, the input-output data were obtained from a distributed parameter model of the ACUREX plant rather than the plant itself. A second key contribution is that the model is estimated taking into account the dynamic phenomena of resonant modes and the prior knowledge of the process. This technique resulted in a model order reduction when compared to the models available in the open literature and hence enabled a less complex control design. Finally, the model served as a platform for a dual mode control strategy for tracking and disturbance rejection and also including plant safety constraints.

The control strategy is shown to have satisfactory performance around a nominal operating point for two different and commonplace scenarios. As expected, when operating far from the nominal operating point a poor performance was observed which is consistent with Camacho et al. (1997); Johansen et al. (2000). Hence, the need to extend the work to cover more operating points is evident.

While this paper as clearly demonstrated that the proposed approach is feasible and effective, obvious avenues for future work, in addition to a comprehensive evaluation and comparison with alternatives, include the extension to a gain scheduling control strategy through the estimation of LTI state space models around different operating points and the design of the correspondent dual mode MPC controllers. There is also a need to develop algorithms which can incorporate and exploit feedforward information in order to improve disturbance rejection.

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