GREENHOUSE CLIMATE MODELING :
Observability and Identification for Supervision

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Abstract: The greenhouse model is defined using the energitic formulation of the various components for which the state variables are supposed to be homogeneous. This model is a priori complex and difficult to obtain. A various simplified and operational physical models of the greenhouse will be necessary, for simulation and control. This paper try to propose some behavioural models for this system.

1 INTRODUCTION

For several years, studies on greenhouse climate modeling has made the monitoring and control a challenge of several research tasks. In the literature we can find a differents models structure for this system. Mathematical models developped by Singh (Singh et al., 2006), Gupto (Gupta and Chandra, 2002) et Ghosal (Ghosal and Tiwari, 2004), hierarchical fuzzy models developped by Salgado (Salgado and Cunha, 2005) and Lafont (Lafont and Balmat, 2002) or dynamical models presented by Abdel-Ghary (Abdel-Ghany and Kozai, 2006), Luo (Luo et al., 2005) and Takakura (Takakura et al., 1971).
Unfortunantely, the analysis which are done are local and application depend, without generalization possibility. These models are generaly obtained with empirical nature and strongly related to the considered greenhouse type.
However, these models are based on the same principle but their setting in equation differentiates them only according to the desired result. Moreover, these models are defined using energitic formulation of various components of the greenhouse (interior air, crop, ground, cover, heating device) for which the state variables are supposed to be homogeneous.
Considering the complexity of comprehension and setting a single model for the greenhouse system, various simplified models will be proposed in this paper, knowing that the need for simplified and operational physical models is necessary. Then we are interested in a first step, on the simulation and the control of this type of system.
Before, let us describe the physical model of our system and the elements characterizing it. We take as a starting point the description of the complete energitic model given by Monteil in (C. Monteil et al., 1991).

2 GREENHOUSE PHYSICAL MODEL

The dynamic behaviour of the greenhouse-climate is a combination of physical processes involving energy transfer (radiation and heat) and mass transfer (water vapour fluxes and CO_2 concentration) taking place in the greenhouse and from the greenhouse to the outside environment (figure 1).
These processes depend on the outside climate conditions, structure of the greenhouse, type and state of the crop and on the actuating control signals. Typically, we can find ventilation and heating to modify inside temperature and humidity conditions. Shading and artificial light to change internal radiation. And CO_2 injection to influence photosynthesis and cooling by evaporation for humidity enrichment and decreasing the air temperature (Salgado and Cunha, 2005).

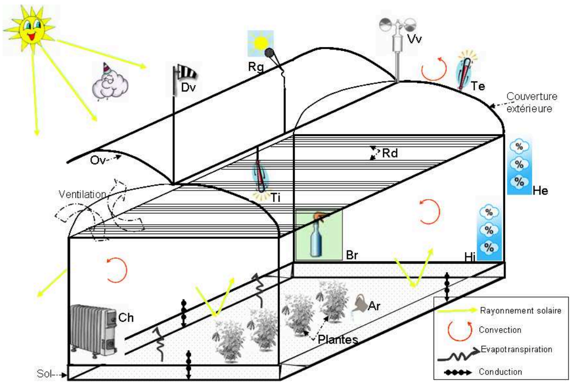

Figure 1: Greenhouse principal schema

The greenhouse climate model describes the dynamic behaviour of the state variables using differential equations for the air temperature, humidity and CO_2 concentrations. In this paper, only the temperature and humidity models are considered. The problem of modeling and control design for our system is then complex and intricate because there are, at least, eight inputs and two outputs involved in a non linear and switched way :

- 4 actuators (heating Ch (boolean), opening Ov (%), shade Rd (%), misting system Br (boolean));
- 4 meteorology disturbance (external temperature $T_{Ae}(°C)$, external hygrometry W_{Ae} (%), solar radiation $Rg(W/m^2)$, wind speed $Vv(m/s)$);
- 2 controlled outputs (internal temperature Ti ($°C$), internal humidity W_{Ai} (%)).

The model equations can be written by deriving the appropriate energy balances for simple wall greenhouse (C. Monteil et al., 1991) :

$$\begin{cases} \Delta_{TAi} = & C_{AiPl} + C_{AiSo} - C_{AiAe} + C_{AiCh} \\ \Delta_{WAi} = & L_{PlAi} + L_{SoAi} - L_{AiCe} + L_{BrAi} \\ 0 = & I_{Ce} - C_{CeAe} - L_{CeAe} + C_{AiCe} + L_{AiCe} \end{cases} \quad (1)$$

where : Δ_{TAi} and Δ_{WAi} are respectively the variations of the internal temperature and the internal humidity. The convection exchange between the internal temperature and respectively the internal faces of the cover (C_{AiCe}), the ground (C_{AiSo}), the crops (C_{AiPl}) and the heating device (C_{AiCh}) can be obtained with the following relation :

$$h = h_1 \left| T_{Ae} - T_{Ai} \right|^{h_2} + h_3 \bar{V}v^{h_4} \quad (W/m^2/°C) \quad (2)$$

where $h_i(i = 1 \text{ to } 4)$ are Kindelan coefficient (see table 1). Moreover, this relation take into account the absolute value of the difference between the temperature of the air inside and outside the greenhouse and mean wind speed value of the inside air of the greenhouse. $T_{Ae}(°C)$ and $T_{Ai}(°C)$ are respectively the external air temperature and the internal air temperature, $\bar{V}v$ mean wind speed value of the inside air is defined by the following relation :

$$\bar{V}v = Lon \frac{R}{3600} \quad (m/s) \quad (3)$$

where Lon (m) is the length of the greenhouse and R $(\frac{\text{volume de serre}}{\text{heure}})$ its time renewal rate air.
On the other hand, the convection exchange between face externs of the cover and outside air of the greenhouse noted C_{CeAe} is only related to speed wind (C. Monteil et al., 1991).

$$h = \begin{cases} h_1 + h_2 Vv & \text{if} \quad Vv < Vv_{limite} = 7,73(m/s) \\ h_3 Vv^{h_4} & \text{if} \quad Vv \geq Vv_{limite} = 7,73(m/s) \end{cases} \quad (4)$$

The assesment of the external cover is obtained from the condensation of the steam of the greenhouse inside air on the internal face (L_{AiCe}), and the external face (L_{CeAe}). The hydrous exchange value, k results from the convection exchange h is given by the Lewis relation :

$$k = \frac{h}{C_{Ae}} \quad (kg/m^2/s) \quad (5)$$

where $C_{Ae}(J/kg/C)$ heat capacity of the greenhouse outside air. Furthermore, we note that the evapotranspiration of the ground (L_{SoAi}) is defined by the same way. On the other hand, with regard to the misting system, the heat flow due to the brumisation is given by :

$$C_{BrAi} = \frac{L_{BrAi} Q_{br}}{3600 Vol} \quad (Kcal/m^3/s) \quad (6)$$

where $L_{BrAi}(Kcal/g)$ is the latent heat of evaporation of the the misting system, $Q_{br}(kg/s)$ is the spray water quantity and $Vol(m^3)$ the total volume of the greenhouse.
When the roof vents is opened, the mass flow rate through the openings can be estimated by the following relation (Kittas et al., 1997) :

$$C_{AiAe} = \frac{\rho_{Ai} Ar}{2} C_d \left(2g \frac{\Delta T Lao}{4 T_{Ae}} + C_r Vv^2 \right) \quad (7)$$

In this equation $Ar(m^2)$ is the total area of roof ventilation openings, $\rho_{Ai}(kg/m^3)$ defined the greenhouse air density, C_d is the discharge coefficient of the window, C_r is the wind effect coefficient when roof vents were opened, $g(m/s^2)$ is the gravitational acceleration, Lao is the vertical height of the roof opening, $\Delta T = T_{Ai} - T_{Ae}$ defined, the difference between the temperature of the air inside and outside the greenhouse and Vv is the speed wind outside the greenhouse.
For the calculation of I_{Ce} in the equation (1), we invite the reader to refer to the appendix in (C. Monteil

et al., 1991). This term is defined by the flux density M_{Ce} and the infra-red illumination E_{Ce}, had with the radiation of the heaven vault and the external ground. By convention, the flux density is defined by the following relation :

$$M_{Ce} = \sigma T_{Ce}^4 \quad (W/m^2) \tag{8}$$

where σ is the Stefan-Boltzmann coefficient ($5.674 \times 10^{-8} m^2/W/K^4$) and $T_{Ce}(K)$ is the cover temperature. With the final one, the coefficient $h_i (i = 1 \text{ to } 4)$, from Kindelan (Kindenlan, 1980), is given in the table 1 :

	h_1	h_2	h_3	h_4
C_{AiCe}	$1,52$	$1/3$	3	$1/2$
C_{AiSo}	$1,52$	$1/3$	3	$1/2$
C_{AiPl}	$4,25$	$1/4$	3	$1/2$
C_{AiCh}	$1,32$	$1/4$	3	$1/2$
C_{CeAe}	$7,50$	$3,88$	$7,30$	$0,80$

Table 1: Numerical parameters for the convection exchange rules

Thus, the energy balances formulation determine a system of nonlinear differential equations. The unknown factors of this system of differential equations are the state variables T_{Ai} and W_{Ai}, and the nonlinear terms of the equations is given by :

- the flux density $\left[T^4\right]$ and
- the convection exchange $\left[\Delta T^{1/3} \text{ or } \Delta T^{1/4}\right]$.

However, let us adopt the following condensed representation for an agricultural greenhouse, which derives from the relation (1) :

$$\begin{pmatrix} \Delta_{TAi} \\ \Delta_{WAi} \end{pmatrix} = f(\Delta T) + g(Vv, Rg, Ch, Br, Ov) \tag{9}$$

where f and g are the non linear function defined by the thermal exchanges detailed previously. To be even more explicit, let us consider the following sets : $e = \{Ch, Br, Ov, Rd\}$ set of input control, $v = \{T_{Ae}, W_{Ae}, Vv, Rg\}$ set of input defining the meteorology disturbance, and $x = \{T_{Ai}, W_{Ai}\}$ set of the continuous state variables of the system. Thus, the following relation is equal to (9) :

$$\dot{x}(t) = f(x,t) + g(e,v,t) \tag{10}$$

As we can note it, the dynamic models resulting from the physical equations offer multiple possibilities of applications as well as a good precision. On the other hand, they are complex and not very easy handling, in particular in the control applications of greenhouse. We are interested on the simulation and the control of this type of system. In this case, the need for simplified and operational physical models is necessary.

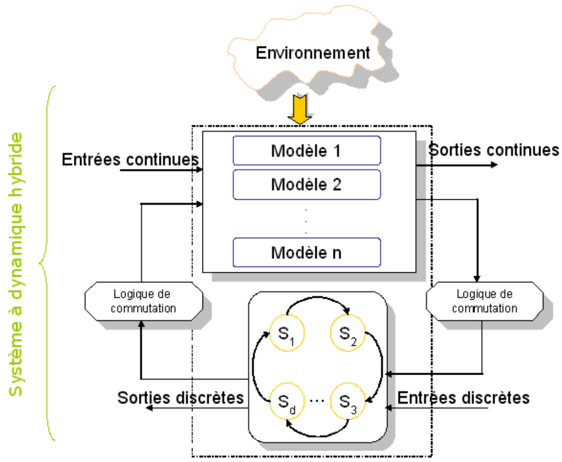

Figure 2: Hybrid complex system representation.

3 SIMPLIFIED MODELS FOR GREENHOUSE

Considering the complexity of comprehension and setting a single physical model for the greenhouse system, various simplified models can be proposed. This simplification is based on the following assumptions :

Assumption 3.1 *we assume that :*

1. *The global dynamic behavior of the greenhouse can be stabilized around some operating modes.*
2. *The evolution of the continuous dynamics of the greenhouse can be approximated by linear models around each operating mode.*
3. *The system behaves like a stationary system around each operating mode.*
4. *Each operating mode can be associated with discrete events characterizing the global dynamic behavior of the system.*

So, we can considered the representation illustrated in the figure 2 to identify the nominal behavior of our system. This representation is composed by :

- A set of behavioral models M_i
- A transition or commutation device
- A discrete events supervisor managing the differents commutation or transition

To describe the global system's dynamic behavior, we have to gather all the locally valid model equations in non linear case and then :

$$\begin{cases} \dot{x}(t) = h_{mi}(x,e,v,t) \\ m_i = \langle Mode, I, O, \delta_{int}, \delta_{ext}, \lambda, t_a \rangle \end{cases} \tag{11}$$

According to the assumption (3.1), we can reformulate this equation in linear case by the following expression :

$$\begin{cases} \dot{x}(t) = & A_{m_i}x(t) + B^e_{m_i}e(t) + B^v_{m_i}v(t) \\ m_i : & \langle Mode, I, O, \delta_{int}, \delta_{ext}, \lambda, t_a \rangle \end{cases} \quad (12)$$

for one simplified representation of the greenhouse models, where : $A_{m_i} \in \mathbb{R}^{n \times n}$ is the state matrix, $B^e_{m_i} \in \mathbb{R}^{n \times me}$ is the control matrix, $B^v_{m_i} \in \mathbb{R}^{n \times mv}$ is the external input matrix. *Mode* is the set of sequential operating modes. I is the set of external events. O is the set of internal events. $\delta_{int} : Mode \longrightarrow Mode$ represents the internal state transition function, $\delta_{ext} : Mode_{-} \times I \longrightarrow Mode_{+}$ is the external state transition function, $\lambda : Mode \longrightarrow O$ is the output function, t_a is the time advance function.
Leads, the identification of this system will be done as follows :

- **Step** 1
  a- Data Acquisition
  b- Pre-treatment of the data and setting on scale
  c- Setting Input/Output variables of the supervisor
- **Step** 2
  a- Identification of the operating modes
  b- Setting data for each operating mode
- **Step** 3
  a- Identification of paramaters of each sub-model
  b- Validation of the structure

3.1 Identification of the operating zone

We retain the variables Rg and Vv like descriptive variables of the environment where our system evolves. The choice of these variables have been done in a previous work (Pessel et al., 2005), (Rajaoarisoa et al., 2006), (M'Sirdi et al., 2007). Moreover, these variables are necessary to construct the transition table 2.

Input	Lower	Middle	Upper
Vv	$< R'_1$	$-$	$\geq R'_1$
Rg	$< R'_1$	$> R'_1$ *and* $\leq R'_2$	$> R'_2$

Table 2: Input values associated with environment specification

Furthermore, the wind speed will take the following values $Vv = \{VvL, VvU\}$ which are respectively *Lower* and *Upper* values of Vv while the global radiation of the sun will take $Rg = \{RgL, RgM, RgU\}$ which are respectively *Lower*, *Middle* and *Upper* values of Rg.

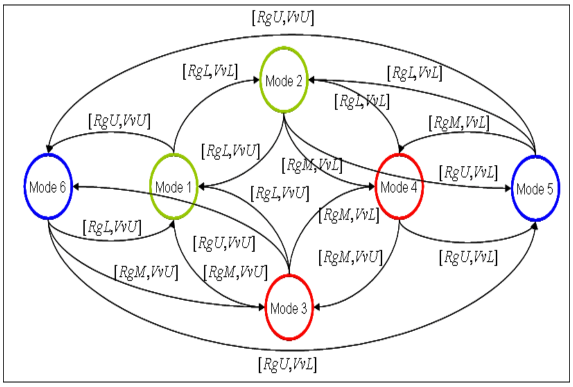

Figure 3: Behaviour of the greenhouse Model transitions

The combination of the descriptive variables values Rg et Vv allows us to have 6 operating modes which are in the table 3 and illustrated in the figure (3).

- All operating modes are defined by : $Mode = \{Mode_1, Mode_2, Mode_3, Mode_4, Mode_5, Mode_6\}$.
- Input variables defined by the set $I = \{I_1, I_2, I_3, I_4, I_5, I_6\}$, associated respectively by the input events set $ev = \{ev_1, ev_2, ev_3, ev_4, ev_5, ev_6\}$
- The set of corresponding output events is described by $O = \{O_1, O_2, O_3, O_4, O_5, O_6\}$

Mode	Name	Input Variable
1	*ColdNight*	$I = \{RgL, VvU\}$
2	*FreshNight*	$I = \{RgL, VvL\}$
3	*ColdDaybreak*	$I = \{RgM, VvU\}$
4	*FreshDaybreak*	$I = \{RgM, VvL\}$
5	*DryDay*	$I = \{RgU, VvL\}$
6	*ModerateDay*	$I = \{RgU, VvU\}$

Table 3: Discrete State designation of the supervision device

The sub-models are in three categories : *day*, *night*, and *daybreak*. In each category they are two classes : *Cold* and *Fresh*. This leads us six sub-models.

3.2 Identification of the sub-models

Let us consider stable linear time-invariant discrete time systems of finite order n, valid in the operating zone m_i. One form of describing such a system is by the state-space equations:

$$\begin{cases} x(k+1) = A_{m_i}x(k) + B_{m_i}u(k) + Fw(k) \\ y(k) = C_{m_i}x(k) + D_{m_i}e(k) + \mu(k) \\ m_i = \langle Mode, I, O, \delta_{int}, \delta_{ext}, \lambda, t_{\alpha i} \rangle \end{cases} \quad (13)$$

with $u = [e\ v]$ is the set of input variables, $B = [B^e\ B^v]$ is the input matrix, F is the disturbance matrix and w and μ are the disturbance inputs.
To identify all parameters of this system we make reference on the general concept in subspace identification that we consider as the good procedure to identify our system. Moreover, subspace identification is by now a well-accepted method for identification of multivariable linear system (VanOverschee, 1995), (Verhaegen, 1994). The advantages of this method are that the user has simple and few desing variables, we don't have to apply some modification for the state matrices forms, is a nonrecursive method and has robust numerical properties and relatively low computational complexity.
The following input-output matrix equation (De Moor, 1988), played a very important role in the development of subspace identification :

$$\mathbf{Y}_{i/i} = \mathcal{O}_i \mathbf{X}_{i/i} + \mathcal{H}_i \mathbf{U}_{i/i} + \mathcal{F}_i \mathbf{W}_{i/i} + \mu_{i/i} \qquad (14)$$

The different terms in this equation are now defined :

- The extended observability matrix $\mathcal{O}_i$:

$$\mathcal{O}_i = \begin{pmatrix} C \\ CA \\ \vdots \\ CA^{i-1} \end{pmatrix} \in \mathbb{R}^{li \times n} \qquad (15)$$

- The deterministic lower block triangular Toeplitz matrix $\mathcal{H}_i$:

$$\mathcal{H}_i = \begin{pmatrix} D & 0 & \cdots & 0 \\ CB & D & \cdots & 0 \\ \vdots & \vdots & \ldots & \vdots \\ CA^{i-2}B & CA^{i-3}B & \cdots & D \end{pmatrix} \in \mathbb{R}^{li \times mi} \qquad (16)$$

- The stochastic lower block triangular Toeplitz matrix $\mathcal{F}_i$:

$$\mathcal{F}_i = \begin{pmatrix} 0 & 0 & \cdots & 0 & 0 \\ C & 0 & \cdots & 0 & 0 \\ CA & C & \cdots & 0 & 0 \\ \vdots & \vdots & \ldots & \vdots & \vdots \\ CA^{i-2} & CA^{i-3} & \cdots & C & 0 \end{pmatrix} \in \mathbb{R}^{li \times ni} \qquad (17)$$

- The input block Hankel matrices are defined as :

$$\mathbf{U}_{i/i} = \begin{pmatrix} u_{i+1} & u_{i+2} & \cdots & u_{i+j} \\ u_{i+2} & u_{i+3} & \cdots & u_{i+j+1} \\ \vdots & \vdots & \ldots & \vdots \\ u_{2i} & u_{2i+1} & \cdots & u_{j+2i-1} \end{pmatrix} \qquad (18)$$

  The Output block Hankel matrices $\mathbf{Y}_{i/i}$ and the disturbance block Hankel $\mathbf{W}_{i/i}$ are defined in the same way.

The basic idea of subspace identification now is to try to recover the $\mathcal{O}_i\mathbf{X}_{i/i}$-term of the equation (14). This is a particularly interesting term since either the knowledge of $\mathcal{O}_i$ or $\mathbf{X}_{i/i}$ leads to the system parameters.
How can an estimate of $\mathcal{O}_i\mathbf{X}_{i/i}$ be extracted from above equation? For this we need to define a notion of orthogonal projection.

Definition 3.1 *The orthogonal projection of the row space of M into the row space of N is denoted by $M\Pi_N$ and defined as :*

$$M\Pi_N = MN^T(NN^T)^{(-)}N \qquad (19)$$

with $.^{(-)}$ is the Pseudo-inverse of Moore-Penrose. $M\Pi_N^\perp$ is the projection of the row space of M into $N^\perp$, the orthogonal complement of the row space of N, for which we have $M\Pi_N^\perp = M - M\Pi_N$

By projecting the row space of $\mathbf{Y}_{i/i}$ into the orthogonal complement $\mathbf{U}_{i/i}^\perp$ of the row space of $\mathbf{U}_{i/i}$ we find :

$$\mathbf{Y}_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp} = \mathcal{O}_i\mathbf{X}_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp} + \mathcal{F}_i\mathbf{W}_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp} + \mu_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp} \qquad (20)$$

The following step consits in weighting this projection to the left and to the right with some matrices $\mathcal{M}_1$ and $\mathcal{M}_2$ can not be chosen arbitrarily but they should satisfy the following 3 conditions :

1. $rang(\mathcal{M}_1\mathcal{O}_i) = rang(\mathcal{O}_i)$
2. $rang(\mathbf{X}_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp}\mathcal{M}_2) = rang(\mathbf{X}_{i/i})$
3. $\mathbf{E}[\mathcal{M}_1(\mathcal{F}_i\mathbf{W}_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp} + \mu_{i/i}\Pi_{\mathbf{U}_{i/i}^\perp})\mathcal{M}_2] = 0$

The first two conditions guarantee that the rank-n property of $\mathcal{O}_i\mathbf{X}_{i/i}$ is preserved after projection onto $\mathbf{U}_{i/i}^\perp$ and weighting by $\mathcal{M}_1$ and $\mathcal{M}_2$. The third condition expresses that $\mathcal{M}_2$ should be uncorrelated with noise sequences $w(k)$ and $\mu(k)$ to obtain unbiased estimations.

3.2.1 Determination of A and C

The matrices A and C can be determined from the extended observability matrix in different ways. All the methods, make use of the shift invariance property of the matrix $\mathcal{O}_i$, which implies that (Kung, 1978) :

$$\hat{A} = \underline{\mathcal{O}_i}^{(-)}\overline{\mathcal{O}_i},\ \text{o}\ \underline{\mathcal{O}_i} = \mathcal{O}_i(1:l(i-1),:)\ \text{et}\ \overline{\mathcal{O}_i} = \mathcal{O}_i(l:li,:) \qquad (21)$$

and

$$\hat{C} = \underline{\mathcal{O}_i}(1:l,:) \qquad (22)$$

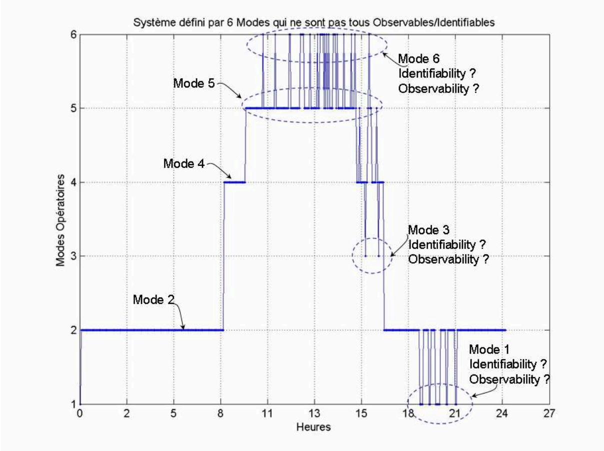

Figure 4: Operating modes commutation for the 10 March day

3.2.2 Determination of B and D

After the determination of A and C, the system matrices B and D have to be computed. From the Input/Output equation (14), we define that :

$$O_i^{\perp}\mathbf{Y}_{i/i}\mathbf{U}_{i/i}^{(-)} = O_i^{\perp}\mathcal{H}_i + O_i^{\perp}(\mathcal{F}_i\mathbf{W}_{i/i} + \mu_{i/i})\mathbf{U}_{i/i}^{(-)} \quad (23)$$

The noise sequences is uncorrelated with the Input, we have:

$$\mathbf{E}[O_i^{\perp}\mathbf{Y}_{i/i}\mathbf{U}_{i/i}^{(-)}] = O_i^{\perp}\mathcal{H}_i \quad (24)$$

We can observe that with known matrices $A, C, O_i^{\perp}, \mathbf{U}_{i/i}$ and $\mathbf{Y}_{i/i}$, the equation (23) is linear in B and D.

4 EXPERIMENTAL RESULTS

In this section we give some results in the identification of the greenhouse models. We have retained one day of March (10 March) to identify all parameters. The simulation done with the discreet events atomic model let us to have an idea on the detectability and observability of all operating modes of the system and the corresponding time range. This is illustrated in figure (4).

So, if we assume that our system is identifiable in a well defined mode thus, it must be observable also. Several researchers work in this framework, unfortunately Bemporad (Bemporad and Morari,) show through counterexamples that observability and controllability properties cannot be easily deduced. Thus, Ramadge (Ramadge and Wonham, 1987) addresses the problem as the determination of the current state of the system, i.e. partial observations may be available concerning both the system state and events. Detectability and observability of the state and events require the exact reconstruction of the discrete component of the state in finite time (De Santis and Di Benedetto, 2005). In fact, a switching system *Mode* is observable if after some time the current continuous component of the state can be exactly reconstructed. Hence *Mode* is observable if and only if all the systems $Mode_i$ are observable. Collins (Collins and Van Schuppen, 2004) has proposed to the observability problem for a finite initial state set reduces to the halting problem by considering an appropriate observation function. Vidal (Vidal et al., 2003) use a conditions based on simple rank test that exploit the geometry of the observability subspaces. Furthermore, the verification of the observability property is very involved due to the complex interactions between the discrete and continuous behavior exhibited by hybrid systems. Thus, Balluchi (Balluchi et al.,), Chaib (Chaib et al., 2005), consider for hybrid systems, the notion of observability regards both the discrete and the continuous components of the hybrid state.

According to these definitions and the result illustrated on figure (4), our system can be considerated a priori as completely observable and implicitily identifiable. On the other hand with our analysis, our system loses its observability due to fact that we have one very short dwell time for several operating modes and they are hardly detectable. However, a small-scale model can be defined to preserve the observability and the identifiability while eliminating modes with short dwell time. Thus we can formulate the following proposition :

Proposition 4.1 .

1. *The switched sub-system must be detectable,*
2. *The switched syb-system must be observable,*
3. *The various operating modes make it possible to check the conditions of persistent excitation to be able to build the various models with continuous dynamics.*

The two first conditions are related to the conditions given in (De Santis and Di Benedetto, 2005).

Therefore, the discreet events atomic model is composed of operating modes defined by $Mode^* = \{Mode_1^*, Mode_2^*, Mode_3^*\}$, input variables defined by the set $I^* = \{I_1^*, I_2^*, I_3^*\}$ associated respectively by the input events set $e^* = \{e_1^*, e_2^*, e_3^*\}$ and the set of output events is described by $O^* = \{O_1^*, O_2^*, O_3^*\}$. This is illustrated in figure (5a). The switching result into the different operating modes for the experimental greenhouse are illustrated in the figure (5b).

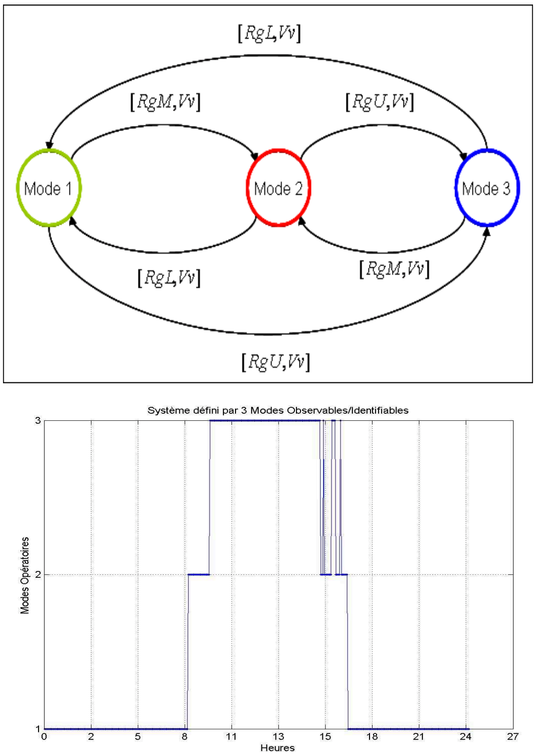

Figure 5: a) Behavioural Models of the greenhouse. b) Operating modes commutation for the 10 March day

Now, we can identify the continous dynamical models parameters according to the algorithm statement above. Thus, we have the following models for each mode :

for the mode : $Mode_1^*$

$$A_{Mode_1^*} = \begin{pmatrix} -0.2128 & 0.0819 \\ 0.1259 & -0.2162 \end{pmatrix};$$

$$C_{Mode_1^*} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix};$$

$$B^e_{Mode_1^*} = \begin{pmatrix} 0.1469 & 0 & 0 & 0 \\ -0.1480 & 0 & 0 & 0 \end{pmatrix};$$

$$B^v_{Mode_1^*} = \begin{pmatrix} 0.0848 & -0.0679 & -0.1323 & 0 \\ 0.0109 & 0.1365 & 0.1780 & 0 \end{pmatrix};$$

for the mode : $Mode_2^*$

$$A_{Mode_2^*} = \begin{pmatrix} -0.2694 & -0.3000 \\ 0.3795 & -0.4274 \end{pmatrix};$$

$$C_{Mode_2^*} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix};$$

$$B^e_{Mode_2^*} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix};$$

$$B^v_{Mode_2^*} = \begin{pmatrix} 0.3946 & 0.3160 & -0.0630 & 0.1335 \\ 0.5616 & 0.6740 & -0.1797 & -0.9603 \end{pmatrix};$$

and **for the mode :** $Mode_3^*$

$$A_{Mode_3^*} = \begin{pmatrix} -0.3235 & -0.0513 \\ -0.2581 & -1.1357 \end{pmatrix};$$

$$C_{Mode_3^*} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix};$$

$$B^e_{Mode_3^*} = \begin{pmatrix} 0 & -0.1304 & -0.2003 & -0.1020 \\ 0 & 0.5993 & -0.5851 & 0.0743 \end{pmatrix};$$

$$B^v_{Mode_3^*} = \begin{pmatrix} 0.3186 & 0.1036 & -0.0076 & 0.2572 \\ 0.9125 & 0.9130 & 0.2010 & -0.1596 \end{pmatrix};$$

In the experimentation, we have considered three days of March. Its the 10, 11, 12 and 15March. These choices were made owing to the fact that these days comprise in them even behaviors which all are not similar. The figure (6) gives us the result of simulation between the interior temperature and hygrometry of the estimated and mesured values. For the same, we can show the effectiveness of this approach, in modelling case while considering only the 3 modes where our system is observable and identifiable.

5 CONCLUSION

We propose of this work an approach to modelling a greenhouse system. The system is composed by different sub-models. Each model switches to another instantaneously when the thresholds that define some operating modes, is reached. In the goal to build the best prediction of system outputs, we have to get the best switching and supervision device depending on operating point, the behavior and environment.

The presented experimental results emphasize efficiency of this approach for modeling, behavior analysis and prediction for such class of multivariable hybrid complex systems.

The extension of this methodology in diagnosis of the complex systems framework is perspective of this work. The measurement or operation failures of the system must be able to be distinguished from an occurrence of the events not observed or risks.

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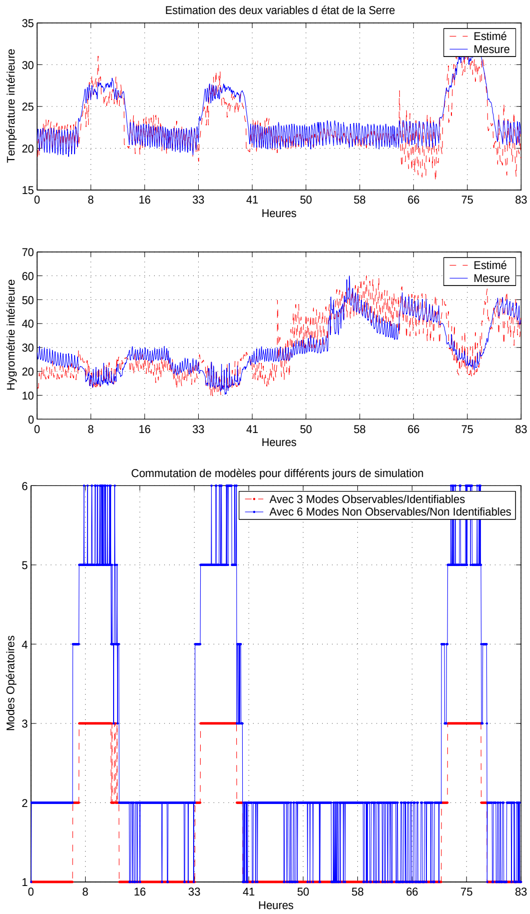

Figure 6: a) Simulation results between real internal temperature and humidity (solid line) and estimated internal temperature and humidity (dashed line), b) Operating modes commutation between 6 operating modes (solid line) and 3 operating modes (dashed line)

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