Diagnosis of a Solar Power Plant using fuzzy sliding mode observer

Zahra. Taif, M. M. Lafifi, B. Boulebtateche
Laboratoire d'Automatique et Signaux (LASA),
Département d'Electronique,
Université Badji-Mokhtar, Annaba.B. P. 12
zahraautomatique@gmail.com,
mohamed.mourad.lafifi@univ-annaba.org; brahim.boulebtateche@univ-annaba.org

Abstract —At present the technologies of solar concentration are the one which present most possibilities for commercial use. Thus, it is necessary not only to design processes of conversion of energy, but it is also important to assure an availability of these equipment by the conception of fault detection and isolation (FDI) systems. In this paper we use a robust method for state reconstruction of nonlinear systems subject to unknown inputs. The multiple model methodologies can contribute significantly to the achievement of this objective since they can provide accurate approximation properties. We focus on the design of observers for dynamic Takagi-Sugeno fuzzy systems that can be used in a model-based fault detection and diagnosis scheme. A nonlinear system of this class is composed of multiple affine local linear models that are smoothly interpolated by weighting functions resulting from a fuzzy partitioning of the state space of a given nonlinear system subject to observation. The design methodology of the so-called fuzzy sliding mode observer for fault detection and diagnosis is based on extending Luenberger observers schemes to the case of interpolated multiple models. Stability conditions are performed by using Linear Matrix Inequalities (LMIs). The performance of the proposed approach is pointed out by focusing on a model of solar power plant through numerical results.

Key words* —*solar power plant, Fault detection and isolation (FDI),* T-S fuzzy models, *Sliding Mode Observers, LMI.

I. INTRODUCTION

The solar radiation, which is used to heat the working fluid as it circulates through the receivers, is adopted in all solar thermal power plants (SPP). This heated fluid is used in many applications such as the generation of high pressure superheated steam which supplies the turbine (or conventional generators); the production of electricity or heating water for industrial use...etc..Therefore, the use of solar energy in the production industrial process heat not only retains the non-renewable sources of energy but also reduces emissions of anthropogenic gases [1], [2] and [3]. Several parameters affect the quality of The collector outlet temperature : variations in solar radiation; the inlet temperature, the flow of oil; the ambient temperature and wind speed.It has been shown in [4], [5] and [6] that partial differential equations (PDEs) can describe the plant's non-linear behavior that links the internal state variables (T_{out},T_{in},T_{EXP},T_{steam}) . This state representation is well adapted to the synthesis of control laws and monitoring the process.

In recent years, the monitoring and the diagnosis of nonlinear processes has received an increasing interests from the scientific and engineering practitioners. In general, the nonlinear systems are firstly linearized at an operating point, and then robust techniques are applied to generate residuals, which are robust against limited parameter variations. The strategy only works well when the linearization does not cause a large mismatch between linear and nonlinear models; when the system operates near the specified operating point. Therefore such techniques have limited robustness when considering gross plant changes and nonlinearity.

In case of lack of first-principle models, empirical models like neural networks can be used for the purpose of process supervision. The main problems with these approaches are the difficulty in analyzing, in a rigorous mathematical way, their robustness/sensitivity and their scalability; i.e. a network trained for a specific plant may be inappropriate for other plant. To overcome the problem of precision and accuracy in FDD, various approaches based on fuzzy logic have been also suggested [7].

However, the fuzzy logic approach is not only required on its own, but as a framework for combining different paradigms. More specifically, quantitative model-based and soft-computing are combined to exploit the benefit of each [8].Another powerful approach for residual generation is based on observers. The common way is to obtain a set of residuals by comparing the actual measurements with their estimates obtained with the help of observers. Unfortunately, the design of nonlinear observers is not a straightforward task, even if the nonlinear process is completely known.

In this paper, we propose a methodology for the diagnosis of dynamic nonlinear processes by combining fuzzy logic with variable structure systems theory to formulate the so-called fuzzy sliding mode observers. Typically, the design of a fuzzy observer requires a precise mathematical description of the plant under interest in the form of a fuzzy dynamic model, which includes both local linear and fuzzy membership functions. The local linear models are state space affine models that can be derived directly from first principle or from empirical models

The present paper is structured as follows: the section II presents the description of the components of process (precise model) and simplified mathematical model of the solar power plant. The fuzzy modeling of the nonlinear systems is described in section III. In section IV the design of fuzzy sliding mode observer is treated and in particular the fuzzy sliding mode observers. Finally, the obtained simulation results are shown in Section V and the conclusion is given in section VI.

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.

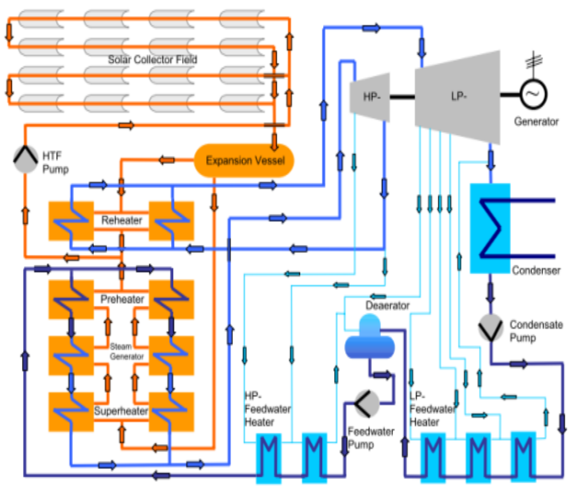

Figure1. Flow Diagram of the 30 MWe SEGS VI Plant for Pure Solar Model.

II.1.THE 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 [9]. These coefficients were obtained experimentally at SANDIA.

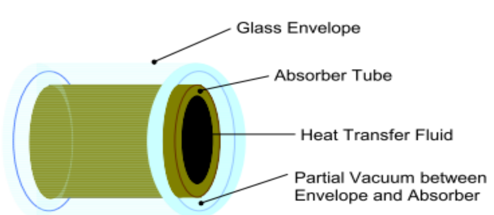

Figure2. The Heat Collection Element.

The heat collection element (HCE) present in Figure2 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 [10].

II.2. THEPOWER 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 [9].

The plant can be present by a simplified model showing in Figure3:

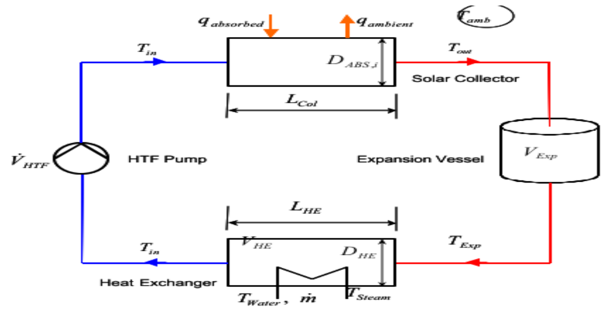

Figure 3.The Structure of the Simplified Model

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

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

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

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

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

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.

$1/\tau_{col}$ (t) $= V'/Vcol$ and $1/\tau_{exp}$ (t) $= V'/Vexp$, $1/\tau_{HE}$ (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'.

III. MULTI-LINEAR MODELS

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

$$x'(t) = f\big(x(t), u(t)\big)$$
$$y(t) = g(x(t), u(t)) \tag{5}$$

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

The Takagi-Sugeno Fuzzy modelling has recently been found 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 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 where all local models have one common state vector [12],[13].

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:

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

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 twopremise variables:

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

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

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:

$$x' = A\big(\xi(t)\big)x + B\big(\xi(t)\big)u. \tag{7}$$

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

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

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

Where:

$$a_1 = A_{col}.\rho_{HTF}(T_{out}).C_{HTF}.$$
$$a_2 = \frac{UA_{HE}}{2.A_{HE}\rho_{HTF}(Tin)C_{HTF}(Tin)}. \tag{10}$$
$$\mathrm{a} = \mathrm{b} = 0.4375.$$

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

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

Considering definitions (12) 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 $\xi_j^{\partial_i^j}, i = 1, .., 2^q$:

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

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

In the definitions of (20) and (21), 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.

The i^{th} rule of the fuzzy model has the following form:

Model rule i : $IF\ \varepsilon_1(t) is\ M_1^i\ and\ \dots\ \varepsilon_q(t)\ is\ M_1^i$

$$Then \begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) \\ y(t) = C_i\ x(t) \end{cases}$$

Consequently, the nonlinear model (10) can be proposed as:

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

IV. FUZZY SLIDING MODE OBSERVER

Sliding mode observers are known for their robustness and insensitivity with respect to many kinds of uncertainty. These observers are more robust than Luenberger observers, as the discontinuous term enables the observers to reject disturbances, and ~~are~~ also independent of a class of mismatch between the system and the observer. The discontinuous term is designed so that the state estimation error vector remains on a surface in the error space. The induced motion is referred to as the sliding mode .In most cases, the sliding surface is the difference between the observer and system output which is therefore forced to be zero. Several authors have proposed sliding mode observers design methods [14] .The method of Walcott and Zak [15] requires a symbolic manipulation package to solve the design problem which is formulated. Edwards and Spurgeon [16] proposed a canonical form for sliding-mode observer design and they give a numerically tractable algorithm to compute the gain matrices and the state transformation matrix to obtain the canonical form. The observer developed in this section is based on ideas found in [17]. The main idea behind it is to extend the sliding mode observers to dynamical systems described by a multiple model. In this context, the design of fuzzy Luenberger observers are proposed in [18], and lately applied for the detection and isolation of faults in nonlinear dynamic systems [19].

Assume that the fuzzy approximation of a nonlinear system reads:

$$x' = \sum_{i=1}^{M} w_i(z)(A_i x + B_i u + a_i) + f(t,x,u) \quad (17)$$
$$y = Cx$$

And the following assumptions are satisfied:

$A_1.\ f(t,x,u) = R\bar{u}(t)$

$$A_2.\ R = \sum_{i=1}^{M} w_i(z) R_i \quad (18)$$

$A_3.\ \bar{u}(t) \in R^q, R_i \in R^{n\times q}$, and $C \in R^{p\times n}$ with $p \geq q$.

The function $\bar{u}(t)$ represents the matched uncertainty due to the existence of unknown inputs. For the sake of simplicity, $\bar{u}(t)$ is denoted by $\bar{u}$.

$$\begin{cases} \dot{x} = \sum_{i=1}^{M} w_i(z)(A_i x + B_i u + R_i \bar{u} + a_i) \\ y = Cx \end{cases} \quad (19)$$

Such that:

$$\begin{cases} \sum_{i=i}^{M} w_i(\xi) = 1 \\ 0 \leq w_i(z) \leq 1 \quad \forall\, i = \{1, \ldots, M\} \end{cases} \quad (20)$$

Where $x(t) \in R^m$ is the state vector, $u(t) \in R^m$ is the input vector, $\bar{u}(t) \in R^q$, $q < n$, the vector of unknown inputs and $y(t) \in R^p$ the vector of measurable output. For the *ith* local model $A_i(t) \in R^{n\times n}$ is the state matrix, $B_i(t) \in R^{n\times m}$ is the matrix of inputs, $R_i(t) \in R^{n\times q}$ is the matrix of influence of unknown inputs, $a_i(t) \in R^{n\times 1}$ is the offset vector which depends on the operating point and $C(t) \in R^{p\times n}$ is the matrix of output. Finally, Z represent the scheduling vector which is formed by a subset of the input and/or the measurable state variables to define the validity regions of the local models.

The problem considered here consists in the reconstruction of the state variables by using the information provided by the input and output signals and, in the case of sliding mode, the reconstruction of faults is also treated. The proposed observer for the multiple models (6) is a linear combination of local observers, each of them having the structure proposed by Walcott and Zak. In this context, we consider that the inputs $\|\bar{u}(t)\| \leq \eta$, where η is scalar and ‖‖ represents the Euclidean norm. It is also assumed that there exists matrices $G_i(t) \in R^{n\times P}$, such that $A_{0i} = A_i - G_i C$ have stable eigen values and that there exists Lyapunov pairs (P,Q_i) of matrices and other matrices $F_i(t) \in R^{q\times q}$ respecting the following structural constraints:

$$\begin{cases} A_{0i}^T P + pA_{0i} = -Q \\ F_i C = R_i^T P\ ,\ \forall\, i \in 1, \ldots, M \end{cases} \quad (21)$$

The proposed observer has the form:

$$\begin{cases} \dot{\hat{x}} = \sum_{i=1}^{M} w_i(z)(A_i \hat{x} + B_i u + a_i + G_i e_y + R_i V_i) \\ y = C\hat{x} \end{cases} \quad (22)$$

Where e_y is the output error defined as follows:

$$e_y = y - \hat{y} = C(x - \hat{x}) = Ce \quad (23)$$

With e(t) represent the state estimation error, such as:

$$e(t) = x(t) - \hat{x}(t) \quad (24)$$

The matrices G_i and the control variables V_i, with $V_i(t) \in R^t$ must be determined in order to guarantee the asymptotic convergence of $\hat{x}(t)$ towards $x(t)$. The terms $V_i(t)$ compensate errors due to the unknown inputs. The dynamic of state estimation error is given as follows:

$$\dot{e} = \sum_{i=1}^{M} W_i(Z)(A_i - G_i C)e + R_i \bar{u} - R_i V_i) \quad (25)$$

V. DIAGNOSIS SIMULATION RESULTS

V.1. Faults affecting SPP

Due to anomalies of the hydraulic system functioning for the transfer of calories to the storage tank, during an accidental stop (ruling) of the flow of heat transfer fluid, concentrated calories at the tube will not be evacuated. The hydraulic system is then in danger because there is risk of overheating of boiling putting the fluid under overpressure. On the other hand, if the temperature of the water in the tank is close to the boiling point, it becomes useless and dangerous as it continues to want to store more calories.

V.2. Simulation

The TS fuzzy model of the plant described in section 2 is formed by four IF-THEN logical rules that have a fuzzy antecedent part and a functional consequent part. Concerning the dynamics of the solar power plant and its nonlinear model structure, two fuzzy variables are considered in the antecedent part of the TS fuzzy model. The memberships functions of the scheduling variables are depicted in figure4.The local dynamic models are deduced from the nonlinear model (1) through dynamic linearization by sector transformation.

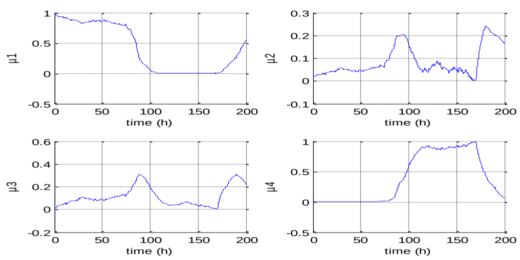

Figure4. Membership functions of scheduling variables.

V.3.State estimation

To see the effectiveness of the proposed observer, simulation results are presented in figures 5 and 6. Figure 5 shows the unknown inputs presented to the system while Figure 6 shows the state estimation. Based on Figures 5 and 6, it can be seen that the observer performs as expected despite the presence of the unknown inputs and the real and estimated states are found to be close.

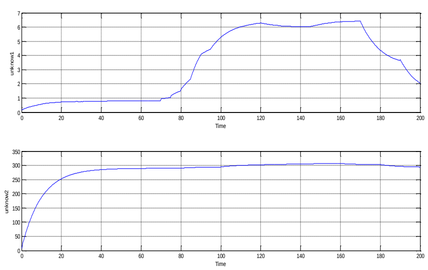

Figure 5: The unknown inputs

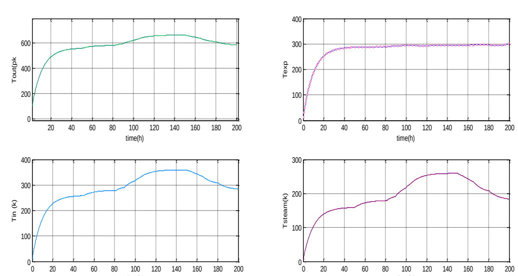

Figure 6: The four states: Dotted line: estimated state; solid line: real state

V.4.Fault detection and isolation for SPP model

The objective of this part is to generate residuals that reflect the faults acting on the system (16). An ideal residual signal should remain zero in the fault-free case and non zero when fault occurs. Once a fault has been detected, it must be estimated. The fault estimation will specify the type of fault, its duration, its amplitude and eventually its probable evolution, knowing that the threshold used in our case being fixed

V.4.1.Sensor fault detection:

In order to identify the sensor fault, we consider that the Actuator is faultless ($\bar{u} = 0$) while the output vector y is corrupted by the sensor fault $\Delta y = 0$.

Three fuzzy sliding mode observers are designed, one based on the outlet collector temperature observer $y_1 = T_{out}$, the second based on the steam temperature $y_2 = T_{steam}$and the last is based on the two outputs T_{out} and T_{steam}.

This implies that it is possible to estimate the state through either the first output $T_{out}(y_1)$or the second one $T_{steam}(y_2)$

The sensor fault detection and localization is based on the analysis of the residuals generated by three observers $r_{y_{i,k}} = y_i - y_{i,k}$The three observers, diagrammed in figure7, estimates the states of the system from the input (the HTF volume flow rate), the measured disturbances (environmental data, steam mass flow rate, heat exchanger water inlet temperature), and the measurement of the collector outlet temperature.

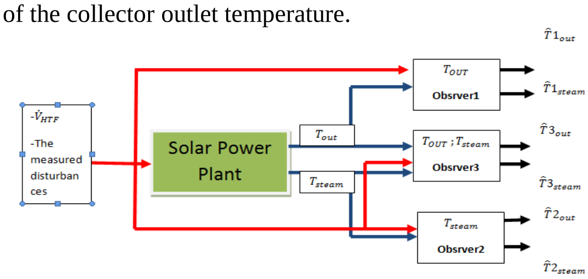

Figure7. Block diagram of the banc observer-based FDI

Figures 8 and 9 show signals that represent sensor failures, the first one has been added to sensor 1 output y_1 between 11 and 13 hr, and the second one has been added to sensor 2 output $y_2$between 09 and 10hr .

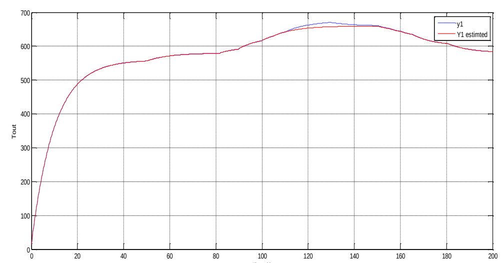

Figure8.T_{out}: Dotted line: estimated state; solid line: real state

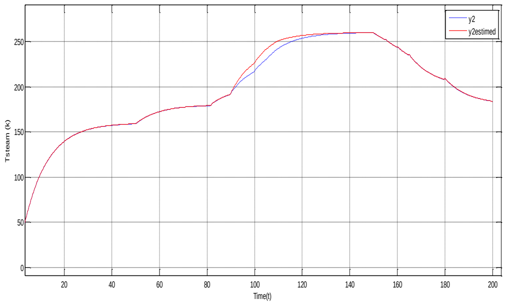

Figure9.T_{steam}: Dotted line: estimated state; solid line: real state

The figure 10 illustrated the evolution of residues generated by banc observer.

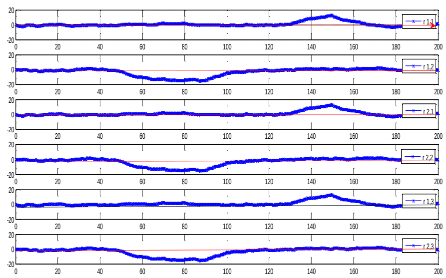

Figure10. Residue Evolution

V.4.1.1.FDI using global sliding mode observer3

The simulation results of the fault detection and isolation based on the global observer3are illustrated on the figures10 (part5 and part6). The residuals $r_{1,3}$and $r_{2,3}$show only the momentof the appearance and disappearance of sensor faults without being able to locate the fault. So, there is instantaneous fault detection at time of appearance and disappearance

V.4.1.2.FDI using sliding mode observer1

The simulation results of the fault detection and isolation based on theobserver1are illustrated on the figures 10 (part1 and part2). The residuals $r_{1,2}$and $r_{2,1}$ generated by the observer1 allow to detect and locate the fault sensor on the y1. The fault detection and localization is possible by this observer1, because this observer does not depend on the faulty output2.

VI. CONCLUSION

As to the interest of the technology of solar power plants, it is necessary not only to design processes of conversion of energy, but it is also important to assure availability of these equipment by using the concept of the fault detection and isolation (FDI).
A suitable sliding mode observer for dynamic nonlinear processes subject to unknown inputs is developed in this paper. The nonlinear system is decomposed by nonlinear transformation sector used to design different kinds of fuzzy observers. An application to sensor fault diagnosis based on the synthesis of the proposed fuzzy sliding mode observer is realized. The numerical simulation results for solar power plant show that sensor fault detection can be performed as well by this type of observer. Also for the near future we plan to apply in this FDI structure adaptive detection threshold which will lead to a marked improvement in the latter.

REFERENCES

[1] M. A. Demetriou, “Using unknown input observers for robust adaptive fault detection in vector second-order systems,” *Mechanical Systemsand Signal Processing*, 2005.
[2] Thorsten Stuetzle, Nathan Blair, “Automatic Control of a 30 MWe SEGS VI Parabolic Trough Plant ”ISES 2001 Solar World Congress.
[3] Y. Zhou, J. Liu, Estimation of an incipient fault using an adaptive neuro fuzzy sliding-mode observer, *Energy and Buildings*(2014)
[4] J t econoniou and p c i luk “an intelligent approach to modelling of a solar power plant ”proceedings of the 6th internauonal conference on advances in power system control.
[5] Z. Taif , M. M. Lafifi, B. Boulebtateche, “Diagnosis of a solar power plant using TS fuzzy-based multimodel approach” 16th International Power Electronics and Motion Control Conference and Exposition , IEEE , 2014.
[6] Fan, K. K., and J. G. Hsiech, LMI approach to design of robust state observer for uncertain systems with time-delay perturbation, IEEE Int. Conf. on Industrial Technology, (2002)..
[7] Akhenak, A., M. Chadli. J. Ragot and D. Maquin, Sliding mode multiple observer for fault detection and isolation, 42th IEEE Conference on Decision and Control, Hawai, USA, (2003).
[8] B. Pourbabaee, N. Meskin, K. Khorasani, Sensor Fault Detection, Isolation and Identification Using Multiple Model-based Hybrid Kalman Filter for Gas Turbine Engines, Systems and Control,2015
[9] T. A. Johansen and R. Babuska, “Multiobjective identification of takagi-sugeno fuzzy models,” *IEEE Transactions on Fuzzy Systems*, 2003.
[10] H.O. Wang, K. Tanaka, M.F. Griffin. An Approach to Fuzzy Control of Nonlinear Systems: Stability and Design Issues. IEEE Trans. Fuzzy Syst.
[11] Yimin Zhou. G .XuM., Overview of Fault Detection and Identification for Non-linear Dynamic Systems. Proceeding of the IEEE International Conference on Information and Automation (2014).
[12] A. Akhenak, M. Chadli, J. Ragot, and D. Maquin, “Design of sliding mode unknown input observer for uncertain takagi-sugeno model,”*15th Mediterranean Conference on Control and Automation, MED’07,Athens, Greece, June 27-29*, 2007..
[13] Tan, C. P., and C. Edwards, An LMI approach for designing sliding mode observers, Int. J. Control, (2001).
[14] Lippke F. (1995), Simulation of the part-load behavior of a 30 MWe SEGS plant, SAND95-1293, Sandia National Laboratories, Albuquerque, NM.
[15] Duffie, J.A and Beckman, W.A. Solar Engineering of Thermal Process, John Wiley & Sons, Inc., NewYork. (1991),
[16] Mancini, T., Sloan, M., Kearney, D. Appel, F., Mahoney, K., Cordeiro, P. (2001), LUZ Heat Collection Element Heat Transfer Analysis Model, Sandia National Laboratory.
[17] K. Tanaka. H. Wang, fuzzy control systems Design and Analysis; A linear Matrix Inequaity approach, Wiley, New York 2001
[18] Sandy Rahme, Nader Meskin « Adaptive sliding mode observer for sensor fault diagnosis of an industrial gas turbine » Control Engineering Practice 38 (2015)
[19] C. Edwards, “A comparison of sliding mode and unknown input observers for fault reconstruction,” *IEEE Conference on Decision and Control*, pp. 5279–5284, 2004.