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Chapter 2

ADVANCED CONTROL ALGORITHMS AND NEW CHALLENGES IN PARABOLIC TROUGH SOLAR PLANTS: A REVIEW

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ABSTRACT

The majority of solar thermal plants which produce electricity and deliver it to the grid use parabolic trough technology. As examples of large scale solar trough plants we can mention the SOLANA power station (280 MW of electricity power with 6 hour of thermal storage) or the 280 MW Mojave solar complex.

As stated by the National American Academy and the European Commission, one of the main challenges is to improve the overall

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efficiency of the solar energy plants. To address this challenge, advanced control techniques play a decisive role.

This chapter presents a review of the main control techniques applied to parabolic solar trough plants as well as modeling approaches used to describe the behavior of these kind of plants. Since modeling a large scale solar plant very precisely would involve taking into account many elements which compose the plant, the resulting model can be very demanding from the computational time point of view. In this chapter, the general equations to model the solar plant are presented as well as a simple approach used for the commercial solar trough plants of Mojave. This approach provided a very good trade off between precision and complexity.

As far as control algorithms are concerned, the chapter mainly focuses on the Model predictive control algorithm and optimization. The control objective of this kind of plants is explained and a description of several control strategies applied to solar trough plants is provided. A example of a model predictive control strategy applied to the old ACUREX solar collector field at the Plataforma Solar de Almería is given. However, the majority of the control strategies existing in the literature are applied to small scale solar trough plants. When dealing with large scale solar trough plants, new problems and challenges appear which have to be addressed.

Current commercial solar trough plants have a considerable size and cover a vast extension. They pose additional challenges from the control and optimization point of view. New control algorithms have to be designed to address this issue. Due to the size of these plants, there can be groups of loops affected by different radiation levels due to passing clouds. Furthermore, the efficiency of the loops can be different because a group of them is cleaned and another is not.

Some preliminary results published in the literature are reviewed and possible future directions for research are given. Additionally one illustrative example is provided to show the advantage of implementing advanced control strategies using a model of a large scale solar trough plant.

Keywords: solar parabolic, model predictive control, large scale, modeling, optimization

ACRONYMS

AC	Adaptive Control
CC	Cascade-Control
CSP	Concentrating Solar Power
FLC	Fuzzy Logic Control
FDMC	Filtered Dynamic Matrix Control
FF	Feed-Forward
GS	Gain-Scheduling
GPC	Generalized Predictive Controller
HTF	Heat Transfer Fluid
IMC	Internal Model Control
LQG	Linear Quadratic Gaussian Controller
MPC	Model Predictive Control
NNC	neural network controllers
PDE	Partial Differential Equation
PID	Proportional Integral Derivative Controller
RC	Robust Control
TES	Thermal Energy Storage
TDC	Time Delay Compensation
UKF	Unscented Kalman Filter

INTRODUCTION

The pressing need to reduce the impact of fossil fuels has increased the interest in tapping renewable energy sources. In particular, the use of solar energy has experienced a great impulse during the last two decades [1]. Governments are promoting the construction and exploitation of solar energy power plants around the world as a way to overcome the drawback of producing energy using exhaustible energy sources [2].

During the last decades, a high number of commercial solar power plants have been constructed and commissioned around the world. The first commercial solar trough plants were the 30 MW SEGS plants in California (USA), commissioned in the 80s [3]. From 2000 onwards, the construction of commercial solar trough plants received a very important impulse. For example, we can find the four 50 MW trough plants Solaben I,II, III and VI in Extremadura (Spain) and the three 50 MW Solnova I, III and IV in Solucar in southern Spain commissioned in 2010 all of them owned by Atlantica Yield [4]. The 50 MW solar trough plants Andasol I, II and III owned by Cobra/ACS group were constructed in Guadix (Southern Spain) [5]. In the USA we can mention Solana and Mojave Solar parabolic trough plants constructed and operating in Arizona and California respectively [6, 7], each of 280 MW of electrical power production. Currently, there are many concentrating solar plants projects around the world. For example, the parabolic trough plant of Gulang of 100 MW of power with 7h of storage capacity [8].

One of the great challenges of the century, identified by the National Academy and the European Commission, is to make solar energy economical and competitive [9, 10]. To address this important topic, the application of advanced control strategies, optimization algorithms and the use of mathematical models to predict the plant evolution and adapting the production schedule can play a decisive role in improving the overall efficiency of the solar energy plants. Thus, the penetration of solar energy plants in the market can also be improved [11, 12].

Most of the research and the application of advanced control techniques have been carried out using the experimental ACUREX solar trough plant at the plataforma solar de Almería as a testbench [13]. This was an east-west oriented solar trough plants which was able to produce 0.5 MW of electrical power [14]. In [15, 16] a review of some control strategies applied to the ACUREX solar field is presented. In [17], adaptative control and nonlinear schemes are described for the ACUREX solar field. In [18] a nonlinear neural predictive controller is developed and tested at the real ACUREX plant. In [19], a review of the application of linear and nonlinear model predictive control algorithms to the ACUREX plant is presented. In [20], the optimization of the operation procedures and control for a 50 MW solar trough plant is carried out. All the techniques explained in the foregoing papers are applied to an experimental solar trough plant or to a mathematical model. However, there is a lack of experimental research applied to commercial solar trough plants.

Current commercial solar trough cover vast extensions of land. For example, the two 140 MW solar trough plants of Mojave Alpha and Beta are composed of 282 loops each and cover about 700 hectares of land [21]. The solar trough plant of SOLANA is even bigger: it covers about 780 hectares of land and it consists of 808 loops [7]. Large scale solar plants pose new problems from the control and optimization point of view. New advanced control techniques have to be developed to cope with these issues.

Developing of new advanced control strategies for large scale solar plants as well as optimizing power production is a very challenging topic. The Advanced Grant Optimal Control of solar energy systems (OCONTSOLAR) funded by the European Research Council aims at contributing to these problems. One of the main objectives of this project is to develop radically new model predictive control (MPC) algorithms which use mobile solar sensors to obtain estimations and predictions of solar radiation mapping [22]. The control strategies proposed in the literature to regulate the outlet temperature of the solar field around a desired set-point use the solar radiation measured by pyrheliometers. It is usually considered that this level of direct normal irradiance affects the whole solar field. For small solar fields such as the ACUREX plant, this assumption can be considered correct. But in large scale plants clouds may affect one part of the field whereas other parts are uncovered or viceversa [23]. Furthermore, the efficiency of the loops is usually considered the same for all the loops forming the plant. When there is a high number of loops, their efficiency can vary substantially if a set of them are cleaner or more affected by dust than the rest. The paradox is that the most efficient loops have to be defocused to avoid overheating problems causing energy losses [24].

To avoid this energy loss, the valves of the most efficient loops would have to be opened to increase the HTF flow. However, any movement of the valve in one of the loops will influence the flow of the rest of the loops. Loop valves are only used in current plants for steady state flow balancing.

A preliminary work has recently been published using a model of the ACUREX field as a test-bench [25]. The input valves of each loop were manipulated every 30 minutes, to compensate for the different optical efficiency of the loops. Results showed that energy losses are minimized by manipulating the input valves to distribute the flow. Because the most efficient loops have to receive a higher flow than the less efficient ones. In [26] a nonlinear model-based optimization control algorithm was presented to improve the thermal balance of the solar field. The algorithm was tested on a model of a 50 MW solar trough plant. The algorithm computed the aperture of the valves every 5 minutes and was compared to the case where the input valves were not manipulated. The thermal energy losses due to defocusing actions were significantly reduced, thus improving the efficiency of the plant.

In this chapter, a simulation result showing the advantages of using advanced control techniques in large scale solar trough plants is presented. The optimization problem uses an unscented Kalman filter (UKF) to estimate the loop temperatures along the pipe and a concentrated parameter model is used to estimate loop efficiencies. Opening the input valves of the most efficient loops increases the incoming flow-rate and reduces the flow in the less efficient loops. This will prevent, in many cases, the activation of the defocus control, avoiding energy losses and minimizing the deterioration of actuators. Moreover, a loop clustering is implemented to avoid high computation times. Simulations carried out on a 50 MW solar trough plant model shows that energy gains are obtained when the proposed algorithm is applied [27].

The chapter is organized as follows: section 2 describes the modeling problem of solar trough plants and different modeling approaches. Section 3 describes the main control objectives of a solar trough plant and reviews the main control strategies for solar trough plants. New problems appearing when controlling large scale solar trough plants are described. Section 4 presents an illustrative example of the advantages of the application of advanced control strategies to a 50 MW large scale solar trough plant. Finally, the chapter draws to a close with concluding remarks.

MODELING APPROACHES

In this section, the general equations to model a solar trough field are presented. A review of the different modeling approaches for a solar trough plant is carried out. Finally, a simple way to model a large solar trough plant is presented using the Mojave solar trough plants [28] as an example. These kinds of models are useful for control design and optimization purposes.

A solar trough plant consists of a set of solar collectors (see Figure 1) which heat up a heat transfer fluid, typically synthetic oil, by concentrating the solar radiation onto a metal tube. A power conversion system where the heated fluid is used in turbine to produce electricity. The plant is also composed of pipes and the oil pumps and thermal energy storages (TES) if available [1, 29]. This chapter focuses on solar trough plants without TES.

The HTF is heated up in the solar field and then is delivered to the steam generator through the pipe connecting both (figure 2). The hot HTF delivers heat to the steam generator by means of a heat exchanger. The overheated steam is used by the turbine to produce electricity.

Source: [30].

Figure 1. EUROTrough Prototype at the Plataforma Solar de Almería.

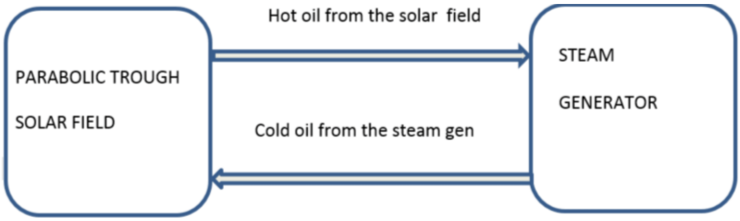


Figure 2. Solar plant scheme.

Because the HTF transfers heat its temperature decreases. The steam generator returns the cold oil to the solar field to be heated up again.

Models of solar trough plants can vary from simple models to very complex. Complex models have the advantage of a more detailed modeling but at the cost of a higher computational burden. In general, two points have to be considered:

- To obtain complex models, a great amount of data is needed to identify all the model coefficients. If there are many coefficients to be identified, the resulting nonlinear optimization problem may be very difficult or even impossible to solve in an adequate time frame. Another important problem is that many coefficients may lead to over-fitting problems. A big amount of data with sufficient variability would be required. An adequate simplification is indispensable, since in real plants the measurable variables are limited and measurements of certain variables may not be available.
- The computational time to simulate different environmental conditions and situations should be as fast as possible. If the computational time is high, the optimization required for tuning parameters is difficult and the commissioning of the controller may be delayed.

Complex models can be used to simulate and test the control strategies developed for the plant.

MATHEMATICAL MODELING OF THE SOLAR COLLECTOR FIELD

In order to describe the dynamics of a solar collector field, two models are usually considered: the distributed parameter model and the concentrated parameter model [31, 32]. The distributed parameter model has the advantage of taking into account the spatial distribution of the loop while the concentrated parameter model is usually used for control purposes due to its simplicity. Both are described below:

Distributed Parameter Model of a Loop

The loop dynamics can be described by the following system of partial differential equations (PDE) describing the energy balance [16, 31]:

$$\rho_m C_m A_m \frac{\partial T_m}{\partial t} = I K_{opt} cos(\theta) G - H_l G(T_m - T_a) - L H_t (T_m - T_f) \quad (1)$$

$$\rho_f C_f A_f \frac{\partial T_f}{\partial t} + \rho_f C_f q \frac{\partial T_f}{\partial x} = L H_t (T_m - T_f) \quad (2)$$

where m subindex refers to metal and f subindex refers to a fluid. In Table 1, parameters and their units are shown.

Table 1. Parameters description

Symbol	Description	Units
t	Time	s
x	Space	m
ρ	Density	kgm^{-3}
C	Specific heat capacity	JK^{-1}kg^{-1}
A	Cross sectional area	m^2
$T(x, y)$	Temperature	K,ºC
$q(t)$	HTF flow rate	m^{3}s^{-1}

Table 1. (Continued)

Symbol	Description	Units
$I(t)$	Direct Solar radiation	Wm^{-2}
$cos(\theta)$	Geometric efficiency	Unitless
K_{opt}	Optical efficiency	Unitless
G	Collector aperture	m
$T_a(t)$	Ambient temperature	K, ºC
H_l	Global coefficient of thermal loss	$\mathrm{Wm}^{-2}\,{}^{\circ}\mathrm{C}^{-1}$
L	Length of pipe line	m
$H_t(t,T,q)$	Coefficient of heat transmission metal-fluid	$\mathrm{Wm}^{-2}\,{}^{\circ}\mathrm{C}^{-1}$
S	Total reflective surface	m^2
$C_T(t,T)$	Thermal capacity of the whole sector	$\mathrm{J/K}$
H_{lc}	Lumped parameter model global coefficient of thermal loss	$\mathrm{Wm}^{-2}\,{}^{\circ}\mathrm{C}^{-1}$

The optical efficiency (K_{opt}) takes into account elements such as reflectivity, metal absorptance, interception factor and others. All the equations for computing the parameters can be found in [34, 33].

The equations presented here are general and can be used for all kind of loops and collectors, Only the parameters change accordingly. The complete plant can be modeled by adding several loops in parallel.

Concentrated Parameter Model

A concentrated parameter model provides a lumped description of the loop [31]. The variation in the internal energy of the fluid can be described by the equation:

$$C_T\frac{dT_{out}}{dt} = K_{opt}cos\phi SI - qC_f\rho_f(T_{out}-T_{in}) - H_{lc}S(\bar{T}-T_a) \qquad (3)$$

where q is the HTF flow of the whole sector and T and T_{in} are the outlet and inlet oil temperatures of the model respectively. The outlet temperature of the lumped parameter model T is the final average temperature of the sector and T_{in} is the outlet temperature of the distributed parameter model.

The variable $\bar{T}$ is the average value between inlet and outlet temperatures and T_a is the ambient temperature. C_T is the thermal capacity of the sector, K_{opt} is the optical efficiency (which incorporates the effects of mirror reflectivity, tube absorptance, and interception factor), I is the direct solar irradiance and S is the total reflective surface.

SIMPLE MODELING APPROACH: MATHEMATICAL MODEL OF A LARGE SCALE SOLAR PLANT

In this subsection, a simple approach to model large scale solar trough plant is presented. This approach is useful to obtain a simple model for tuning advance control strategies properly and is described in [28].

Since a commercial solar plant is composed of many loops (90 or more), simulating an exact model of the the plant would require 90 loops to be computed. In the case of the Mojave solar plants, which are composed of 282 loops each, the computational time required to simulate a few hours of operation would be too high to tune the parameters of a control strategy properly.

If the models are used in an optimization algorithm, the computational time has to be drastically decreased.

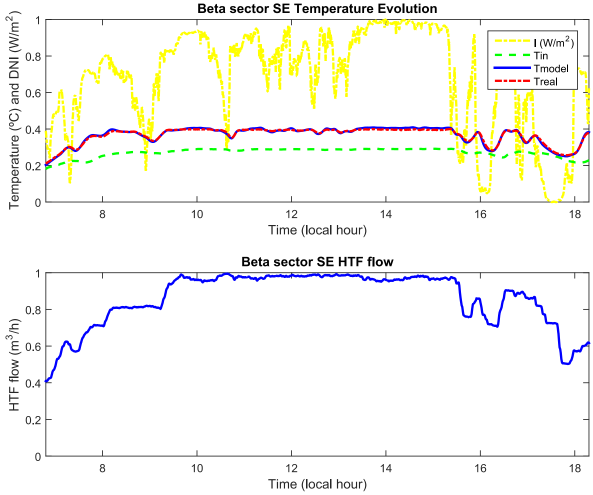
Since the control objective of this kind of plant is to regulate the average temperature of the loops and the thermal balance is achieved by manipulating the input valves, the approach is to model a given sector (a sector is a set of loops) as an equivalent loop. The main advantage of choosing this approach is its simplicity and a lower computational requirements. Furthermore, all the measurements needed are available: the average outlet temperature of the loops, the inlet temperature of the sector, the oil flow, the direct normal irradiance, the number of defocused collectors (to compute the overall optical efficiency) and the average reflectivity. The main drawback is that the spatial distribution of the sector is not modeled, but this issue is mitigated since we are modeling average temperatures.

Two assumptions are made:

a) The dynamics of each sector is considered as a one equivalent loop, that is, all the loops forming the quadrant are considered to have the same efficient (the overall efficiency of the quadrant). This assumption is based on the fact that the most efficient loops compensate the less efficient ones. The flow of this equivalent loop is considered to be the mean flow of the sector (flow divided by the number of loops). A distributed parameter model is used to model this equivalent loop.
b) For sectors with a great number of loops although the average temperature of the quadrant has an additional dynamics due to different distances from the input of the sector to each loop and the different flows of each loop. This dynamics can be modeled as a lumped parameter model with a determined area, length and a thermal losses coefficient. The flow of this model is equal to the flow of the whole sector.

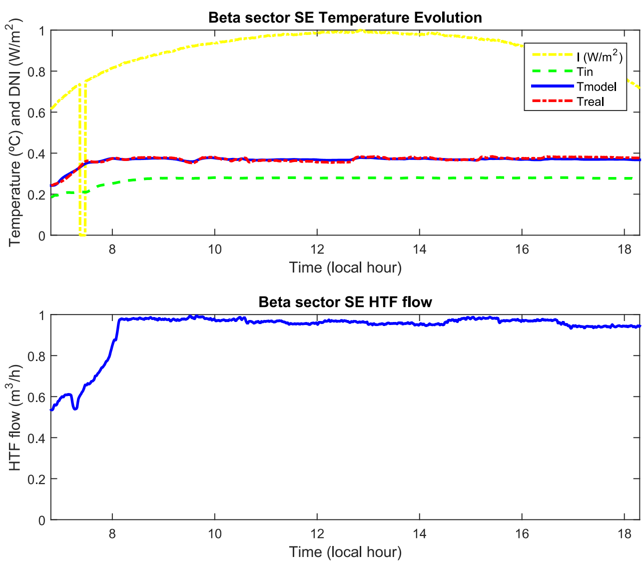
This approach has demonstrated a good performance as shown below. All the parameters value, thermal losses and mathematical expressions can be found in [28]. All simulation results for these plants are scaled between 0 and 1. The real data cannot be provided due to confidentiality and intellectual property issues.

The considered solar trough plant is composed of six sectors: east (42 loops), north-east (46 loops), north-west (38 loops), south-east (40 loops), south-west (38 loops) and west (78 loops). Figure 3 shows the comparison between the model output and the real average temperature of the Mojave Beta East sector. It is a transient day where passing clouds are affecting the sector. As can be seen, the dynamics of the model is quite similar to that of the real sector evolution. Mojave Alpha solar trough plant consists of four sectors: north-west (68 loops), north-east (20 loops), east (102 loops) and west (92 loops). Figure 4 presents the evolution of the Alpha North-East sector in a clear day of summer. As can be seen, the evolution of the model is very similar to that of the real sector.



Source [28].

Figure 3. Beta East sector, model vs. real evolution: (top) model (blue solid) and real (red dash-dotted); and (bottom) HTF flow.



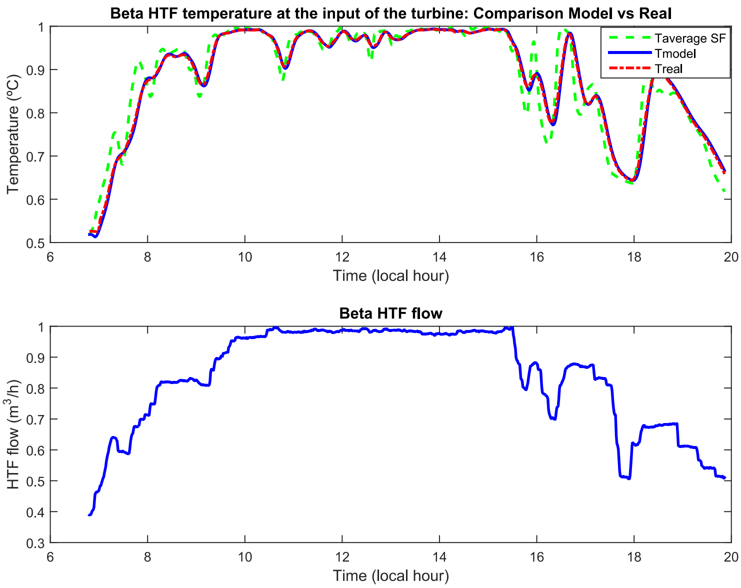
Source [28].

Figure 4. Alpha North-East sector, model vs. real evolution: (top) model (blue solid) and real (red dash-dotted); and (bottom) HTF flow.

The maximum error obtained is about a 5.8% which constitutes an acceptable result taking into account the simplifications.

Mathematical Model of the Piping System

The equations of all the pipes modeling are the same as those presented for the distributed parameter model, but considering the irradiance to be equal to 0.



Source [28].

Figure 5. Mojave Beta, HTF temperature at the input of the steam generator: (top) model (solid blue) and real (red dash-dotted); and (bottom) HTF flow.

The system of partial differential equations are given by Equations (4,5):

$$\rho_m C_m A_m \frac{\partial T_m}{\partial t} = -H_l G(T_m - T_a) - L H_t (T_m - T_f) \qquad (4)$$

$$\rho_f C_f A_f \frac{\partial T_f}{\partial t} + \rho_f C_f q \frac{\partial T_f}{\partial x} = LH_t(T_m - T_f) \qquad (5)$$

The parameter to be identified are the cross sectional Area A_f, the total length of the pipe and the coefficient of the thermal losses H_l.

Figure 5 shows a comparison between the model output of the pipe connecting the solar field and the steam generator, and the HTF temperature measured at the input of the steam generator. As can be seen, the model evolution is quite close to the real measurement. The maximum error is about 2.8%.

Modeling of the Steam Generator Variables

In this subsection, a procedure to obtain a model for the steam variables useful for simulation is described.

To model a power block, many components have to be modeled. Thus, the model of this part is usually complicated and requires a great deal of data to obtain the models parameter [35]. The model of this part can be addressed by using simulation languages such as modelica if very detailed models are needed. In [36], a complex model developed in modelica of a CSP power plant is presented. In [37], a complex and detailed model developed in TRNSYS of the steam generator is presented to study the start-up stage. In [35], a complex model of a steam turbine is developed. The model parameters were identified using a genetic algorithm.

This approach can be useful to obtain an exact model but more simple models are required to test and tune advanced control strategies. Furthermore, most of the data required for a more complex model are not available.

To address this issue, a black-box approach is used here [38]. In this kind of models, the output is a function of the inputs, but the model structure is unknown a priori [39].

The model structure is chosen based on experience. Data for five days of operation are used to obtain the model parameter. The model output is then compared with all the data available to find if it works well in all conditions. The steam variables needed to simulate advanced control strategies are the following: steam temperature, high pressure, gross power, HTF return temperature, the steam temperature gradient and the superheating temperature. The models of these variables are explained below.

Although the models structure are not known, to figure out what variables are more suitable to be included in a particular model structure, a correlation analysis was carried out.

To illustrate the proposed procedure, the steam temperature model and the HP pressure model are presented.

A first-order dynamic model is chosen for the steam temperature. The evolution of this model depends on the HTF temperature of the steam generator, the oil flow and the ambient temperature as follows (Equation (6)):

$$T_{steam}(k) = a_1 T_{steam}(k-1) + a_2 T_{HTF} + a_3 q_{HTF} T_{HTF} + a_4 (T_{HTF} - T_a) +$$

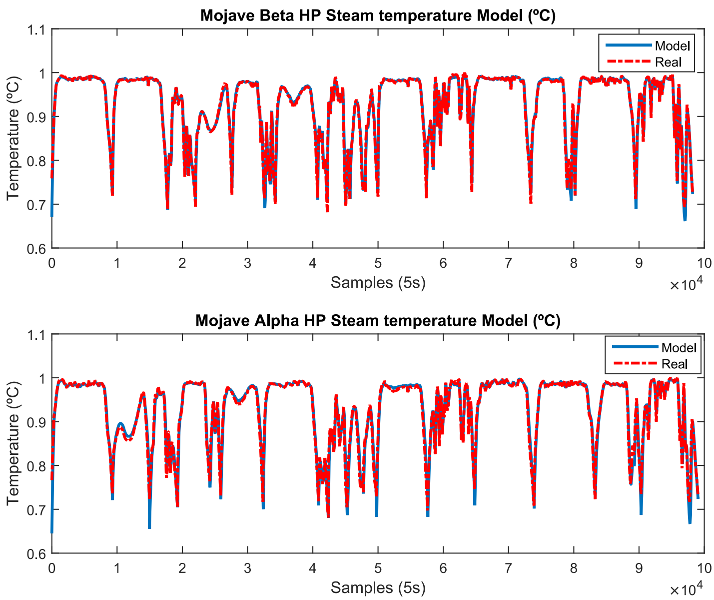
$$+a_5 (T_{HTF} - T_a)^2 + a_6 \tag{6}$$

$T_{steam}(k)$ is the steam temperature at instant k. T_{HTF} is the HTF temperature at the input of the steam generator, q_{HTF} is the oil flow reaching the steam generator and T_a is the ambient temperature.

Constants a_1–a_6 have to be obtained. A comparison between the model and real data is shown in Figure 6 for Mojave Beta (Figure 6, top) and Mojave Alpha (Figure 6, bottom). As can be seen, the model evolution is quite close the real measurement.

One of the most important variables in the steam generator is the high steam pressure. This variable has to be supervised and controlled to avoid dangerous situations, including shutdowns of the plant. The structure of the model is chosen based on the fact that the steam pressure depends on the temperature and the flow. The model structure is as follows (Equation (7)):

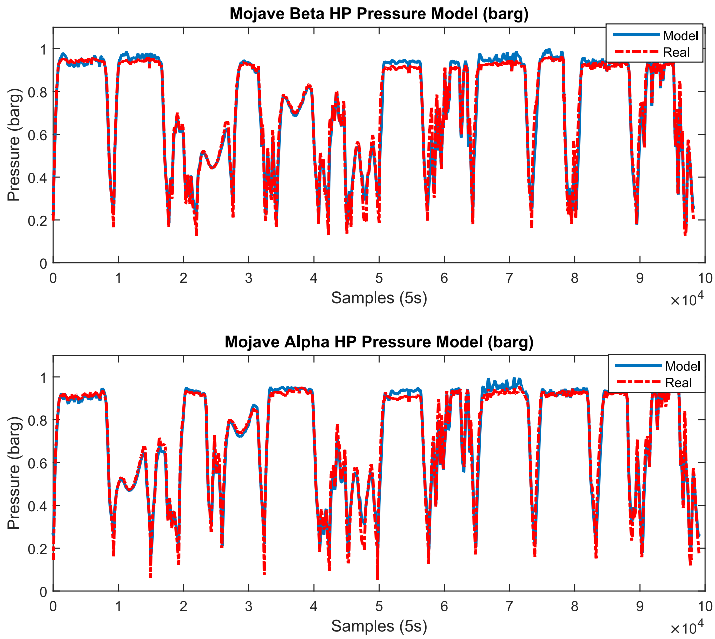
$$Pressure_{HP}(k) = a_1 T_{steam} + a_2 T_{steam}^2 + a_3 q_{HTF} T_{HTF} + a_4 \qquad (7)$$



Source [28].

Figure 6: Mojave Beta and Alpha: Steam temperature model: (top) Mojave Beta model showing real evolution (red dash-dotted) and model output (blue solid); and (bottom) Mojave Alpha model showing real evolution (red dash-dotted) and model output (blue solid).

A comparison between real data and the model is shown below. Figure 7 shows the comparison between the model and the measured HP Pressure for Mojave Beta (Figure 7, top) and Mojave Alpha (Figure 7, bottom). The model replicates properly the real pressure evolution in both cases.



Source [28].

Figure 7. Mojave Beta and Alpha: HP Pressure Model: (top) Mojave Beta model, showing real evolution (red dash-dotted) and model output (blue solid); and (bottom) Mojave Alpha model, showing real evolution (red dash-dotted) and model output (blue solid).

CONTROL STRATEGIES FOR SOLAR PLANTS AND NEW CHALLENGES: A REVIEW

In this section, a review on control strategies for solar trough plants is presented.

The main control objective of this kind of plant is to regulate the solar field temperature (the outlet temperature of the solar field), around a desired set-point. Since the primary energy source, solar energy, cannot be manipulated, the oil flow q is used as a control signal. The set-point may change substantially throughout the daily operation due to changes in the production requirements, solar radiation conditions, solar hour etc [40].

The activities performed by the control research community related to this field cover modeling, identification and simulation, classical proportional- integral-derivative control (PID), feedforward control (FF), model based predictive control (MPC), adaptive control (AC), gain-scheduled control (GS), cascade control (CC), internal model control (IMC), time delay compensation (TDC), optimal control (LQG), nonlinear control (NC), robust control (RC), fuzzy logic control (FLC) and neural network controllers (NNC) [16]. This section focuses on Model Predictive control strategies applied to solar power plants.

Many MPC controls strategies have been applied to solar trough plants. The main idea of a model predictive control strategy is to use a mathematical model of the plant to predict the output future evolution, and compute a sequence of control actions which minimizes a cost function subject to constraints. Then, the first element of the optimal sequence is applied and the optimization problem is solved again (receding horizon strategy) [41].

Most of the MPC control strategies were tested on the ACUREX solar collector field. They include, in general a feedforward term computed using the concentrated parameter model (equation (3)) [42] and [15]. In particular, the highly nonlinear dynamics of the distributed solar collector field hinders the application of fixed controller parameters. In [43], a gain scheduling generalized predictive controller (GPC) is designed for the ACUREX plant. This controller achieved a very good performance. In [44] a GPC control strategy which uses a nonlinear free response obtained with a simplified distributed parameter model is presented. That scheme achieves a good performance without using a feedforward term. In [45], a linear MPC controller is proposed for the SEGS plants.

Since the distributed solar collector field possesses a highly nonlinear dynamics which changes with the operating conditions, adaptative, robust and nonlinear model predictive techniques have also been applied. In particular, in [46] an adaptative GPC is tested at the ACUREX solar field, the model parameters are obtained by means of an adaptation mechanism working online. In [47], a cascade controller is applied to the ACUREX field with good results. In [48], a variable sample time state-space adaptative controller is proposed. The work developed by Lemos and coworkers collects extensively some of the adaptative schemes proposed for the ACUREX solar field [49].

More recently some adaptative and nonlinear schemes using state-space models and parameter identification techniques such as the unscented Kalman filter (UKF) have been developed [50]. In [51], a nonlinear model is used for the MPC control strategy and the unscented Kalman filter is used to estimate optical efficiency, thermal losses and a free parameter by using a bilinear state-space Euler model. In [52], a robust tube-based MPC control technique is applied successfully to the ACUREX field. In [23], the UKF is used to estimate the metal-fluid temperature profiles and the effective solar radiation. In [53], a practical nonlinear MPC implementation is used to control the temperature of the ACUREX solar field. In [54], a non-linear adaptive constrained model-based predictive control scheme with steady-state offset compensation is developed and implemented. In [55], a nonlinear continuous-time generalized predictive control is applied to a solar power plant. In [56] the output temperature control of a solar collector field is presented using a Filtered Dynamic Matrix Control (FDMC). Results showed that if the strategy is properly tuned, it provides a similar performance to that obtained with nonlinear control strategies.

As a practical example of an MPC control strategy performance, in [57] a model predictive controller which uses a robust Luenberger observer was tested at the ACUREX plant. The idea is similar to that presented in [23], but the observer is a robust Luenberger observer. The main advantage is that using this approach, performance constraints can be imposed in the observer. The control scheme is shown in Figure 8. Every $t_s = 36$ s, the data acquisition system receives measures from the field, which are used by the observer to obtain an estimate of the state vector. The next step consists in updating the linear matrices, computing the free response through the nonlinear model, and solving the MPC problem given by (8).

The resulting signal q_{pred} is then added to the feedforward signal q_{ff} to obtain the oil flow setpoint for the pump.

It is worth pointing out that besides being a component of the final control action q, the feedforward signal is needed for the prediction of the free response with the nonlinear PDE, considering a constant input flow along the control horizon. Such free response provides a kind of feedforward compensation. However, it is not sufficient to avoid the use of the feedforward block. Indeed, the MPC controller is linear: the forced response is computed by using a linear model and the MPC control signal q_{pred} is obtained by solving a QP problem.

$$\min_{\Delta u} J(\Delta u, y(t)) = \sum_{k=0}^{N_y} (y_{t+k|t} - w_{t+k})^T Q\left(y_{t+k|t} - w_{t+k}\right) +$$

$$+ \sum_{k=0}^{N_c} \Delta u_{t+k}^T R \Delta u_{t+k} \tag{8}$$

s.t:

$$y_{min} \leq y_{t+k|t} \leq y_{max}, k = 1, \dots, N_y$$

$$\Delta u_{min} \leq \Delta u_{t+k} \leq \Delta u_{max}, k = 1, \dots, N_c$$

$$U_{min} \leq U(t+k|t) \leq U_{max}, k = 1, \dots, N_c$$

$$U(t+k|t) = U(t+k-1) + \Delta u(t+k-1), k = 1, \dots, N_c$$

$$x(t+k+1|t) = F(x(t+k), U(t+k)), k = 1, \dots, N_y$$

$$y(t+k) = H(x(k)), k = 1, \dots, N_y$$

The real test was performed in a sunny day with scattered clouds which forced the first day of tests to end at about 14:00. The upper plot in Figure 9 shows the inlet and outlet oil temperatures, relative to the experiments carried out at the ACUREX field in 2013. The bottom plot in Figure 9 shows the direct solar radiation and the value of the input oil flow for the same day. After the plant starting procedure, at 12.6 h the test began with some setpoint changes for the outlet temperature. The controller achieved rise times of less than 3 minutes, and overshoots smaller than 2 ºC during the test (about 15%). Notice that the temperature setpoint given at 12.6 h could not be reached because of the maximum input flow constraint (8.8 l/s). At 13.7 h there was a drop in the inlet temperature and the controller steers the outlet temperature to the reference. At the end of the test, several passing clouds affect the field and the temperature cannot reach the desired reference.

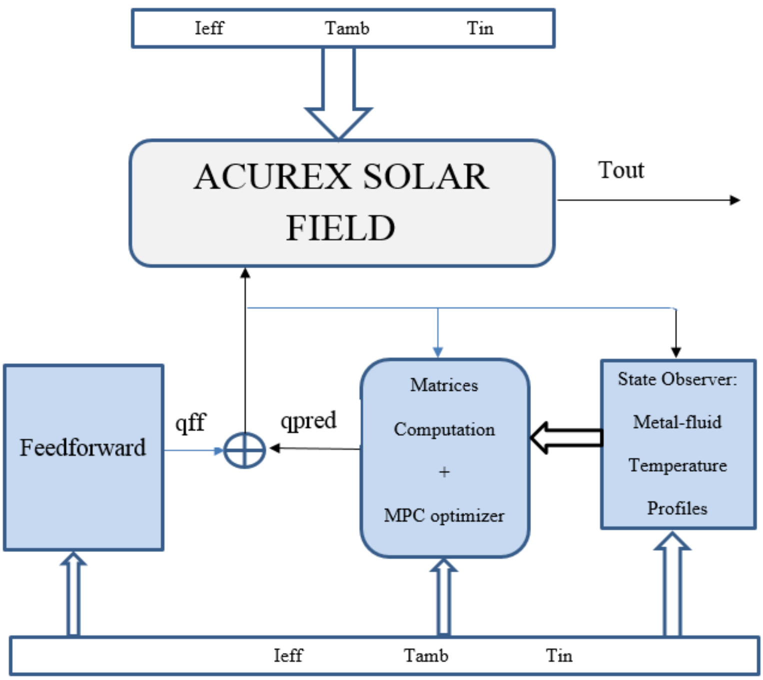


Figure 8. Final Control Scheme.

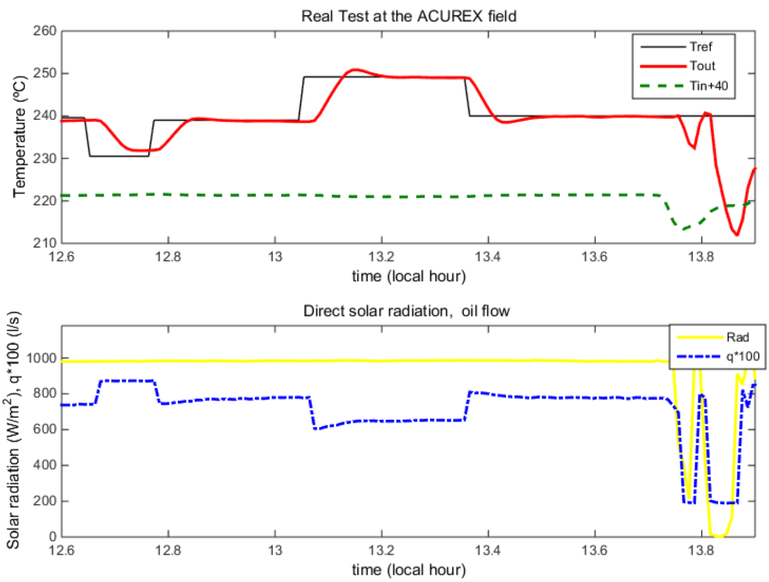


Figure 9. Test carried out at the ACUREX field, 2013.

The previous research work are mainly related to the control of the solar field temperature. However, one important topic is determinng which is the temperature producing the best yield, that is, the optimal operating temperature. In [58] and [14], hierarchical control strategies were presented consisting in two layer: the first layer computes the set-point for the solar field an the second layer is devoted to the control of the temperature.

For a long time, the general feeling was that the best operating temperature was the highest. In [59] a hierarchical control strategy was presented and the procedure for obtaining the optimal operating temperature was developed. It was shown that the best operating temperature is not, in general, the highest but it depends on the environmental conditions and the state of the plant.

More recently, several papers related to optimizing the plant operation have been published [60]. In [61], a model predictive control approach is proposed for scheduling of concentrating solar power plants with Thermal Energy Storage (TES). It uses forecasting to optimize the plant schedule. In [20], a study that focuses on the search for the optimal strategies of operation by a mathematical model of a 50 MWe parabolic trough thermal power plant with thermal storage. The analysis of the different ways of operation throughout a whole year, including model verification via a currently operating plant, provides meaningful insights into the electricity generated. In [62], a scheduling strategy for concentrating solar power plants with thermal energy storage is studied.

Currently, since the commercial solar trough plants cover vast land extensions, new challenges appear to the development of advanced control strategies. These challenges can be summed up as follows (but not limited to):

- As stated in the introduction, the input valves of the loops can be manipulated to achieve a proper thermal balance and avoiding thermal losses of the most efficient loops due to defocusing actions [63]. Due to the high number of loops of commercial plants, the resulting control problem is a nonlinear optimization problem with many decision variables (90 or more) which is very difficult to be solved in real time.
- Solar plants performance depends on multiple factors such as solar irradiance, ambient temperature, reflectivity of the collectors, operating temperatures of the different subsystems and many other operational and environmental variables. The main energy source, the solar irradiance, cannot be manipulated. Advanced control strategies requires the knowledge of solar radiation, but extrapolating the local measurement of pyrheliometers to the whole solar field is not reasonable. Scattered clouds may only affect the location where the sensor is placed, while the rest of the loop may be under the effect of intense DNI, or viceversa. Advanced control strategies require a solar radiation mapping or nowcasting to take anticipative actions.
- Another important issue is to develop plant-wide dynamic online optimization methods for solar energy systems to achieve optimal operation while meeting internal and external constraints (dispatchability).

Some preliminary results have been published in [25, 27] where it has been demonstrated that, using model-based optimization for computing the input valves aperture can produce substantial gains in power production and the reduction of defocusing actions due to overheating problems.

Another important issue in commercial plants is the operation under power limitation. In this case, the oil flow is limited by the gross power restriction and the temperature has to be controlled by defocusing the collectors. This is usually done in commercial plants by activating or deactivating the defocusing mechanism if the temperature is above a safety value. In [63] and [24] two model predictive control algorithms are proposed showing that the number of defocusing actions are drastically reduced thus, increasing the life of actuators, and avoiding that the HTF surpasses the safe temperature.

THERMAL BALANCE OF A LARGE SCALE SOLAR TROUGH PLANT: AN EXAMPLE

In this section, an example of the advantages provided by the application of advanced control strategies to a large scale solar trough plants is presented. The algorithm described here is tested on a model of a 50 MW solar trough plant described thoroughly in [27, 63].

As mentioned above, the main control objective of a solar trough plants is to regulate the average temperature of all the loops around a desired set-point by manipulating the HTF flow. The large number of loops existing in current commercial solar plants and the vast extension of land covered make the estimation of the efficiency of every loop becomes a very difficult task. Parameters related to the optical efficiency such as reflectivity, metal absorptance, optical efficiency of the glass covering the metal tube may exhibit a great disparity. This difference in the loops efficiency the most efficient loops to reach very high temperatures and they have to be defocused to avoid overheating situations that degrade the HTF [25].

The main idea is that the aperture of the solar field loops inlet valves is computed through a nonlinear optimization problem. Opening the input valves of the most efficient loops to increase the flow-rate and reducing the flow in the less efficient loops will improve the thermal balance of the solar field. The advantages of the proposed algorithm are the following [27]:

- Achieving a better thermal balance of the field.
- Reducing energy losses. Due to thermal balance defocusing actions will be reduced in many cases avoiding possible energy losses.
- Reducing the deterioration of the actuators and structures by reducing the control actions.

The control strategy applied to the solar field consists of two levels: the first one is a GS-GPC which controls the average of the outlet temperature of all loops. The GS-GPC control algorithm manipulates the flow-rate of the main pumps every 30 seconds to achieve this goal. The controller receives a desired set-point for the average temperature, obtains a linear model depending on the plant flow Q to predict the future evolution of the plant, and then computes a temperature reference for the feedforward compensator. The feedforward compensator uses this temperature reference and the measurable disturbances (inlet temperature T_{in}, ambient temperature T_a and the effective solar radiation I_{eff}) to compute a flow reference for the plant [24, 27]. The scheme of this controller is shown in Figure 10, where Qff represents the global flow-rate provided by the controller (equal to q_{ff}*N, where N = 90 loops in this particular plant) for the complete field and Q is the measured flow-rate.

The second level computes the aperture of the inlet valves for achieving a better thermal balance of the field. This is carried out by solving a nonlinear optimization problem.

The objective of the non-linear optimization is to obtain the values of the manipulated variables, apertures of the loops inlet valves, which make the field outlet temperature of the loops as homogeneous as possible.

Improving the thermal balance of the solar field avoids thermal energy losses produced by defocus actions. The general formulation of the nonlinear problem is presented in equation (9). The nonlinear optimization problem needs the estimation of the system states (metal-fluid temperatures) which is done by using an UKF algorithm.

$$
\begin{aligned}
minJ \quad & = \sum_{n=1}^{N_{Loop}} \left(\sum_{j=N_1}^{N_2} \delta(j)[\hat{y}_n(t+j|t) - w(t+j)]^2 \right. \\
& \left. + \sum_{j=1}^{N_u} \lambda(j)[\Delta u_n(t+j-1)]^2\right) \\
s.t: & \\
& U_{min} < U(t+j) < U_{max} \\
& \Delta u_{min} < \Delta u(t+j) < \Delta u_{max} \\
& x = g(x, U), y = f(x)
\end{aligned} \tag{9}
$$

where $\hat{y}_n(t+j|t)$ is an optimum j step ahead prediction of the system output, N_{Loop} is the number of loops, N_u is the control horizon, $\delta(j)$ and $\lambda(j)$ are weighting sequences and $w(t+j)$ is the future reference trajectory (set-point). Regarding the constraints, U_{min} and U_{max} are the minimum and maximum control signals while Δu_{min} and Δu_{max} are the minimum and maximum control signals increments.

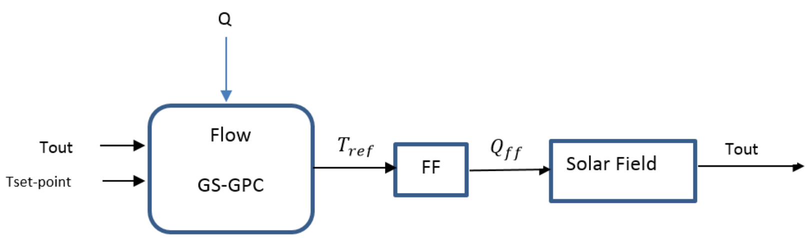


Figure 10. GS-GPC + FeedForward control scheme.

Notice that the main objective of this strategy is not to track a given reference which is the main objective of the flow controller. The aim is minimizing the difference among the outlet temperatures of the loops in steady state. By minimizing those distances, the outlet temperatures of all loops become closer and the thermal disparity is minimized. The only constraint for this optimization is the minimum and maximum value for the valves apertures, $U_{min} < U(t+j) < U_{max}$. Since the evolution of the efficiency disparity is considered to be slow, the problem is solved every 30 minutes.

One important problem is that solving the optimization problem considering 90 decision variables is computationally demanding. To be able to solve the optimization problem within the time required, the number of decision variables has to be decreased. It has been found that Solving the problem with 10, 20 or 30 variables (valves) is feasible [27]. The solution proposed is grouping loops of similar efficiency using a clustering algorithm. The k-means algorithm has been used to obtain the clusters. The classical method uses an iterative heuristic technique by means of which the centroids of the clusters are obtained, known as Lloyd's algorithm [64]. For the case of the solar plant, the main variables to cluster the loops are the loop outlet temperature and the estimated efficiency. Furthermore, in order to obtain a robust clustering, the defocus angle applied to every loop is also taken into account in the Euclidian distance calculation by the clustering technique. This helps to discriminate better if several loops have a similar outlet temperature and a similar estimated efficiency but may be defocusing with different angles. These loops can be grouped in the same cluster [27].

In the simulation case, the plant is affected by a stable radiation levels. The proposed strategy is tested with 10 and 20 decision variables (group of valves). The valves are grouped using the above-mentioned k-means clustering algorithm. Both scenarios are graphically and numerically compared to the case where no valve control is considered. A great disparity in the optical efficiency for all loops is considered.

The case when no control of the input valves is considered is shown in Figures 11 and 12. In Figure 11 the temperatures and defocus angles of each of the 90 loops are shown. The disparity in the outlet temperatures of the loops is observed due to the different efficiencies. This will cause the loops with higher efficiency to be defocused in order to maintain safe loop temperatures. In spite of this, the global controller GS-GPC manages to regulate the average temperature around the desired set-point, but thermal losses due to defocus actions are produced.

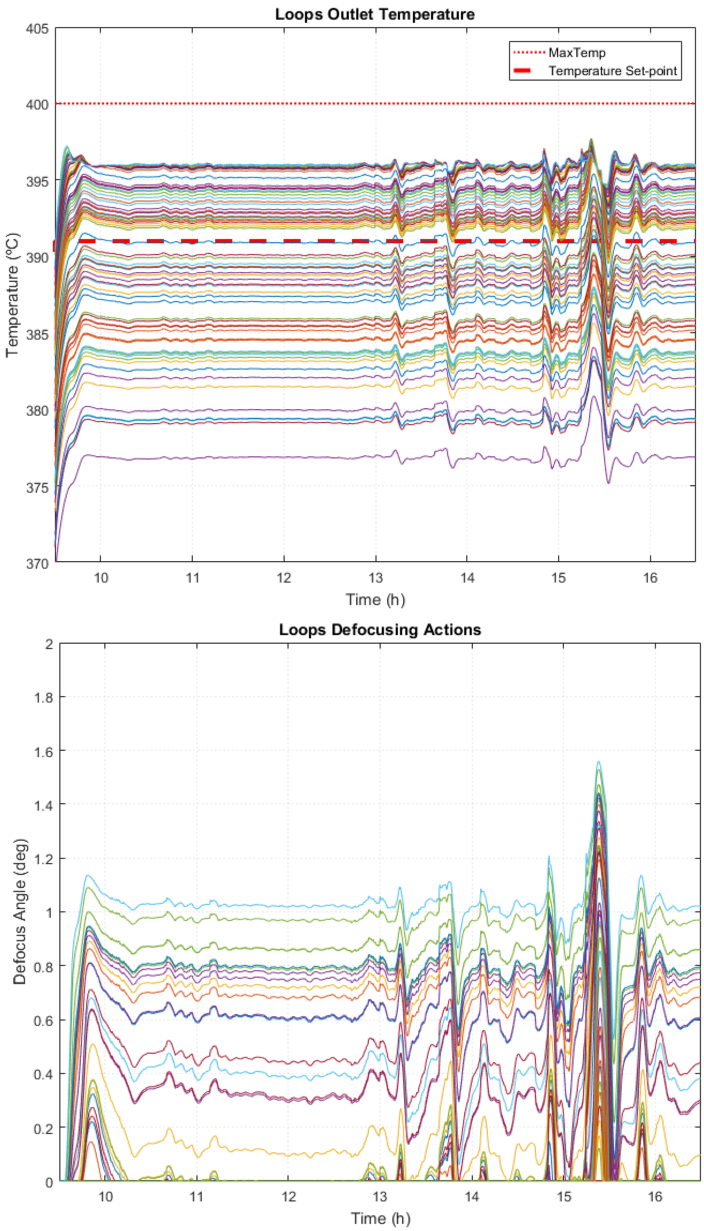


Figure 11. Loops temperatures (top) and defocus angles (bottom) when there is no valve control under stable radiation.

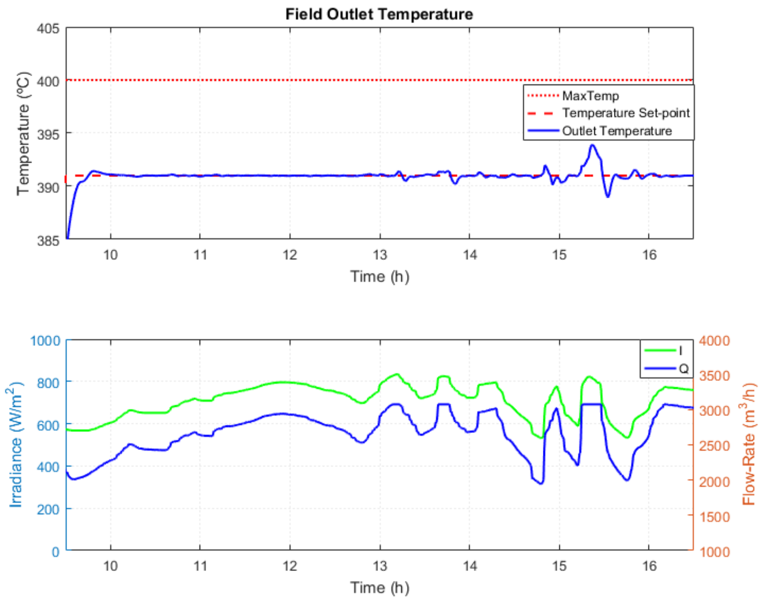


Figure 12. Field outlet temperature (top) and field flow-rate/irradiance (bottom) (No valve control).

Using the proposed strategy with 10 decision variables (10 cluster of valves), a thermal equilibrium of the field as seen in Figure 13 is obtained. The loops temperatures are concentrated in a much narrow range than the case without valve control, Figure 11. It can also be observed how the defocusing actions have diminished to a great extent compared to that of Figure 11 since the temperatures are now more homogeneous. An average temperature difference of 20°C is reduced to a 4°C approximately. This reduction of the defocusin actions constitutes a very good result: it saves energy because the total movement of the actuators are drastically reduced and also extends the life of the actuator.

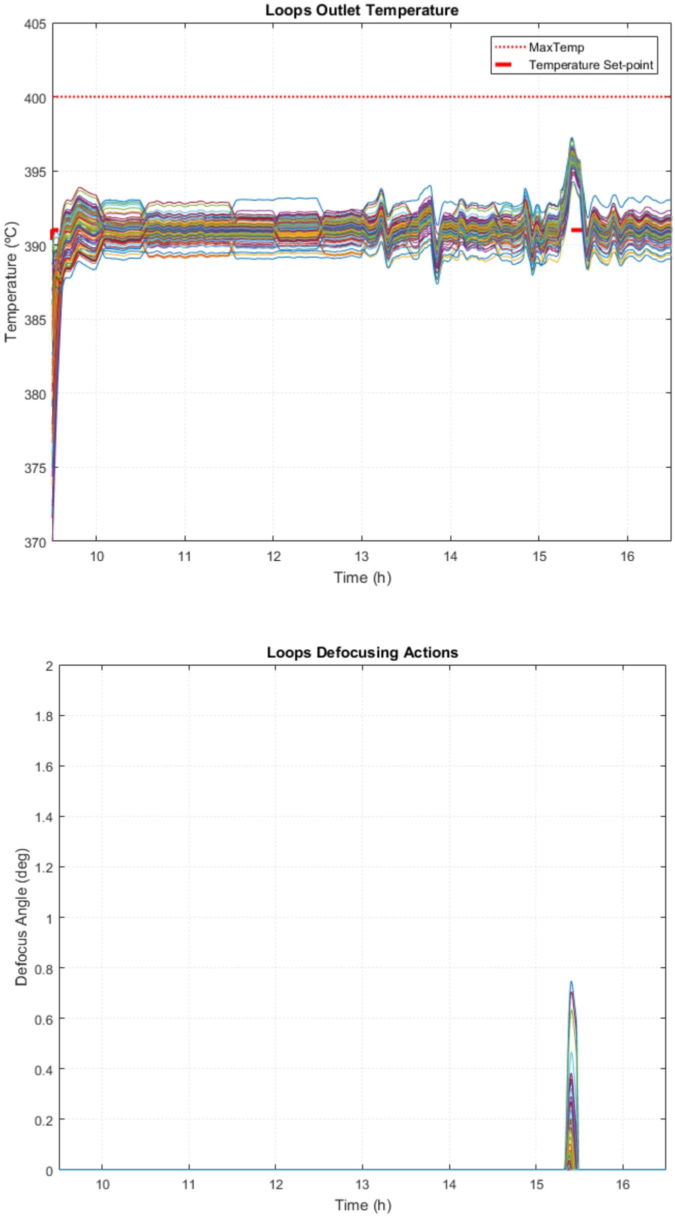


Figure 13. Loops temperatures (top) and defocus angles (bottom) results of the valve control strategy for thermal balance with 10 clusters for a stable radiation.

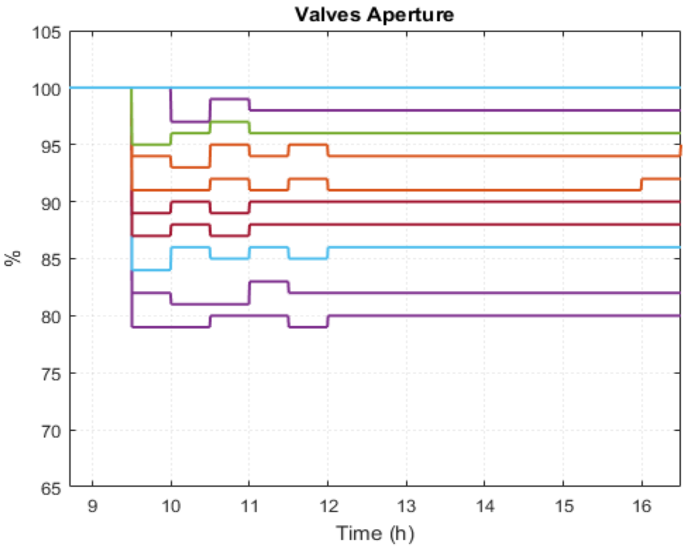


Figure 14. Valve control actions for the 10 clusters simulations with stable radiation.

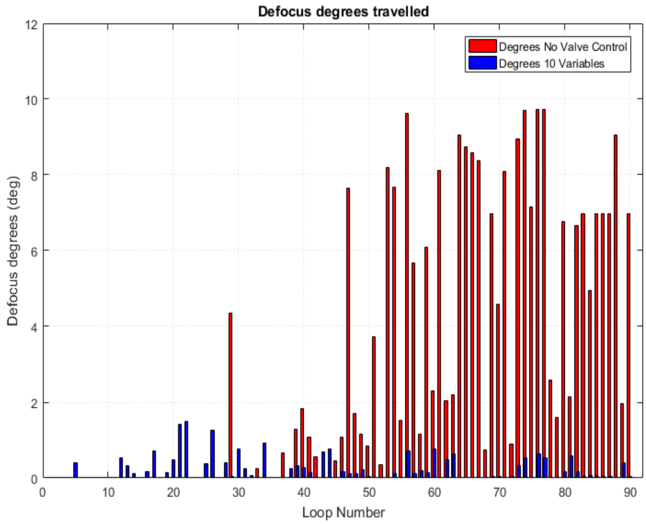


Figure 15. Total travelled defocus angle: valve control (blue) vs no valve control (red).

Table 2. Number of defocus and valve actions, case 1 (stable radiation)

Control	Defocusing Actions	Valve Actions	Total Traveled Degrees
No Valve Control	20534	0	253.52
Valve Control 10	579	420	19.97

The control actions are shown in Figure 15 and the total travelled defocus angle is shown in Figure 15 for both cases: valve control and no valve control.

Finally, Table 2 shows the numerical results where it can be seen that the number of actions and angles traveled with the thermal equilibrium has decreased considerably in the whole field. As can be seen, the number of defocusing actions is drastically reduced due to the better thermal balance achieved.

This example shows that by using a clustering of 10 loops, the actions of the valves, calculated by the optimization process, considerably reduce the difference between the outlet temperature of loops. This results in a reduction of the defocus actions applied on the loops as well as possible energy losses due to defocusing

CONCLUSION

As stated by the National American Academy and the European Commission is to improve the overall efficiency of the solar energy plants. In order to address this challenge, advanced control techniques play a decisive role.

In this chapter, within the framework of the OCONTSOLAR project, a review of the control techniques applied to parabolic solar trough plants as well as modeling approaches used to describe the behavior of these kind of plants has been presented.

The general equations to model a solar trough plants are described and a possible approach to model large solar field as an equivalent loop is presented. The example of the Mojave solar trough plants is provide.

The second part presents a review of the control strategies applied to this kind of plants. The majority of the control strategies existing in the literature are applied to small scale solar trough plants. When dealing with large scale solar trough plants, new problems and challenges appear which have to be addressed. Those problems are described.

Finally, one illustrative example is provided to show the advantage of implementing advanced control strategies using a model of a 50 MW solar trough plant. This example shows that by manipulating the input valves of the loops, a substantial reduction in the defocusing actions is attained minimizing the energy losses.

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REFERENCES

[1] Goswami, D., Kreith, F. and Kreider, J. (2000). Principles of Solar Engineering. (2th ed.). Taylor & Francis.

[2] Craig, O. O., Brent, A. C. and Dinter, F. (2017). The current and future energy economics of concentrating solar power (csp) in South Africa. *South African Journal of Industrial Engineering* 28(3), 1–14.

[3] SolarPaces (2017). *Csp project development.*

[4] Atlantica Yield (2018). http://www.atlanticayield.com/. (accessed May 1, 2019).

[5] Power Technology (2019). *The Andasol Solar Power Station Project*. https://www.power-technology.com/projects/andasolsolarpower/. (accessed May 1, 2019).

[6] National Renewable Energy Laboratory (NREL) (2015a). *Concentrating Solar Power Projects. Mojave Solar Project.* https://solarpaces.nrel.gov/mojave-solarproject. (accessed May 1, 2019).

[7] National Renewable Energy Laboratory (NREL) (2015b). *Concentrating Solar Power Projects. Solana Generating Station.* https://solarpaces.nrel.gov/solanagenerating-station. (accessed May 1, 2019).

[8] SolarPaces (2019). *Concentrating solar power projects by country.*

[9] N. A Engineering (2008). National Academy of Engineering. *Grand challenges for engineering*. www.engineeringchallenges.org. (accessed May 1, 2019).

[10] European Comission (2015). *Communication of the Commission to the European Parlament and the Council concerning the Paris Protocol-A blueprint for tackling global climate change beyond 2020*. https://ec.europa.eu/commission/publications/paris-protocol-blueprinttackling-global-climate-change-beyond-2020 en. (accessed May 1, 2019).

[11] Camacho, E. F., Samad, T., Garcia-Sanz, M. and Hiskens, I. (2011). Control for renewable energy and smart grids. The Impact of Control Technology, *Control Systems Society*, 69–88.

[12] Badal, F. R., Das, P., Sarker, S. K. and Das, S. K. (2019, Apr). A survey on control issues in renewable energy integration and microgrid. *Protection and Control of Modern Power Systems* 4(1), 8.

[13] Berenguel, M., Cirre, C. M., Klempous, R., Maciejewski, H., Nikodem, M., Nikodem, J., Rudas, I. and Valenzuela, L. (2005). Hierarchical control of a distributed solar collector field. In Computer Aided Systems Theory. *EUROCAST* 2005, pp. 614–620.

[14] Cirre, C. M., Berenguel, M., Valenzuela, L. and Klempous, R. (2009). Reference governor optimization and control of a distributed

solar collector field. *European Journal of Operational Research* 193, 709–717.

[15] Camacho, E. F., Rubio, F. R., Berenguel, M. and Valenzuela, L. (2007). A survey on control schemes for distributed solar collector fields. Part II: Advanced control approaches. *Solar Energy* 81(10), 1252 – 1272.

[16] Camacho, E. F., Soria, M. B., Rubio, F. R. and Martínez, D. (2012). *Control of Solar Energy Systems* (1st ed.). Springer-Verlag London.

[17] Lemos, J. M., Neves-Silva, R. and Igreja, J. M. (2014). *Adaptive Control of Solar Energy Collector Systems.* Springer-Verlag.

[18] Gil, P., Henriques, J., Cardoso, A., Carvalho, P. and Dourado, A. (2014, March). Affine neural network-based predictive control applied to a distributed solar collector field. *IEEE Transactions on Control Systems Technology* 22(2), 585–596.

[19] Camacho, E. F. and Gallego, A. J. (2015). Model predictive control in solar trough plants: A review. In *5th IFAC Conference on Nonlinear MPC*, September 17-20, Sevilla (Spain).

[20] Llamas, J. M., Bullejos, D. and Ruiz, M. (2019). Optimal operation strategies into deregulated markets for 50 mwe parabolic trough solar thermal power plants with thermal storage. *Energies* 12, 935–953.

[21] Power Technology (2015). *Mojave Solar Thermal Power Facility*, San Bernardino County, California. https://www.powertechnology.com/projects/mojave-solar-thermal-power-california-us/.

[22] European Comission (2018). *Community Research and Development Information Service OCONTSOLAR*. https://cordis.europa.eu/project/rcn/216250 es.html. (accessed May 1, 2019).

[23] Gallego, A. J. and Camacho, E. F. (2012). Adaptative state-space model predictive control of a parabolic-trough field. *Control Engineering Practice* 20(9), 904 – 911.

[24] Sánchez, A. J., Gallego, A. J., Escaño, J. M. and Camacho, E. F. (2019). Adaptive incremental state space mpc for collector defocusing of a parabolic trough plant. *Solar Energy* 184, 105–114.

[25] Sánchez, A. J., Gallego, A. J., Escaño, J. M. and Camacho, E. F. (2018, May). Temperature homogenization of a solar trough field for performance improvement. *Solar Energy*. 165C, 1–9.

[26] Camacho, E. F., Sánchez, A. J. and Gallego, A. J. (2019). Solar Energy Systems: Progress and Future Directions, *Chapter Model Predictive Control of Large Scale Solar Trough Plants*. Number 1. Nova.

[27] Sánchez, A. J., Gallego, A. J., Escaño, J. M. and Camacho, E. F. (2019). Thermal balance of large scale parabolic trough plants: A case study. *Solar Energy* 190, 69–81.

[28] Gallego, A. J., Macias, M., de Castilla, F. and Camacho, E. F. (2019). Mathematical modeling of the mojave solar plants. *Energies* 12(21), 4197.

[29] Blanco, M. J. and Santigosa, L. R. (2017). *Advances in Concentrating Solar Thermal Research and Technology* (1 ed.). Woodhead Publishing.

[30] CIEMAT, CRES, DLR, FICHTNER, FLABEG, INABENSA, and SBP. (2001). *Development of a low cost European parabolic trough collector - Eurotrough.* Technical report, European Commission. CORDIS. FP4-NNE-JOULE C. Grant agreement ID: JOR3980231.

[31] Carmona, R. (1985). *Analisis, modelado y control de un campo de colectores solares distribuidos con sistema de seguimiento en un eje.* PhD Thesis. Universidad de Sevilla. [*Analysis, modeling and control of a distributed solar collector field with tracking system on one axis*. PhD Thesis. University of Seville].

[32] Camacho, E. F., Berenguel, M. and F. R. Rubio (1997). *Advanced Control of Solar Plants.* Springer Science & Business Media.

[33] Gallego, A. J., Yebra, L. J., Camacho, E. F. and Sánchez, A. J. (2016, September). Mathematical modeling of the parabolic trough collector field of the tcp-100 research plant. In *Modelling and Simulation - 9th EUROSIM* 2016, Oulu (Finland).

[34] Reviriego, A. N., del Olmo, F. H. and Ávarez-Barcia, L. (2017). Nonlinear adaptive control of heat transfer fluid temperature in a parabolic trough solar power plant. *Energies* 10, 1–12.

[35] Chaibakhsh, A. and Ghaffari, A. (2008). Steam turbine model. *Simulation Modelling Practice and Theory* 16, 1145–1162.

[36] Montañés, R. M. M., Windahlb, J., Palssonb, J. and Thern, M. (2018). Dynamic modeling of a parabolic trough solar thermal power plant with thermal storage using modelica. *Heat Transfer Engineering* 39(3), 277–292.

[37] Ferruzza, D., Topel, M., Basaran, I., Laumert, B. and Haglind, F. (2017). Startup performance of parabolic trough concentrating solar power plants. In *AIP Conference Proceedings*.

[38] Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F. and Predeschi, D. (2018). A survey of methods for explaining black box models. *ACM Computing Surveys* 51(5), 1–42.

[39] Arendt, K., Jradi, M., Shaker, H. R. and Veje, C. T. (2018). Comparative analysis of white-, gray- and black-box models for thermal simulation of indoor environment: Teaching building case study. In *2018 Building Performance Modeling Conference and SimBuild*, Chicago (U.S.A). ASHRAE and IBPSAUSA.

[40] Igreja, J. M., Lemos, J. M., Barao, M. and Silva, R. N. (2003, Sept). Adaptive nonlinear control of a distributed collector solar field. In *European Control Conference* (ECC), pp. 2733–2738.

[41] Camacho, E. F. and Bordons, C. (2007). *Model Predictive control* (2th ed.). Springer-Verlag London.

[42] Camacho, E. F., Rubio, F. R., Berenguel, M. and Valenzuela, L. (2007). A survey on control schemes for distributed solar collector fields. Part I: Modeling and basic control approaches. *Solar Energy* 81(10), 1240 – 1251.

[43] Camacho, E. F., Berenguel, M. and Rubio, F. R. (1994). Application of a gain scheduling generalized predictive controller to a solar power plant. *Control Engineering Practice* 2(2), 227–238.

[44] Camacho, E. F. and Berenguel, M. (1994, Aug). Application of generalized predictive control to a solar power plant. *In 1994 Proceedings of IEEE International Conference on Control and Applications*, Volume 3, pp. 1657–1662.

[45] Stuetzle, T., Blair, N., Mitchell, J. and Beckman, A. (2004). Automatic control of a 30mwe segs vi parabolic trough plant. *Solar Energy* 76, 187–193.

[46] Camacho, E. F., Berenguel, M. and Bordons, C. (1994, Dec). Adaptive generalized predictive control of a distributed collector field. *IEEE Transactions on Control Systems Technology* 2(4), 462–467.

[47] Coito, F., Lemos, J., Silva, R. and Mosca, E. (1997). Adaptive control of a solar energy plant: exploiting acceptable disturbances. *International Journal of Adaptive Control and Signal Processing* 11, 327–342.

[48] Silva, R., Lemos, J. and Rato, L. (2003). Variable sampling adaptive control of a distributed collector solar field. *IEEE Control Systems Technology* 11, 765–772.

[49] Lemos, J. M., Neves-Silva, R. and Igreja, J. M. (2014). *Adaptive Control of Solar Energy Collector Systems*. Springer-Verlag.

[50] Pin, G., Falchetta, M. and Fenu, G. (2007). Adaptative time-warped control of molten salt distributed collector solar fields. *Control Engineering and Practice* 16. ISSN 0967-0661. doi 10.1016, 813–823.

[51] Pin, G., Falchetta, M. and Fenu, G. (2009). Modeling and control of concentrating solar power systems: a discrete-time adaptative scheme for temperature control in molten-salt solar collector-fields. In *Solar Collectors: Energy Conservation, Design and Applications Series: Renewable Energy: Research, Development and Policies*. Nova Publishers, 15–39.

[52] Limon, D., Alvarado, I., Alamo, T., Arahal, M. and Camacho, E. F. (2008). Robust control of the distributed solar collector field acurex using mpc for tracking. In *IFAC World Congress*.

[53] Andrade, G. A., Pagano, D. J., Álvarez, J. D. and Berenguel, M. (2013). A practical nmpc with robustness of stability applied to distributed solar power plants. *Solar Energy* 92, 106–122.

[54] Gil, P., Henriques, J., Cardoso, A., Carvalho, P. and Dourado, A. (2014). Affine neural network-based predictive control applied to a

distributed solar collector field. *IEEE Transactions on Control System Technology*, 22(2), 585–596.

[55] Khoukhi, B., Tadjine, M. and Boucherit, M. S. (2015, May). Nonlinear continuous-time generalized predictive control of solar power plant. *Int. J. Simul. Multisci. Des. Optim*. 6.

[56] Lima, D. M., Normey, J. L. and Santos, T. L. M. (2016). Temperature control in a solar collector field using filtered dynamic matrix control. *ISA Transactions* 62, 39–49.

[57] Gallego, A. J., Fele, F., Camacho, E. F. and Yebra, L. J. (2013). Observer-based model predictive control of a solar trough plant. *Solar Energy* 97, 426–435.

[58] Berenguel, M., Cirre, C. M., Klempous, R., Maciejewski, H., Nikodem, M., Nikodem, J., Rudas, I. and Valenzuela, L. (2005). *Hierarchical control of a distributed solar collector field. Computer Aided Systems Theory – EUROCAST* 2005 Volume 3643/2005, 614–620.

[59] Camacho, E. and Gallego, A. (2013). Optimal operation in solar trough plants: A case study. *Solar Energy* 95, 106 – 117.

[60] He, G., Chen, Q., Kang, C. and Xia, Q. (2016, July). Optimal offering strategy for concentrating solar power plants in joint energy, reserve and regulation markets. *IEEE Transactions on Sustainable Energy* 7(3), 1245–1254.

[61] Vasallo, M. J. and Bravo, J. M. (2016). A mpc approach for optimal generation scheduling in csp plants. *Applied Energy* 165, 357 – 370.

[62] Cojocaru, E. G., Bravo, J. M., Vasallo, M. J. and Santos, D. M. (2019). Optimal scheduling in concentrating solar power plants oriented to low generation cycling. *Renewable Energy* 135, 789 – 799.

[63] Sánchez, A. J., Gallego, A. J., Escaño, J. M. and Camacho, E. F. (2018, November). Event-based mpc for defocusing and power production of a parabolic trough plant under power limitation. *Solar Energy* 174, 570 – 581.

[64] Lloyd, S. P. (1982). Least squares quantization in pcm. *IEEE Transactions on Information Theory* 28(2), 129–137.

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Publications from the Last 3 Years (5 publications):

1. A. J. Gallego, A. J. Sánchez, M. Berenguel and E. F. Camacho. "Adaptative UKF based Model Predictive Control of a Fresnel Collector Field," *Journal of Process Control*, 2020, 85 pp:76-90.
2. A. J. Gallego M. Macías, F. de Castilla and E. F. Camacho. "Mathematical modeling of the Mojave solar plants," *Energies*, November 2019, 12 pp:1-20.
3. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, "Thermal balance of large scale solar trough plants: A case study." *Solar Energy*, September, 2019, 190:69-81.
4. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, "Adaptative incremental state space MPC for collector defocusing of a parabolic trough solar plant." *Solar Energy*, May, 2019, 184:105-114.
5. A. J. Gallego, G. M. Merello, M. Berenguel and E. F. Camacho. "Gain scheduling model predictive control of a Fresnel collector field." *Control Engineering Practice*, January (2019), 82 pp: 1-13.

Adolfo Juan Sánchez del Pozo Fernández

Affiliation: University of Sevilla

Education: PhD student. Master degree. Researcher.

Business Address: Avenida de los descrubrimientos s/nº, 41092, Sevilla (Spain)

Research and Professional Experience: Research concerning Automatic control, solar energy plants and advanced control algorithms, in special model predictive control and nonlinear optimization algorithms.

Professional Appointments: PhD researcher in the Advanced Grant OCONTSOLAR.

Publications from the Last 3 Years:

1. A. J. Gallego, A. J. Sánchez, M. Berenguel and E. F. Camacho. "Adaptative UKF based Model Predictive Control of a Fresnel Collector Field," *Journal of Process Control*, 2020, 85 pp:76-90.
2. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, "Thermal balance of large scale solar trough plants: A case study." *Solar Energy*, September, 2019, 190:69-81.
3. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, "Adaptative incremental state space MPC for collector defocusing of a parabolic trough solar plant." *Solar Energy*, May, 2019, 184:105-114.
4. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, "Event-based MPC for defocusing and power production of a parabolic trough plant under power limitation." *Solar Energy*, November 2018, 174 pp: 570-581.

5. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, “Temperature homogenization of a solar trough field for performance improvement.” *Solar Energy*, May 2018, 165 pp: 1-9.

Eduardo F. Camacho

Affiliation: University of Sevilla

Education: Full Professor

Research and Professional Experience: He has served on various IFAC technical committees and chaired the IFAC publication Committee from 2002-2005. He was the president of the European Control Association (2005-2007) and chaired the IEEE/CSS International Affairs Committee (2003-2006), the IFAC Policy Committee (2005-2011) and a member of the IEEE/CSS Board of Governors. He has acted as evaluator of projects at national and European level and was appointed Manager of the Advanced Production Technology Program of the Spanish National R&D Program (1996-2000). He was one of the Spanish representatives on the Program Committee of the Growth Research program and expert for the Program Committee of the NMP research priority of the European Union.

He has carried out review and editorial work for various technical journals and many conferences. He was one of the editors of the IFAC journal, Control Engineering Practice, editor at large of the European Journal of Control and subject editor of the journal Optimal Control: Methods and Applications. He was Publication Chair for the IFAC World Congress b’02 and General Chair of the joint Control and Decision Conference and European Control Conference (CDC-ECC’05). He is an IEEE fellow and IFAC fellow. Recently he has been awarded with an Advanced Grant from the European Research Council.

Professional Appointments: Full Professor at the Systems and Automatics department of the University of Sevilla.

Honors: IEEE Fellow, IFAC Fellow

Publications from the Last 3 Years (5 publications):

1. A. J. Gallego, A. J. Sánchez, M. Berenguel and E. F. Camacho. “Adaptative UKF based Model Predictive Control of a Fresnel Collector Field,” *Journal of Process Control*, 2020, 85 pp:76-90.
2. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, “Thermal balance of large scale solar trough plants: A case study.” *Solar Energy*, September, 2019, 190:69-81.
3. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, “Adaptative incremental state space MPC for collector defocusing of a parabolic trough solar plant.” *Solar Energy*, May, 2019, 184:105-114.
4. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, “Event-based MPC for defocusing and power production of a parabolic trough plant under power limitation.” *Solar Energy*, November 2018, 174 pp: 570-581.
5. A. J. Sánchez, A. J. Gallego, J. M. Escaño and E. F. Camacho, “Temperature homogenization of a solar trough field for performance improvement.” *Solar Energy*, May 2018, 165 pp: 1-9.