Model Predictive Control of a Solar Power plant Based on Fuzzy Kalman Filter

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Abstract— **This paper presents a predictive control model for standalone Solar Power Plant (SPP) via Takagi-Sugeno (T-S) Fuzzy model. An approach to design MPC based on Fuzzy Kalman Filter (FKF) has been proposed. The aim of this suggested method is to maintain a specified set point of the collector outlet temperature by adjusting the flow rate of the heat transfer fluid circulation. Firstly, the plant model is discussed in this paper. Simulation result on the SPP show the performance of the design control.**

***Index Terms*— model predictive control, Solar Power Plant, Takagi-Sugeno Fuzzy model, state estimation, Fuzzy Kalman Filter.**

I.INTRODUCTION

A solar electric generating system (SEGS), shown in Figure 1, refers to a class of solar energy systems that use parabolic troughs in order to produce electricity from sunlight.
The solar field has many parallel rows of solar parabolic trough collectors aligned on a north-south horizontal axis. A working (heat transfer) fluid is heated as it circulates through the receiver pipes and returns to a series of heat exchangers at a central location. Here, the fluid circulates through pipes so it can transfer its heat to water to generate high-pressure, superheated steam. The steam is then fed to a conventional steam turbine and generator to produce electricity. When the hot fluid passes through the heat exchangers, it cools down, and is then recirculated through the solar field to heat up again [1].

In this solar power plant, the main control goal is to maintain constant outlet oil temperature, despite the operation conditions changes, by manipulating the field oil flow. To maintain constant outlet temperatures during the day while the solar conditions changes, significant flow variations are required. This produces considerable change in the dynamics of the process. Make the implementation of a control scheme a difficult task [2]. Dealing with this problem requires an improved modeling effort and modern state estimation strategies. Model Predictive Control is very suitable control technology for this application [3] , [4].
Model Predictive Control (MPC) is a powerful tool for multivariable systems control. It has become a major research topic during the last few decades and, unlike many other advanced techniques, it has also been successfully applied in industry. One major advantage for the success of this method is the ability to control multivariable systems under various constraints in an optimal way. The idea behind MPC scheme is to calculate a control vector trajectory over a finite time horizon by solving at each sampling period and optimization problem in order to force the controlled system response to follow the reference trajectory [5]. Therefore, the system behavior must be predictable by an appropriate model. Recently, industrial applications of MPC have relied on linear dynamic models even though most processes are inherently nonlinear. The extension of MPC to nonlinear processes is straightforward and leads to nonlinear model predictive control (NMPC) algorithms, where a nonlinear model is used for prediction. It is generally accepted that the performance of this control strategy is highly dependent on a reliable mathematical model that represents the salient nonlinearities of the process, as it is the case for state estimators. Several advanced research have reported a various number of NMPC algorithms that work with different types of nonlinear models [6].

According to the Takagi–Sugeno (T-S) fuzzy model representation, [4], [7], [8], nonlinear systems can be described by IF–THEN fuzzy rules that have local linear dynamic subsystems in the consequent part. From the local linear dynamic model, linear control theory is extensively applied to nonlinear systems by using parallel distributed compensation (PDC). The main advantage is that the controller gains can be designed from linear matrix inequality (LMI) techniques [9]. The local models form a global nonlinear model by including the activation function for each of these models, and it is embedded into a model predictive control scheme.

There are many different applications of MPC with different types of multiple linear prediction models have been reported in the control literature such as Takagi-Sugeno fuzzy model [10], [11], local model networks [5] or fuzzy neural model [12]. A Takagi-Sugeno fuzzy model is used in this work.
One of the main characteristics of a solar power plant is that the primary energy source (solar radiation) cannot be manipulated. Besides, the solar radiation intensity depends on daily and seasonal cycle variations, like clouds, atmospheric humidity, and air transparency. This justifies the relevance of solar power plant control. Therefore, state estimation is required here with a lot of advantages [13], it makes use of extended Kalman filter for nonlinear systems. The Kalman filter for linear systems generates optimal

estimates of state from observations and the EKF is a natural extension of the linear theory to the nonlinear domain through local linearization [14]. For the TS fuzzy model, Simon [15] has proposed a fuzzy Kalman filter that generates accurate state estimates in the absence of unknown input. Recently, Senthil et al. [16], [17], have developed a nonlinear model predictive control scheme for the solar power plant using fuzzy Kalman filter. The FKF was found to be good alternative for the EKF. In this paper, the fuzzy Kalman filter will supply the estimated value of the internal states of the fuzzy model and the major disruption of the process to the MPC.

The present paper is structured as follows: Section II presents the description of the process components and the simplified mathematical model of the plant. The basic elements of Model Predictive Control are outlined in Section III. Sections IV and V discuss about the fuzzy model and fuzzy Kalman filter, respectively. In Section VI the fuzzy observation based MPC design is presented. Finally, the obtained simulation results are shown in Section VII and the conclusion is given in Section VIII.

II.THE PLANT MODEL

In the following, the plant is divided into two subsystems: the solar collector field and the power plant. Both are shown schematically in Figure 1 [4].

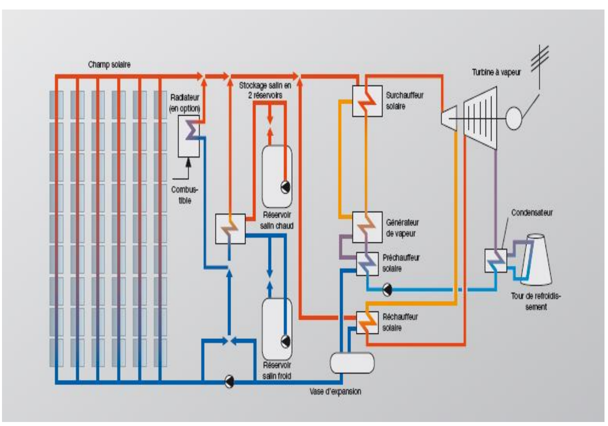


Figure1, *Flow Diagram of the 30 MWe SEGS VI Plant for Pure Solar Model.*

II.1THE SOLAR COLLECTOR FIELD

The thermal performance model of the SEGS VI parabolic trough plant is based upon steady-state efficiency model for the collector using empirical coefficients [18], [4]. These coefficients were obtained experimentally on a test facility at SANDIA.

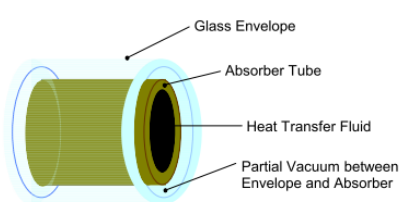


Figure2*. The Heat Collection Element.*

The heat collection element (HCE) present in Fig. 2 derives the appropriate differential equations. The HCE comprises the absorber tube in which circulates the HTF covered with a glass envelope which is not supposed to have radial temperature gradients. Furthermore there is a partial vacuum in the annular space between the absorber tube and the glass envelope. A glass envelope line covers the absorber with no radial temperature gradients. Partial vacuum exists in the annular space between the absorber tube and the glass envelope [19].

II.2THEPOWER PLANT

The unit (Fig. 01) is the Rankine cycle with reheating and heating of the feed water. Each heat exchanger network consisting of preheating (economizer), steam generator (boiler), and the super heat is treated as a single heat exchanger in the model. The model of the plant is a stable. Both power water heater high pressures are modelled as a feed water heater high pressure and three power water heater low pressures as a single stream of heating the water at low pressure. The effectiveness and heat transfer coefficients in the heat exchangers are functions of the flow rate of water vapour mass. The efficiency of pumps and turbines is assumed to be constant, with values drawn from [4].

The plant can be present by the simplified model shown in Fig 03 [4]:

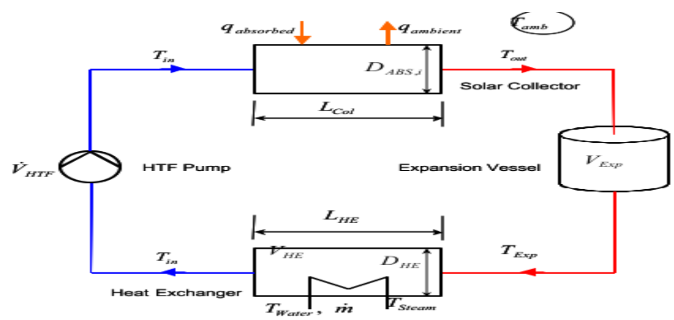


Figure 3.*The Structure of the Simplified Model*

The dynamic of plant are described by the flowing differentials equations (thermo dynamical equations):

$$\frac{dT_{out}(t)}{dt} = \frac{1}{\tau_{col}(t)}\left(T_{in}(t) - T_{out}(t)\right) + \frac{q_{absorbed} - UA_{col}\left(T_{out}(t) - T_{amb}(t)\right)}{A_{col}\rho_{HTF}\left(T_{ouut}(t)\right)c_{HTF}\left(T_{ouut}(t)\right)} \quad (1)$$

$$\frac{dT_{Exp}(t)}{dt} = \frac{1}{\tau_{Exp}(t)}\left(T_{out}(t) - T_{Exp}(t)\right) \quad (2)$$

$$\frac{dT_{in}(t)}{dt} = \frac{1}{\tau_{HE}(t)}\left(T_{Exp}(t) - T_{in}(t)\right) + \frac{UA_{HE}(T_{Exp}(t) + T_{in}(t) - T_{steam}(t) - T_{water}(t))}{A_{col}\rho_{HTF}(T_{ouut}(t))c_{HTF}(T_{ouut}(t))} \quad (3)$$

$$\frac{dT_{steam}(t)}{dt} = 0.01.\left((-T_{steam}(t)) - \varepsilon_{HE}(t)\left(T_{Exp}(t) - T_{water}(t)\right) - T_{water}(t)\right) \quad (4)$$

Where T_{out} , T_{Exp} , T_{in} and T_{steam} denote respectively the outlet collector temperature, the expansion vessel temperature , the inlet collector temperature and the heat exchanger temperature.

ρ_{HTF} ,c_{HTF} are the HTF density, specific heat of the fluid flow rate.

$q_{Absorbed}$: The absorbed solar energy.

ε_{HE} : The heat exchanger effectiveness.

$1/\tau_{col}\,(\mathrm{t}) = V'/Vcol$ and $1/\tau_{exp}\,(\mathrm{t}) = V'/Vexp$, $1/\tau_{HE}\,(\mathrm{t}) = cte.V'/VHE$; The time constant for the collector expansion vessel, heat exchanger.

Then the state vector is defined by : $x = [T_{out}(t) T_{exp}(t) T_{in}(t) T_{steam}(t)\ ]^T$.

The other variables *present at the model are*:

Ambient temperature:	T_{amb}
Water temperature:	T_{water}
Absorbed solar energy:	$q_{absorbed}$
Volume flow rate:	V'_{HTF}
Working fluid mass flow:	m'

In Figure 4 it is present the input system and the simulation of the model

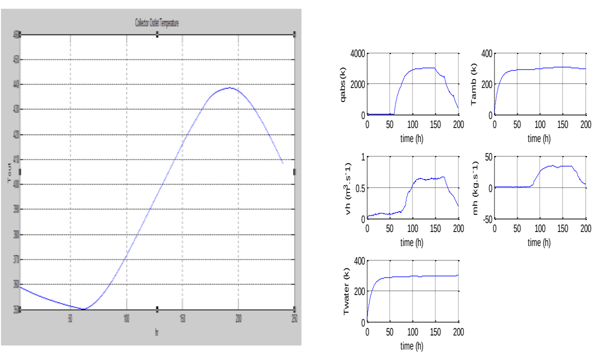
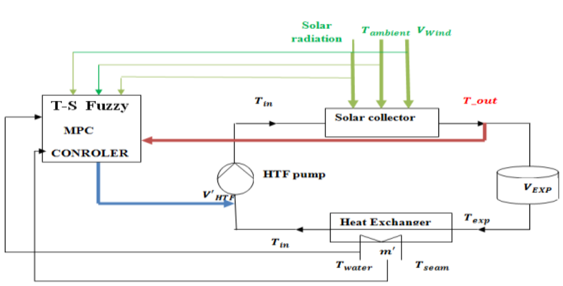


Figure 4, *The input system and the collector outlet temperature of the Solar collector Field*

III. *Model predictive control*

The model predictive control refers to model based control strategies in which an explicit model used to predict the future behavior of a process and optimize its performance. The general principle of MPC schemes is the same as illustrated in fig.5.



Figuire5. *Block Diagram with Plant Model and Controller.*

The volume flow rate, is the input that is used to control the collector outlet temperature, the cooling water, the steam mass flow rate. The environment measures (sun intensities, ambient temperature) are the inputs of the plant but non manipulable.

The MPC controller adjusts in the fluid input aimed to eliminate the change in outlet temperature caused by the variation of environment measures inputs (measures of collector outlet temperature and calculate the volume flow rate, which is then injected into the plant model).

Where the structure of T-S fuzzy MPC Controller represented by fig.6

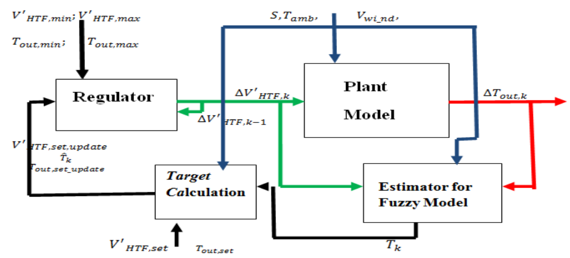


Figure6. *T-S fuzzy MPC Controller*

III.1. Fuzzy modelling for controller design

The simplified model of the plant (1), (4) is of a general non linear system:

$$x'(t) = f\big(x(t), u(t)\big)$$
$$y(t) = g\big(x(t), u(t)\big) \qquad (5)$$

Where $x \epsilon R^n$ is the vector of state variables, $u(t) \epsilon R^m$ is the vector of input variables, $y \epsilon R^p$ is the vector of output variables, g and f are nonlinear functions.

The Takagi-Segeno Fuzzy modelling is recently very suitable to model a large class of nonlinear systems. The use of this approach allows transferring and generalizing many methods developed in the linear control domain applied to the nonlinear systems and yield good approximation properties which can be used for control purposes.

In this work, the dynamic TS model is used to represent the nonlinear system of the plant (5) using locally linearized state space models with local models have one common state vector.

Several methods exist to perform the TS models, such as the approach of transformation of the nonlinear sector: it provides an accurate representation of the model generated without loss on a compact state space together:

$$x'(t) = A_i x + B_i u + a_i$$
$$y = C_i x + D_i u + c_i \qquad (6)$$

The local state spaces are given as the following step:

Firstly, the number of local sub model is depending at the nonlinearities of system $r = 2^q$, where q is the number of premise variable (term of non linearity)

Here the above model is constituted by two premise variables:

$\xi_1(t)$=$V'(t)$.

$\xi_2(t) = -0.1(V'/2.V_0 + m'(t)/2.m_0) + 1.025$.

Notice that several choices of these premise variables are possible, due to the existence of different equivalent quasi-LPV forms [18]

The system (5) can be rewritten as:

$$\dot{x} = A(\xi(t))x + B(\xi(t))u. \tag{7}$$

Where $\xi(t) = [\xi_1(t)\xi_2(t)]^T$and the matrices$A(\xi(t))$and $B(\xi(t))$ are expressed as follows:

$$A(\xi) = \begin{pmatrix} \frac{\xi_1(t)}{V_{col}} - \frac{Ucol}{a_1} & 0 & \frac{\xi_1(t)}{V_{col}} & 0 \\ \frac{\xi_1(t)}{V_{EXP}} & \frac{\xi_1(t)}{V_{EXP}} & 0 & 0 \\ 0 & (\mathrm{a+b})\frac{\xi_1(t)}{V_{HE}} - \mathrm{a2} & (\mathrm{a+b})\frac{\xi_1(t)}{V_{HE}} & a_2 \\ 0 & \xi_2(t) & 0 & -0.01 \end{pmatrix} \tag{8}$$

$$B(\xi) = \begin{pmatrix} \frac{1}{a_1} & \frac{u_{Acol}}{a_2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_2 \\ 0 & \xi_2(t) & 0 & 0 & \xi_2(t) \end{pmatrix} \tag{9}$$

Where

a_1=$A_{col}.\rho_{HTF}(T_{out}).C_{HTF}$.

$$a_2 = \frac{UA_{HE}}{2.A_{HE}\rho_{HTF}(Tin)C_{HTF}(Tin)}. \tag{10}$$

$\mathrm{a = b} = 0.4375.$

Under the assumptions

$$\begin{cases} \xi_1^{min} \le \xi_1(t) \le \xi_1^{max} \\ \xi_2^{min} \le \xi_2(t) \le \xi_2^{max} \end{cases} \tag{11}$$

The local weighting functions defined by:

$$w_1^1 = \frac{\xi_1(t)-\xi_1^{min}}{\xi_1^{max}-\xi_1^{min}}. \qquad w_1^2 = \frac{\xi_1^{max}-\xi_1(t)}{\xi_1^{max}-\xi_1^{min}}$$
$$w_2^1 = \frac{\xi_2(t)-\xi_2^{min}}{\xi_2^{max}-\xi_2^{min}}. \qquad w_2^2 = \frac{\xi_2^{max}-\xi_2(t)}{\xi_2^{max}-\xi_2^{min}} \tag{12}$$

Finally, the weighting functions of the derived T-S model are given by

$$\mu_1(\xi) = w_1^1 w_2^1 \qquad \mu_2(\xi) = w_1^1 w_2^2 \tag{13}$$
$$\mu_3(\xi) = w_1^2 w_2^1 \qquad \mu_4(\xi) = w_1^2 w_2^2$$

Considering definitions (18) the reader should remark that these functions respect the conditions (5) and (6).

The constant matrices A_i, B_i defining the 4 submodels, are determined by replacing the premise variable ξ_j in the matrices $A(\xi)B(\xi)$ with the scalars $\xi_j^{\partial_i^j}, i = 1,..,2^q$:

$$A_i = A\left(\xi_j^{\partial_i^1}, \xi_j^{\partial_i^2}\right) \quad i = 1,..,4 \tag{14}$$

$$B_i = B\left(\xi_j^{\partial_i^1}, \xi_j^{\partial_i^2}\right) \quad i = 1,..,4 \tag{15}$$

In the definitions of (14) and (15), the indexes $\partial_i^j (i = 1,..,4\ and j = 1,2)$ are equal to min ore max, and indicate witch partition of the jth premise variable ($w_j^1\, or\, w_j^2$) is involved in the i[th] sub models. Consequently, the nonlinear model (10) ,can be proposed as:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{4} \mu_i(\xi(t))(A_i x(t) + B_i u(t)) \\ \qquad y(t) = Cx(t) \end{cases} \tag{16}$$

As showing in fig.5 the structure of NMPC controller is structure consists of three elements receding horizon regulator, the state estimator for fuzzy model and the target calculator.

III.2. *Receding horizon regulator:*

A cost function that is to be minimized for optimal control must increase with an increasing difference between the forecasted HTF collector field outlet temperatures and the set point temperature. In addition, it must increase with an increasing rate of change in the HTF volume flow rate. Thus the receding horizon regulator is based on the minimization of the following infinite horizon quadratic objective function at time *k:*

$$\emptyset_{\boldsymbol{k}} = \frac{1}{2}[\sum_{j=0}^{\infty} \boldsymbol{Q}(\boldsymbol{T}_{\boldsymbol{out,k+j}} - \boldsymbol{T}_{\boldsymbol{out,set}})^2 + \boldsymbol{S}\Delta\boldsymbol{V'}^2_{\boldsymbol{HTF,k+j}}] \tag{17}$$

Where: *Q* is a penalty parameter on the difference between the actual collector outlet temperature and the set point temperature. The parameter *S* is a penalty parameter on the rate of change of the HTF volume flow rate as the input in which $\Delta\Delta V'_{HTF,k+j} = \Delta V_{HTF,k+j} - \Delta V_{HTF,k-j}$. Penalizing the rate of change of the input can be useful for a better attenuation of possible oscillations, which might occur in the controlled collector outlet temperature.

III.3.State estimator for fuzzy model

In the section about the regulator, it was assumed that the states $\hat{x}_k$ are measured in fact, from the state only the collection outlet temperature $T_{out,k}$ is measured. The state estimator is a fuzzy Kalman filter design. Ideally the fuzzy estimator must be predict the same state of the actual process , it is possible to make optimal(in the minimum variance sense) predictions of state and input using a local Kalman filter. Accordingly, let $\hat{x}_k$ and $\hat{y}_k$ represent estimates of the state and output at the current time instant k. Then the local linear observer associate with the sub model using stander Kalman filter theory is described by:

Rule i (i = 1, ... l)

$IF\ \varepsilon_{i,1}(k)\ is\ M_{i,1} \quad and\ ...and\ \varepsilon_{g,1}(k)\ is\ M_{g,1} \quad Then$

$$\hat{x}_i\,(k+1/k) = A_i\hat{x}\,(k/k) + B_i u\,(k) + a_i$$
$$\hat{x}_i\,(k+1/k+1) = \hat{x}\,(k+1/k) + k_i\,(k+1)[y(k+1) - C_i\hat{x}_i\,(k+1/k) \tag{18}$$
$$P_i\,(k+1/k) = A_i P_i\,(k/k) A_i^T + G_i S_w G_i$$
$$K_i\,(k+1/k) = P_i\,(k+1/k) C^T [C_i P_i\,(k+1/k) C^T + S_v]^{-1}$$

$$P_i\,(k+1/k+1) = (I - K_i\,(k+1/k)C) + P_i\,(k+1/k)$$

Where P is the covariance matrix of the estimation error and K is the Kalman gain matrix. We define $P_i\,(k+1/k)$ and $P_i\,(k+1/k+1)$ as predicted and updated covariance of i_{th} local linear observer, respectively. The whole observer dynamics is derived by a linear combination of the local observer outputs as follows

$$\hat{x}\,(k+1/k+1) = \sum_{i=1}^{l} \mu_i\,(\varepsilon(k)) \left\{ \hat{x}_i \left(k+\frac{1}{k}\right) + K_i\,(k+1)[y(k+1) - C\hat{x}_i \left(k+\frac{1}{k}\right)] \right\} \quad (19)$$

III.4.Target calculation:

For offset-free control, the set point used in the receding horizon regulator has to be updated with respect to the measured disturbance and the estimated difference between the collector outlet temperature prediction and the measurement. The latter represents the second part of the integral action implementation. The target calculation is formulated as a mathematical program to determine the new set point.

This control technology offers a various possibilities for the desired performance by appropriately selecting the following parameters: control horizon, prediction horizon and the weighting matrices.

IV. *Simulation results:*

The plant model inputs not used for control are the cooling water inlet temperature at the condenser, the steam or water mass flow rate in the power plant, m_{Steam}, and environmental data as the solar radiation, S, the ambient temperature, T_{amb}, and the wind speed, v_{Wind}. The input that is used to control the collector outlet temperature, T_{out}, is the HTF volume flow rate, V_{HTF}.

The MPC controller measures the collector outlet temperature and calculates the HTF volume flow rate, which is then injected into the plant model.

The performances of the proposed controller have been tested by performing extensive simulation experiments. The Solar Power Plant has been simulated by numerical integration of the model described earlier (Section II) and the real state variables are computed by differential equation solver in Matlab environment.

For the design of FKF, the TS fuzzy model is formed by four local model. Concerning the dynamics of the spp and its nonlinear model structure, two fuzzy variables are considered in the antecedent part of the TS fuzzy model with respect to each input variable. The membership functions of the scheduling variables are depicted in figure 6. The local dynamic models are deduced from the nonlinear model (06) through dynamic linearization (sector transformation).

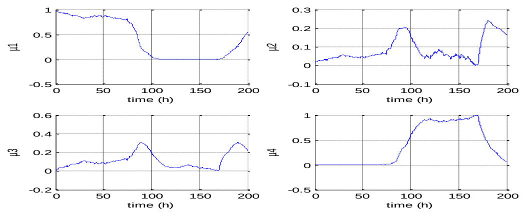


Figure7. Membership functions of scheduling variables.

The performance of the controller is shown in Figures 8, 9, 10 and 11. Two different days are considered.
These figures show the tracking assessment capability of the implemented inferential FKF based MPC scheme, the controller is able to follow the set point changes and presents a good performance

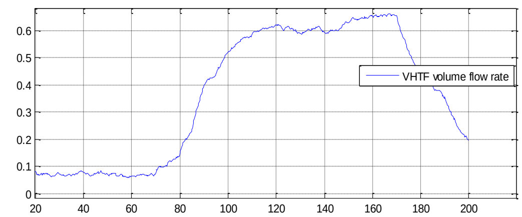


Figure8. Control inputs V_{HTF}(HTF Volume Flow Rate) for June

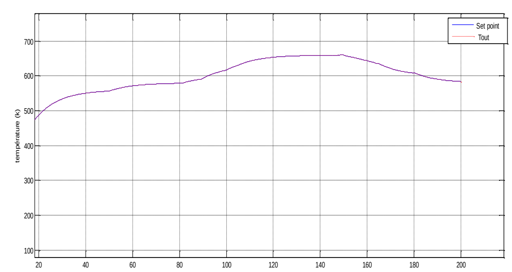


Figure9. Controlled output Tout and set point for June

In Figures 8 and 9 shows the collector outlet temperature and the HTF volume flow rate for June,
The HTF volume flow rate shown in Figures 8 represents the input calculated through model predictive Control. The automatic controller is turned on at 8.00 hr in the morning and turned off at 18.8 hr. The automatic controller obtains the ability to hold the collector outlet temperature at a constant set point (653.9 K) for a long time throughout the day.

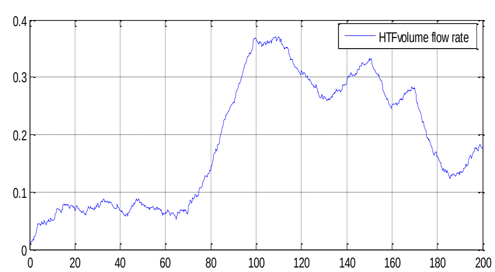


Figure10. Control inputs HTF Volume Flow Rate for December

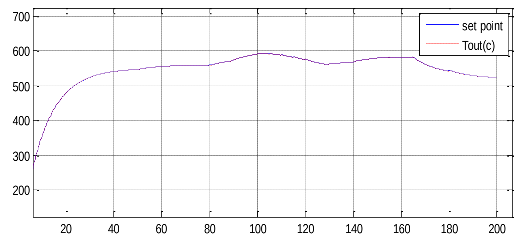


Figure11. Controlled output Tout and set point for December

In Figures 10 and 11, the collector outlet temperature and the HTF volume flow rate are shown for December.

During winter days, when the energy in the system is relatively low, the model behavior tends to become more nonlinear. That's why integral action is excluded on that day in the automatic controller. The Takagi-Sugeno (T-S) Fuzzy model used to control on a winter day is different from the (T-S) Fuzzy model used for the control on a summer day. The automatic controller is turned on at 9:00 hr and turned off at 16:00 hr. Although a small offset between the automatically controlled collector outlet temperature and the set point (597.3 K) can be seen.

It can be seen the error between the real and estimated states are found to be close as shown in figure 12.

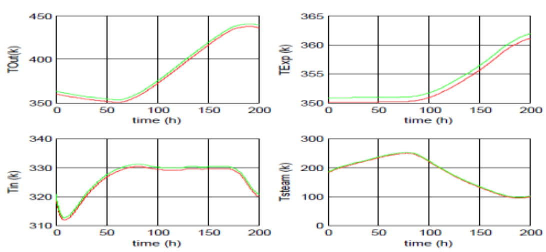


Figure12. State Estimation Errors.

It should be noted that we have simulated the TS fuzzy model with only two fuzzy regions for each decision variable with simplification reasons, and the controller was tested in absence of hard constraints to set the stability conditions. Unlike in practical case, the industrial processes have to satisfy the physical constraints imposed on the actuators. In our future works we will solve a constrained optimization problem.

V. Conclusion:

A nonlinear model of the solar power plant has been established. The model consists of a dynamic model for the collector field and a steady-state model for the power plant. The controller synthesis is based on the design of a fuzzy Kalman filter to predict the future plant behavior. The fuzzy observer generates optimal estimates of the system states and outputs from the noisy discrete fuzzy model and the model predictive control strategy for maintaining a specified constant collector outlet temperature on a summer day and a winter day when the power plant was operating in pure solar mode. The implemented MPC controller showed the capability to hold the collector outlet temperature close around the specified set point for a long time during a day.

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