Abstract—Solar towers are electrical power production systems that use highly concentrated solar radiation as energy source that is collected by means of a heat-transfer fluid. This master thesis studies the application of several control strategies with the aim of maintaining the working fluid at a temperature that maximizes the electrical production. The main difficulties are the nonlinear fluid temperature dynamics, plant thermal constraints, and a variable energy source that cannot be manipulated. The temperature dynamics flow dependence demands for a changing parameter controller that results from a gain scheduling scheme or from a multi-model adaptive control strategy, in which the manipulated variable is adjusted by one of the set of local controllers designed for different operating regimes. The former is accomplished through a PI control and the latter via LQG optimal control. In addition, the MUSMAR control algorithm that adjusts its gains to every plant dynamic change, including parameters, is tested. Although the mentioned control concepts are applied considering the flow as the only manipulated variable, the combination of the latter with the radiation flux reflected by the heliostat field is also studied through PI control. The solar tower electrical power production has a maximum for a given outlet temperature that changes with plant parameters and disturbances. The improvement of production levels is conducted by adjusting the temperature reference with a static optimization procedure.

Index Terms—Solar tower model, PI control, LQG control, MUSMAR, coordination, static optimization.

I. INTRODUCTION

Solar radiation energy can be directly converted to electricity using Photovoltaic (PV), or indirectly through Concentrating Solar Power (CSP). Although PV electricity production is popular, electricity production using CSP (the so called “solar thermal electricity”, STE) has the current advantage of providing a mean for energy storage. Indeed, there are current industrial STE plants that are able to produce electrical power 24 hours per day. The last mentioned technology uses sun tracking mirrors (heliostats) to focus the sunlight onto a exchanger that absorbs energy through a heat transfer fluid, as water or molten salt. The collected energy can be stored in a thermal storage system that retains heat efficiently over days before being used in conventional electricity generation cycle [1].

In contrast to traditional plants, solar power generating systems are unable to manipulate the energy source, that is variable. Therefore, CSP technologies must have a control scheme that handles solar radiation variation in order to regulate the fluid temperature and avoid plant thermal constraints infringement.

The solar towers or Central Receiver Systems (CRS) have a superior thermal efficiency compared to other CSP technologies due to a higher incident radiation flux concentration allowance that leads to superior working temperatures, and therefore to a higher efficiency.

A. Solar Tower Description

Solar power towers use hundred of heliostats to focus the sun energy on a heat-exchanger located on the top of a tall tower, as shown in figure 1. The concentrated solar radiation is captured and stored at a hot tank, in thermal form, by means of a heat transfer fluid that flows through the tower receiver. The stored energy can be extracted to a steam generator that is connected to a conventional turbo-generator in order to produce electrical power. The resulting cooled fluid obtain from passing the molten salt through the steam generator is driven to the cold storage tank, where it is pumped to the heat-exchanger by means of flow controlled valve. The nominal inlet and outlet temperatures are $T = 290^\circ C$ and $T = 565^\circ C$, respectively. The valve flow is controlled in order to maintain a constant outlet temperature since solar radiation varies.

Although figure 1 only illustrates one receiver flow path and one valve, the solar tower considered as a paradigm in this thesis has a doubled fluid circuit, with two valves, for the east and west parts of the receiver.

B. State of The Art

The model for the outlet temperature of solar plants with distributed solar collectors has been developed via physical principles or empirically through data recovered from plant operation [2]. The solar tower dynamics is similar to the aforementioned plants and thus the receiver outlet temperature can also be described by a distributed parameter model given by a partial differential equation.

Several automatic control systems for the solar plants have been established. In [3], the quadratic-optimal control based on the linearized process dynamics of the steam boiler in a solar-powered central receiver is investigated and equations for the optimal regulator are given.

Under the distributed parameter model it was designed a nonlinear feedback linearization controller that showed improved results at plant startup [4]. In [5], a viable controller
for tackling the collector optical efficiency uncertainty in ACUREX is addressed by combining the last mentioned technique with the Lyapunov based adaptation. The optimal control is derived for the last mentioned model in order to control the collector fluid velocity by maximizing the net energy collected, while also considering a bilinear lumped parameter model for the storage fluid temperature, the \([6]\). Furthermore, a static PI controller is explored in \([5]\). However, the change of the operating temperature and parameters uncertainties degrades the controlled system response. In the same work, successful results from applying the MUSMAR predictive adaptive controller are shown. The development of a variable sampling adaptive controller has proven to yield an increased control performance \([7]\). Experimental results demonstrated the capability of making fast temperature set-point changes with a reduced overshoot.

The existence of anti-resonance modes at process \([8]\) motivated the development of an adaptive controller based on frequency methods to counter such dynamics \([8]\). The same approach was used to develop an internal model controller in \([9]\).

Other approaches include the use of a neural network model within model based predictive control \([10]\), and the application of predictive sliding mode controllers that have proved satisfactory results for reference tracking and disturbance rejection \([11]\). In addition, the flexibility at characterizing goals and constraints of the plant is achieved through fuzzy model based predictive control \([12]\).

Regarding to optimal operation, the design and implementation of a two-layer hierarchical control strategy for a distributed solar collector field is described in \([13]\). The upper layer of the hierarchical strategy determines the optimal plant operating point while considering plant constraints and maximizing the profit from selling the electricity generated. However, the temperature dependence of the electric power generating system efficiency is set to be constant. In addition, a three layer algorithm is developed in \([14]\), where the first layer computes the electrical power to be produced and delivered. The second layer computes the optimal set-point for the solar plant taking into account the information yielded from the first and economic profit optimization. The aforementioned work describes the Distributed Collector Solar Field through a concentrated parameter model.

II. Process Modeling

This work presents two models of the Solar Two CRS, one developed via physical principles and the other by input/output data collected from tests performed at the plant. The first method yields a nonlinear continuous model that allows the inspection of the system behaviour as a consequence of modifying parameters or variables, whereas the latter results in a linear discrete model that is only valid near a given operating point but that has the advantage of allowing controller design. Since Solar Two no longer exists, the data is gathered using simulations in the first model.

A. Reduced Complexity Model

The dynamics of a solar tower receiver panel is modelled by an hyperbolic partial differential equation, obtained from energy conservation. The fluid temperature is described by a scalar function \(T(z, t)\) where \(z \in \mathbb{R}\) is a space dimension measured along the pipe, and \(t \in \mathbb{R}\) is continuous time \([15]\). The corresponding equation is derived from the analysis of the net enthalpy in time and space, in a small section of pipe between \(z\) and \(z + \Delta z\). The partial differential equation is obtained by approaching time and space intervals to infinitesimal values and adding the loss coefficient term \(\gamma\) to the model,

\[
\frac{\partial}{\partial t} T(z, t) = -F \frac{\partial}{\partial z} T(z, t) + \frac{\bar{\alpha}}{\rho_f c_f A_f} R(t) - \gamma (T_{av}(z, t) - T_a).
\]

(1)

where \(F\) is the fluid velocity, \(\rho_f\) is the fluid density, \(c_f\) is the specific heat, and \(A_f\) is the pipe’s cross section area, \(R\) is the solar radiation power and, \(\bar{\alpha}\) is a parameter related to the efficiency of the energy absorption by the fluid that depends on fluid thermal characteristics and also on mirror optical efficiency and geometry \([15]\). Moreover, \(T_{av}\) and \(T_a\) are the average and ambient temperature, respectively.

B. System Identification

The process modeling performed is discrete time-based and it is established through a polynomial model. The system identification is conducted between the input flow \(u\) of the controlled valve and the outlet temperature \(y\), while maintaining all the perturbations constant.

A good representation of the plant transient response, without allowing to the appearance of non-minimum-phase zeros or a too extensive open loop functioning between sampling instants, is achieved by choosing a sampling period ten times smaller than the rise time, \(T_r\) \([16]\). In order to avoid nonlinearities, \(T_r\) is determined by the step response of a reference amplitude reduction of 3% of the nominal flow \(F = 80\ kg/s\). The resulting sampling period is \(T_s \approx 4s\).
Since a computer model is used for identification purposes, a high duration signal may be applied without suffering from the influence of solar radiation drifts [2]. Thus, a PRBS with binary values of ±3% from the operating point flow rate is applied, in order to avoid the appearance of nonlinearities.

The modeling approach presented assumes that the system is unknown and that all model parameters are adjusted without considering physical information. Thus, it is represented by a black-box model. The ARMAX structure is adequate to use since the system noise is coloured and the process has load perturbations. Such model is given by the following expression,

\[ A(q^{-1})y(h) = B(q^{-1})u(h - n_k) + C(q^{-1})e(h) \]

where \( e(h) \in \mathbb{R} \) is a Gaussian white-noise disturbance, \( q^{-1} \) represents the backward shift operator, \( n_k \) is the value of the pure delay and,

\[ A(q^{-1}) = 1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-n_a} \]
\[ B(q^{-1}) = 1 + b_1 q^{-1} + \ldots + b_{n_b} q^{-n_b} \]
\[ C(q^{-1}) = 1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c} \]

where \( n_a, n_b, n_c \) and \( n_k \) are the tuning variables. The polynomial coefficients are estimated through the quadratic prediction error criterion that avoids parameter estimation polarization, using armax MATLAB function. The goodness of fit between the obtained model and the data collected from the plant test is measured through the Normalized Root Mean Square Error, that is given by

\[ fit(\%) = 100 \times \left( 1 - \frac{\sqrt{\sum_i(y_i - \bar{y}_i)^2}}{\sqrt{\sum_i(y_i - \bar{y}_i)^2}} \right) \]

where \( y_i, \bar{y}_i \) are the nonlinear model response and respective mean value and \( \bar{y}_i \) the linear model output. The setting parameters that yields the best results of the above-mentioned function, \( fit(\%) = 98.83\% \), are: \( n_a = 10, n_b = 3, n_c = 10 \) and \( n_k = 1 \).

C. Plant Dynamics

In order to enhance the understanding of the solar tower receiver model given by equation (1), several MATLAB simulations are presented. Neither the extra delay of the solar radiation action due to green-house effect nor the valve dynamics are considered.

The first analysis on the receiver dynamics is conducted by the examination of the the system response in the absence of losses and solar radiation. Moreover, it is assumed that the temperature of the fluid entering the pipe is time constant and equal to \( T(0, t) = 0 \). The transport of the temperature at the foremost panel of the receiver, along the flow path, considering constant and nominal input \( F \), is shown in figure 2.

The loci over the plane \([z, t]\), for which \( T(z, t) \) is constant in time are denominated characteristic lines and are given by the solution of the differential equation,

\[ \frac{dz}{dt} = F. \] (2)

Figures 3 and 4 illustrate examples of the solution of equation (2), for constant fluid flow. The increase of the input variable \( F \) decreases the time necessary for the output temperature to be affected.

The following analysis on the system dynamics considers the existence of solar radiation, temperature losses and fluid entering the pipe with \( T(0, t) = 290^\circ C \). The former perturbation leads to a temperature rise along the receiver’s flow path, ascending from the inlet to the outlet. The output temperature can be adjusted by varying the fluid exposure time to solar radiation that changes the amount of energy absorbed. Figure 5 shows the model response to a step on the fluid flow, with constant and equal radiation through the receiver. It can be concluded that the system has an inverse response. The temperature increases as the flow decreases.

Hitherto, constant values for model parameters and disturbances have been considered, although most alter with time. The major perturbation is the radiation flux concentration that may change due to atmospheric moisture or passing clouds that cause fast changes of low or high amplitudes. Moreover, the Direct Normal Insolation (DNI) varies due to the apparent movement of the sun.
TABLE I: Ultimate sensitivity rules [16].

<table>
<thead>
<tr>
<th>Method</th>
<th>$K_p$</th>
<th>$T_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZN rule</td>
<td>0.45$K_u$</td>
<td>0.833$T_u$</td>
</tr>
<tr>
<td>Modified rule</td>
<td>0.06$K_u$</td>
<td>0.177$T_u$</td>
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III. PROCESS CONTROL

The system to be controlled comprehends a flow controlled valve in series with the receiver model in a cascade structure. Such configuration is feasible since the valve has a dynamics faster than the fluid outlet temperature. The inner loop manipulates the flow, whereas the outer loop actuates over the outlet temperature by manipulating the flow reference. The controller objective is to maintain the output variable at a specified reference, regardless of solar radiation variation. This intent is accomplished considering the existence of maximum and minimum flow and temperature constraints.

The control signal results from the combination of two independent terms. The first is derived from a feedback system that only reacts after the disturbance has taken effect at the receiver output. The second is a feed-forward contribution generated from the sensed DNI that compensates for disturbances before the outlet temperature is perturbed.

The nonlinear fluid temperature dynamics demand for a changing parameter controller that is achieved through a GS scheme, a multi-model adaptive control structure, or a predictive adaptive controller.

A. PI Control

The PI control concept uses the error between a measured process variable and the desired set-point to generate the manipulated variable, in a feedback loop. The aforementioned controller parameters are designed using a modified Ziegler and Nichols ultimate sensitivity rule, since the standard formula yields a closed-loop response with excessive overshoot and oscillation. This method determines $K_p$ and $T_i$ as a function of the ultimate gain $K_u$ and period $T_u$, as stated in table I.

The existence of maximum and minimum valve position limits, require the existence of an anti-windup scheme to avoid continuous integral action above actuating boundaries. The variables $K_u$ and $T_u$ are obtained with the process at stability limit, by using the relay with hysteresis feedback method that limits the oscillation amplitude and avoids random switches caused by noise measurement.

The describing function is a method to determine the condition for oscillation in a nonlinear feedback system composed by a linear element and a static nonlinearity. The former is the plant linear operation while working around the nominal point, whereas the latter corresponds to the relay. The nonlinear block is described by a gain $N(a)$ that represents how a sinusoid of amplitude $a$ propagates through the plant [17].

The plant gain at stability limit results from the ratio of the output amplitude $a$ and the square wave first harmonic amplitude $4d/\pi$ since the plant attenuates higher frequencies,

$$G(i\omega_u) = \frac{-\pi a}{4d}, \quad (3)$$

The condition for oscillation of a process with transfer function $G(i\omega)$ is determined by requiring that the sine wave propagates with constant amplitude and phase,

$$N(a)G(i\omega) = -1. \quad (4)$$

The intersection of $-1/N(a)$ with the Nyquist curve $G(i\omega)$ indicates the possible occurrence of an oscillation. At the crossing point, the amplitude and frequency are equal for both plots. Therefore, the ultimate gain is equal to the relay describing function that is given by,

$$N(a) = \frac{4d}{-\pi \sqrt{a^2 - \varepsilon^2 - i\pi \varepsilon}}, \quad (5)$$

where $\varepsilon$ is the hysteresis width that must be higher than the noise amplitude. The resulting ultimate values obtained with the hysteresis relay feedback procedure for $d = \pm 0.08 F_{nom}$ and $\varepsilon = 15$ are $T_u = 83.8$ and $K_u = -2.53 \times 10^{-5}$. However, the hysteresis alters the cross point between $-1/N(a)$ and the Nyquist curve, leading to a gain and period different from the ultimate values.

1) Gain-Scheduled PI Control: The GS is a control strategy for nonlinear systems in which the controller gains are automatically adjusted as a function of the scheduling variable. In this work, the dependent variable is the outlet temperature and the controller parameters are determined for working conditions of $T = 565 \, ^\circ C$, $T = 550 \, ^\circ C$, $T = 535 \, ^\circ C$ and $T = 505 \, ^\circ C$. The above mentioned functions are found by linearising the dependent variable over $T$. In order to determine the PI controller parameters for each operating condition, it is necessary to adapt the hysteresis relay limit values at the procedure stated in subsection III-A.

B. LQG Control

The optimal controller presented is developed through a state-space approach and is applied to the discrete linear model identified. Such control system generates the manipulated variable by minimizing a quadratic cost function that yields a control signal given by a state feedback law.

The inability to measure the process states demand for a (Linear Quadratic Estimator) LQE coupled with the (Linear Quadratic Regulator) LQR. The use of a Kalman filter as an estimator gives rise to the (Linear Quadratic Gaussian) LQG controller. The LQR and LQE are designed considering the separation principle that express the possibility to design the controller and the estimator separately without leading to any change in the closed loop poles of the LQG controller, for linear state-space systems [16]. Moreover, the resulting LQG system is always stable for a single-input single-output processes [16].

1) LQR: The optimal regulator is designed for linear time-invariant state-space system with a noise free structure, given by,

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = Cx(k), \quad (6)$$
where $k \in \mathbb{R}$ denotes discrete time, $x \in \mathbb{R}^n$ is the state vector, $u \in \mathbb{R}^m$ is the input vector, $y \in \mathbb{R}^p$ is the output vector, $A \in \mathbb{R}^{n \times n}$ is the state matrix, $B \in \mathbb{R}^{n \times m}$ is the input matrix, and $C \in \mathbb{R}^{p \times n}$ is the output matrix. Since the LQR does not guarantee zero output steady-state error, it is necessary to introduce the integral action that is represented by the following state,

$$x_{I}(k) = \frac{T_s}{q-1} e(k) \Leftrightarrow x_I(k+1) = x_I(k) + T_s e(k), \quad (7)$$

where $q$ is the forward shift operator, $T_s$ is the sampling period and $e(k) = y(k) - r(k)$ is the error. The integral is connected in parallel with the control signal $u$, since it provides improved results than the series association. The complete state-space system is obtained by combining the plant linear model and integral states,

$$\begin{align*}
x(k+1) &= \bar{A}x(k) + \bar{B}u(k) \\
y(k) &= \bar{C}x(k),
\end{align*} \quad (8)$$

in which,

$$\bar{x} = \begin{bmatrix} x \\ x_I \end{bmatrix}, \quad \bar{A} = \begin{bmatrix} A & 0 \\ -T_s C & I \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}, \quad \bar{C} = [C \ 0]$$

where $I \in \mathbb{R}^{p \times p}$ is the identity matrix.

The augmented system is controllable but not observable. Such problem is overcome by using the identified and augmented system. The first is used to observe and determine the plant model state feedback gain, whereas the second is used to determine the integral state feedback gain, since $x_I$ does not need to be observed. In order to calculate the latter gain, it is necessary to modify the quadratic cost function,

$$J = \frac{1}{2} \sum_{k=1}^{\infty} \left[ x^\top(k)Qx(k) + x_I^\top(k)Q_Ix_I(k) + u^\top(k)Ru(k) \right]. \quad (9)$$

where $Q_I \in \mathbb{R}^{p \times p}$ is chosen to be the identity matrix. The combination of the state variables into one vector leads to the rearranged quadratic cost,

$$J = \frac{1}{2} \sum_{k=1}^{\infty} \left[ \bar{x}^\top(k)\bar{Q}\bar{x}(k) + u^\top(k)Ru(k) \right], \quad (10)$$

in which,

$$\bar{x} = \begin{bmatrix} x \\ x_I \end{bmatrix}, \quad \bar{Q} = \begin{bmatrix} Q & 0 \\ 0 & I \end{bmatrix}. \quad (11)$$

The feedback control law is now given by,

$$u(k) = -[K_x \ K_I] \begin{bmatrix} x(k) \\ x_I(k) \end{bmatrix}. \quad (12)$$

2) Kalman Filter: The discrete linear model states need to be estimated in order to use the optimal regulator developed in section III-B1. This aim is achieved by considering the following model structure,

$$\begin{align*}
x(k+1) &= Ax(k) + Bv(k) + Gw(k) \\
y(k) &= Cx(k) + v(k),
\end{align*}$$

where $G \in \mathbb{R}^{n \times n}$ is the identity matrix. The process noise $w(k)$ and the measurement noise $v(k)$ are uncorrelated Gaussian sequences with zero mean and covariance given by $Q_n = E[w(k)w^\top(k)]$ and $R_n = E[v(k)v^\top(k)]$, respectively. The Kalman filter is a state estimator that minimizes the estimation error covariance,

$$J_o = E \sum_{k=1}^{\infty} \left[ ||x(k) - \hat{x}(k)||^2 \right]. \quad (13)$$

The minimization of equation (13) that leads to a centred estimator yields a dynamic system that uses the input and output measurements to determine the state estimate. The latter is called an observer and can be developed using the most recent observation. The Kalman filter gain that minimizes the cost function (13) is given by,

$$M = PC^\top(CPC^\top + R_n)^{-1}, \quad (14)$$

where the covariance of the estimation error matrix $P$ satisfies the algebraic Riccati equation.

3) LQG Design: The value of $R$ is designed in order to minimize the outlet temperature response rise time while maintaining a reduced overshoot and valve oscillation. Such consideration yields a weighting parameter of $R = 2.8 \times 10^{14}$. The gain margin, $M_M$, and phase margin, $P_M$, are generally reduced by the Kalman filter, which worsens the controlled system relative stability. In order to approximate the stability indicators of the LQG to the LQR controller, a LTR is conducted by adjusting the covariance matrices $R_n$ and $Q_n$.

Assuming $Q_n = BB'$, the LTR is performed by increasing the covariance matrix $R_n$. As the latter variable rises, the gain and phase margins become more approximate do the LQR. Moreover, for higher values of $R_n$, the gain margin of the LQG controller becomes superior than the LQR. The chosen value for the latter covariance matrix is $R_n = 1 \times 10^{17}$.

4) Multi-Model Adaptive LQG Control: The multi-model adaptive LQG controller consists of a parallel association of a set of controllers designed for different operating temperatures. For each working condition, only one controller contributes to the control signal. The transient behaviour during switching is minimized by initializing the integrator state of the future online controller $C^F$. The initialization compensates the difference between the valve position given by the current controller $C^C$ and the control contribution generated by the feedback system of $C^F$. The integral state is obtained by rearranging the following expression,

$$u(k) = -[K_{LQ} \ K_I] \begin{bmatrix} x(k) \\ x_I(k) \end{bmatrix}. \quad (15)$$
Thus, the future on-line controller $C^F$ initial integral state is given by,

$$x^F_i(k) = -K^F_i^{-1} [u(k)^C + K_{LQ}^F \hat{x}^F_i(k)] ,$$

where $u(k)^C$ is the current valve position.

**C. Feed-forward Control**

The static feed-forward controller developed aims to reject a measured disturbance with a control signal $u_{ff}$ that is proportional to the perturbation. In this work, the external signal is given by the difference between the average incident and nominal DNI. The control action results from,

$$u_{ff} = K_{ff} \delta R,$$

where the controller gain $K_{ff}$ is chosen so that the valve position given by the feedback controller is added with $u_{ff}$, in order to compensate the outlet temperature deviation caused by the average solar radiation change $\delta I$. The gain is positive since the manipulated variable must change accordingly with the sign of the perturbation. The steady-state error for a disturbance of $\delta I = 60W/m^2$ is eliminated by a static feed-forward controller with $K_{ff} = 1.3851 \times 10^{-6}$, that reduces the maximum value of the plant output from $T = 573.8^\circ C$ to $T = 566.4^\circ C$. Furthermore, the developed controller is valid for different amplitude values of the aforementioned perturbation.

The nonlinear temperature dynamics demand for a changing static feed-forward controller. The latter is determined by a quadratic fitting of the static gain as a function of the outlet temperature, for working temperatures of $T_{out} = 505^\circ C$, $T_{out} = 520^\circ C$, $T_{out} = 535^\circ C$, $T_{out} = 550^\circ C$ and $T_{out} = 565^\circ C$,

$$K_{ff} = 2.625 \times 10^{-11} T - 2.187 \times 10^{-8} T + 5.735 \times 10^{-6} .$$

**D. Predictive Adaptive Control**

An adaptive controller uses a scheme for automatic adjustment of the controller gains in real time, so that the performance of the control system is maintained when the process dynamics change. In this work, the former approach is achieved with the Multistep Multivariable Adaptive Regulator (MUSMAR) control algorithm that is based on Model Predictive Control (MPC). In order to obtain a steady-state solution approximate to the optimal control problem, MUSMAR predictors are used.

1) **Model Predictive Control**: The MPC is a controller design concept in which the manipulated variable is determined at the beginning of every sample period by minimizing a multistep cost function defined along an horizon of future discrete time instances such as [15],

$$J_{TP} = \varepsilon \left\{ \sum_{j=1}^{TP} \delta^2 (k+j) + \rho \sum_{j=1}^{T_u} \hat{u}^2 (k+j-1) | I^k \right\},$$

where $\varepsilon [.| I^k]$ is the mean of the information available up to time $k$, $TP$ is the prediction horizon, $T_u$ is the control horizon and $\rho$ is the virtual manipulated variable $\hat{u}$ penalty term. The tracking error is given by

$$\hat{y}(k) = y(k) - r^*(k),$$

in which $y(k)$ is the measured output and $r^*(k)$ is the virtual reference that connects the present value of $y$ with the desired value at the end of the prediction horizon, $r(k + T)$ [15].

The minimization of equation (19) is accomplished by describing the plant dynamics through predictive models that relate the samples of the manipulated variable and the predicted values of the plant output within the prediction horizon [15]. The former optimization yields a sequence of $\hat{u}$, in which only the first is applied to the plant.

2) **MUSMAR Predictors**: The MUSMAR predictive models are developed by constraining the manipulated variable $u$ to be a constant feedback of the pseudo-state $s$, along an horizon from $k+1$ up to $k+TP-1$ [15]. The predictors for the output and future values of the control samples are given by,

$$\hat{y}(k+j|k) = \theta_j u(k) + \psi_j^s s(k),$$

and,

$$\hat{u}(k+j|k) = \mu_j u(k) + \phi_j^s s(k),$$

respectively. The symbols $\theta_j \in \mathbb{R}^{n_s}$, $\psi_j \in \mathbb{R}^{n_x}$, $\mu_j \in \mathbb{R}^{n_x}$ and $\phi_j \in \mathbb{R}^{n_x}$ are parameters estimated from plant data using least squares and $n_s$ is the dimension of $s$. The pseudo-state variable can include feed-forward terms from accessible disturbances, or measurable state variables [15].

3) **MUSMAR Algorithm**: The MUSMAR algorithm determines the manipulated variable through the following procedure [15]:

1. Determine the tracking error $\hat{y}$ through equation (20), by sampling the plant output $y$.
2. Update the estimates of the parameters $\theta$, $\psi$, $\mu$ and $\phi$ using Recursive Least Squares (RLS) with directional forgetting.
3. Determine the controller gains vector,

$$F = -\frac{1}{\alpha} \left\{ \sum_{j=1}^{TP} \theta_j \phi_j + \rho \sum_{j=1}^{T_u} \mu_j \phi_j \right\},$$

where $\alpha > 0$ is the normalization factor given by,

$$\alpha = \sum_{j=1}^{TP} \theta_j^2 + \rho \left( 1 + \sum_{j=1}^{T_u} \mu_j^2 \right).$$

3. Apply the control signal,

$$u(t) = F^s s(t) + \eta(t),$$

in which $\eta$ is the white dither noise of small amplitude.
4) Dynamic Cost: The MUSMAR controller action can be improved if dynamic weights are incorporated at the cost function given by equation (19). In this way, the controlled system has a superior tracking capability since the controller becomes more robust to plant anti-resonance characteristics. Considering the filtered variables [15],

\[ y_H(k) = H(q)y(k), \]  
and,

\[ u_H(k) = H(q)\hat{u}(k), \]

the new cost function is determined,

\[ J_{T_P} = \varepsilon \left\{ \sum_{j=1}^{T_P} \left( H(q)y(k + j) - r^* (k + j) \right)^2 + \rho \sum_{j=1}^{T_P} \left( H(q)\hat{u}(k + j - 1) \right)^2 |I^k| \right\}. \]  

(28)

Hence, the control signal applied to the plant results from,

\[ u(k) = \frac{1}{H(q)} u_H(k), \]  

(29)

where \( u_H(k) \) is the manipulated variable given by the MUSMAR control algorithm.

5) Solar Tower Predictive Adaptive Control: The predictive adaptive controller parameters are selected in order to enhance the controlled system performance. The prediction horizon is chosen so that the cost function given by,

\[ J = \frac{1}{N} \left[ \sum_{k=1}^{N} (y(k) - r(k))^2 + \rho \sum_{k=1}^{N} u(k - 1)^2 \right], \]  

is minimum. Although the lower cost is achieved for \( T_P = 12 \), the value chosen for the prediction horizon is \( T_P = 9 \) since high quality results are obtained. The results hereafter presented are obtained by filtering the desired outlet temperature with the following first order system

\[ M(s) = \frac{1}{T_d s + 1}, \]  

(31)

where \( T_d = 12s \) is the filter time constant. In this way, the reference changes are less abrupt.

The manipulated variable undesirable high frequency oscillations due to plant high frequency anti-resonance modes are reduced by incorporating a dynamic weight in MUSMAR. The latter is considered to be a high pass filter given by,

\[ H(q) = \frac{1 - \alpha q^{-1}}{1 - \alpha}, \]  

(32)

where \( \alpha \) is a constant value that locates the zero of the filter in the frequency domain. The need for a high \( \rho \) leads to the appearance of an offset that is extinguished by using an integrator associated in parallel with the MUSMAR control signal. Table II details the parameters used for simulation purposes.

### Table II: Final configuration of the MUSMAR controller with integral action.

<table>
<thead>
<tr>
<th>Description</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic weight filter zero</td>
<td>( \alpha )</td>
<td>0.9</td>
</tr>
<tr>
<td>Reference filter time constant</td>
<td>( T_d )</td>
<td>12 s</td>
</tr>
<tr>
<td>Integral gain</td>
<td>( K_I )</td>
<td>(-5 \times 10^{-8})</td>
</tr>
<tr>
<td>Penalty term</td>
<td>( \rho )</td>
<td>(8 \times 10^6)</td>
</tr>
<tr>
<td>Dither noise</td>
<td>( \eta )</td>
<td>(1 \times 10^{-17})</td>
</tr>
</tbody>
</table>

E. Coordinated Control

The coordinated control strategy is a mean to maintain the outlet temperature at a desired set-point by manipulating the fluid flow and the radiation flux of the east and west side of the heliostat field. Each mirror region dynamics is considered to be a first order system with a time constant of \( T_h = 4/3 \) s that is related with the time required to refocus the mirrors. The manipulated variable is the heliostat field area that is given by a PI controller with anti-windup wherein its parameters are design to achieve a step response time of approximately 4 s. The same control concept is used for the outlet temperature controller.

The PI control signal is only one and so, the flow reference is multiplied by a constant gain \( \beta \) that is chosen to be the ratio between the nominal flow and radiation flux reflected by the heliostat field,

\[ \beta = \frac{F_{nom}}{R}. \]  

(33)

The flow control signal has a reverse action and represents the increment relative to the nominal operation. For higher values of \( \beta \) the flow and radiation flux are superior. The outlet temperature PI controller parameters are determined through trial and error while considering constant DNI over the heliostat field for all panels.

1) Gain-Scheduled Coordinated Control: The GS scheme is now developed for the coordinated controller using the procedure presented in subsection III-A1. The scheduling variable is also the outlet temperature and the controller parameters are determined for working conditions of \( T = 565 \) °C, \( T = 535 \) °C and \( T = 505 \) °C. The constant \( \beta \) is kept constant.

IV. Optimal Operation

The solar tower efficiency is addressed by taking considerations regarding the energy collecting system and the turbo-generator, that is modelled in conjunction with the Rankine cycle. The former system efficiency decreases as the temperature rises due to the increase of thermal losses while the electric power generating system efficiency increases with temperature. This trade-off leads to maximum power production for a given outlet temperature.

The optimal operation of a solar tower is achieved by considering a two-layer structure. The first layer provides the outlet temperature set-point that optimizes the electrical production, whereas the second corresponds to the outlet temperature controller. In this work, the maximum output power is desired and thus, the electrical production economical dispatch is not considered. The latter could be included in a higher hierarchical layer.
A. Static optimization

The static optimization aims to determine the outlet temperature that leads to the highest power production of the solar plant by examine the system equilibrium operation. Thus, all the variables and parameters are considered to be constant. The analysis of the overall plant performance is divided into power collection, thermal storage and electrical power production systems.

1) Power Collection: The heliostat field and the receiver comprises the energy collection system. The solar power gathered by the mirrors that is focused on the heat exchanger results from,

\[ P_{inc} = \eta_{hel} IS, \]  \[\text{[W]} \quad (34)\]

where is S the total heliostat reflective area, I is the DNI and \( \eta_{hel} \) is a constant parameter that accounts for field availability and mirrors reflectivity, cleanliness and efficiency.

The flow required to achieve a given outlet temperature can be determined using a concentrated parameter model for each receiver tube \( j = 1, ..., n_t \),

\[ \frac{dT_j}{dt} = -F_j \left( \frac{T_j - T_{in}}{L} \right) + \alpha R - \gamma \left( \frac{T_j - T_{in}}{2} - T_a \right), \]  \[\text{(35)}\]

where \( n_t \) is the total amount of tubes. In equilibrium the temperature time derivative is zero thus, the flow of each circuit, \( i = 1, 2 \), can be found,

\[ F_i = n_t \frac{\alpha R - \gamma \left( \frac{T_i - T_{in}}{2} - T_a \right)}{(T_i - T_{in})} L, \]  \[\text{(36)}\]

where L is the flow circuit length. The temperature dependent parameters are set for the average temperature of the fluid path.

The thermal power absorbed by the molten salt results from the contribution of both receiver circuits,

\[ P_{coll} = \sum_{i=1}^{2} \eta_{coll} \rho f_i c f_i \sigma T_{av,i}(T_i - T_{in}). \]  \[\text{[W]} \quad (37)\]

The receiver thermal losses are only considered to be temperature dependent and are obtained by receding from the PDE to the energy conservation equation,

\[ P_{tl} = \sum_{i=1}^{2} \gamma T_{av,i} \rho f_i c f_i \sigma A \alpha L n_t, \]  \[\text{[W]} \quad (38)\]

where \( T_{av} \) is the average temperature. The information regarding the collected power and losses allow the calculation of the receiver efficiency \( \eta_{rec} \). Hence, the efficiency of the power collection system can be found,

\[ \eta_{coll} = \eta_{hel} \eta_{rec}. \]  \[\text{(39)}\]

2) Thermal Storage: The receiver outlet fluid passes through a storage tank before being used. The thermal storage system has an energy delivery efficiency and heat losses to the environment that can be approximately described by the following temperature dependent function,

\[ P_{tsl} = \sigma (T - T_a), \]  \[\text{[W]} \quad (40)\]

where \( \sigma \) is a parameter obtained from tests performed at the tank. For simulation purpose, \( \sigma \) is designed for a storage thermal efficiency of 99.3% at nominal operation. The latter performance index is given by,

\[ \eta_{st} = \frac{P_{salt}}{P_{coll}}, \]  \[\text{(41)}\]

where \( P_{salt} = P_{coll} - P_{tsl} \) is the EPGS input thermal power.

3) Electrical Power Production: The Solar Two EPGS is a Rankine cycle with an efficiency described by,

\[ \eta_{Rank} = K \left( 1 - \frac{T_{cond}}{T} \right), \]  \[\text{(42)}\]

where \( K \leq 1 \) is a constant that models the performance loss with respect to the ideal Carnot cycle and \( T_{cond} \) is the Rankine condenser temperature [14].

The power consumption of the parasitic elements relative to the overall production is considered to be constant. In order to consider such loss, the net electrical power is affected by a weighting parameter \( \eta_p \),

\[ P_e = P_{salt} \eta_{Rank} \eta_p. \]  \[\text{[W]} \quad (43)\]

4) Optimal Temperature Set-point: The optimal outlet temperature reference is obtained by maximizing the net electrical power production subject to the maximum and minimum temperature and fluid flow,

\[ \max P_e(T) \]  \[\text{(44)}\]

s.t.

\[ \left\{ \begin{array}{l} F_{min,1,2} \leq F_p \leq F_{max,1,2} \\ T_{min} \leq T \leq T_{max} \end{array} \right. \]  \[\text{(45)}\]

V. Simulation Results

The controllers performance when rejecting solar radiation disturbance in order to maintain the desired outlet temperature is now evaluated. The simulation experiments are performed for different sorts of reference and disturbance characteristics. The controlled system robustness to changing parameters or plant configuration is also examined. Furthermore, the on-line application of the static optimization algorithm is addressed.

A. Solar Radiation Disturbance

The solar radiation disturbance varies in time due to the apparent movement of the sun, atmospheric moisture or passing clouds. The first two are conjoined assessed, whether the latter is examined separately. The controller tracking capability is evaluated considering equal solar radiation over the receiver surface. The temperature variance at the heat exchanger affects the plant lifetime thus, it is a weighting factor when selecting the proper controller.
1) Atmospheric Moisture: The disturbance caused by the atmospheric moisture and the apparent movement of the sun when the controllers are tracking a constant reference leads to the appearance of an offset at the controlled variable, with the exception of the coordinated controlled system that makes use of two manipulated variables. The latter system controlled variable has a lower variance although, it causes an increased wear of the heliostat field, since the flow is nearly constant. The LQG and the MUSMAR controllers produce a similar response. From the controllers that only manipulate the flow, the PI controlled system is the most capable of rejecting solar radiation disturbances.

2) Passing Clouds: The disturbance caused by passing clouds when the controllers are tracking a constant reference yields a higher outlet temperature peak while using MUSMAR controller. On the other hand, the output variable maximum variance is lower for the coordinated controlled system. The PI and optimal controllers are able to avoid large outlet temperature peaks when in presence of passing clouds however, the actuator lifetime is adversely affected.

3) Lifetime: The lifetime of the receiver system is affected by the temperature rate of change at the tubes. In order to guarantee a lifetime of approximately 30 years, the latter rate must be less than 2.8 \( ^\circ \text{C/sec} \) [18]. The lowest temperature rate of change when the disturbance is due to atmospheric moisture and the apparent movement of the sun is achieved while using the coordinated controller. However, all controllers meet the expectations by a large margin. Nevertheless, since the flux distribution at the receiver is not homogeneous, a different temperature rate of change can be found at the middle of the heat exchanger tubes.

B. Controller Robustness

The controller robustness is assessed by analysing the change of controlled system performance when a parameter or coefficient is modified. Also, it is examined the controller ability to handle a valve fault.

1) Parameter: The controller robustness to parameter change is evaluated by varying the absorption and mirror efficiency \( \alpha \) and the loss coefficient \( \gamma \) of the reduced complexity model. The comparison between the outlet temperature distribution of the nominal and modified parameter provides information regarding to the controller performance change. The increase of the latter parameter cause a minor effect at the system. The controlled processes have a temperature distribution more dispersed than the nominal case. The exception occurs when using the coordinated control strategy that maintains a centred temperature allocation. Such behaviour is verified since the manipulation of the radiation flux is able to compensate the reduction of \( \alpha \). The MUSMAR controlled variable becomes more centred due to the controller gains adaptation. However, for a higher parameter change, the temperature distribution becomes flatter between the boundary values of \( T = 564.5^\circ \text{C} \) and \( T = 565.5^\circ \text{C} \).

The PI, LQG and the coordinated controlled systems do not exhibit significant changes when comparing the outlet temperature variance obtained by increasing \( \gamma \) in 20\% to the use of the nominal value of. The MUSMAR controlled variable becomes more flat yet not dispersed.

2) Valve Fault: The controller robustness to a valve fault is conducted by analysing the situation when the flow stops abruptly at a given receiver circuit path. After the actuator failure, it is considered that the heliostat field takes approximately 4 s to defocus from the heat exchanger area where the circuit is installed. The coordinated controlled system has a smoother outlet temperature response to the valve fault however, the output variance is high. The MUSMAR controlled variable has an even superior temperature peak although, the transition is soft and the time required to recover to the desired setpoint is the lowest. The use of PI and LQG controllers lead to an oscillatory outlet temperature response that reduces the receiver lifetime. Also, it can be seen that variance of the controlled variables of the aforementioned systems increase after the fault recovery. The MUSMAR controller is able to maintain the performance prior to the failure.

C. On-line Static Optimization

The static optimization algorithm is applied to the reduced complexity model while considering the PI controller as the second layer of the optimal operation control structure. The optimal outlet temperature reference is stipulated every 10 minutes.

As expected, the increase of DNI leads to a rise of the optimal output reference while the opposite is verified when the solar radiation decreases. The electrical energy produced while using the optimal reference and \( T = 565^\circ \text{C} \) are similar although, the use of the nominal reference yields an increased electrical energy production of 6 kWWh, at the end of the day. In order to track the optimal reference, the flow needs to decrease. However, since the manipulated variable diminishes faster than the outlet temperature rises, a loss of electrical production is verified. The opposite is verified when the reference decreases. Therefore it can be concluded that the fluid dynamics must be considered when optimizing the plant power production.

VI. Conclusion

The presented master thesis focus on the fluid outlet temperature model and control of a solar tower heat exchanger. The first purpose is achieved by projecting the spacial dependence of a infinite nonlinear partial differential equation model based on physical principles, on a finite dimensional set. The second aim is accomplished by developing a PI, LQG, MUSMAR and a coordinated controller. Moreover, it is established a static optimization algorithm that determines the outlet temperature set-point that leads to the maximum plant power production.

The PI linear controller is developed for several working conditions of the plant nonlinear reduced complexity model wherein the controller parameters are design using a modified Ziegler and Nichols ultimate sensitivity rule. The latter tuning method uses the ultimate gain and period that are determined through the relay with hysteresis feedback procedure. The
LQG controller is based on a discrete linear model obtained through system identification using data collected from the nonlinear model, while functioning near the operating regime. The process nonlinear dynamics is handled by using a GS scheme for the PI controller, where its gains are given as a function of the outlet temperature. For the LQG, it is developed a multi-model adaptive control strategy in which one of a set of LQG controllers is selected to generate the control signal. The transition between the former systems is accomplished by initializing the integrator of the controller to be connected, avoiding transition bumps. In addition, the solar radiation disturbance rejection capability is increased by designing a static feed-forward controller to work in parallel with the aforementioned control systems.

The MUSMAR controller is implemented after configuring its parameters by minimizing a quadratic cost function and observing the controlled and manipulated variables characteristics. The coordinated control strategy that uses the flow and the radiation flux as manipulated variables is designed using the PI control concept with manually adjusted gains. Also, a GS scheme is developed for the former approach.

Subsequent to the controllers development, it is examined their performance by analysing the experimental results obtained through simulation by applying different sorts of reference and solar radiation disturbance characteristics. The regulation of the outlet temperature in presence of the solar radiation variation due to atmospheric moisture and the apparent movement of the sun yields a centred outlet temperature distribution for all controllers, when using the feed-forward action. The improved and worsened results of the aforementioned experiment are achieved while using the optimal or coordinated controller and the MUSMAR algorithm, respectively.

The controlled systems step response provide best results for the optimal control in what concerns the output variable tracking capability however, the use of coordinated control leads to a minor wear of the actuator. Moreover, the latter controller has an outlet temperature fluctuation similar to the LQG.

The regulation of the outlet temperature in presence of the solar radiation variation due to passing clouds are best handled by coordinated control. The PI and LQG also have a low temperature variance however, the actuator is strongly excited. The MUSMAR controlled variable varies between a larger temperature scale, the valve is less fatigued.

The analyses of the controller robustness to changing parameters while considering the regulation problem yields the conclusion that the outlet temperature distribution becomes more disperse, although it only increases half degree for a change in 20% of the heat exchanger absorption and mirror efficiency parameter, that is the most sensible. The coordinated control it is not affected by such change since the radiation flux is manipulated. The MUSMAR controlled variable becomes less disperse however, more flatter.

The controllers robustness to a fault in one valve demonstrates that the MUSMAR and the coordinated controlled systems have a high temperature drop although, the actuator has a smooth behaviour. The MUSMAR controller recovers to the nominal operating condition faster and is able to maintain the performance prior to the failure. In contrast, the PI and LQG controlled variables have an oscillatory behaviour.

The analysis of the outlet temperature rate of change yields the conclusion that the lifetime of 20-30 years is guaranteed, although, the data significance is dependent on the pump considered and the use of high quality sensors.

The application of the static optimization algorithm yielded poor results in several cases since the fluid dynamics is not considered in such approach.

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References


