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# A Hybrid Predictive Control Scheme for Hygrothermal Process

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**Abstract:** This work is focused on developing control algorithms for hygrothermal process represented by mixed logical and dynamical models. An example is the closed newborn incubator. Such kind of system promotes a controlled micro-climate, with small heat transfer between the premature and the environment, leading to comfortable and healthful environment. This device can be represented by a piece-wise linear model having discrete values for the input signal range. A hybrid predictive control scheme is proposed for such a process. The algorithm can also be applied to different dynamic systems having the same characteristics and it is easy to be implemented in real-time environments. System identification results based on orthonormal basis functions for finding the set of linear transfer functions are discussed. Closed-loop control experiments, by using an actual laboratory pilot plant (full scale), are performed and presented to validate the proposed method.

Keywords: predictive control, hybrid control, non-linear systems, orthonormal basis functions, neonatal incubators.

## 1. INTRODUCTION

Many process control problems are related with controlling, at the same time, temperature and relative humidity. An example of this is the HVAC (Heating, Ventilation and Air Conditioning) control device for promoting thermal comfort in buildings. Another example is the neonate incubator.

The neonate care requires an adequate micro-climate to minimize the heat loss. From many years, incubators have been used to create a comfortable and healthful hygrothermal environment for neonates. The aim of such devices is to keep respiratory and epidermal water losses at an appropriate level and to increase the body heat storage.

In closed-type incubators, the neonate environment temperature can be completely controlled. This property decreases the neonate temperature variance due to large differences between air and skin temperatures. An appropriate thermal environment decreases the rate of preterm infant morbidity and mortality. Furthermore, another media of heat exchange between the neonate and its environment is the water loss through the skin and by respiration. When the incubator air temperature is constant, an increase in the air relative humidity (RH) value reduces the skin cooling and increases the body heat storage. Therefore, some incubators have active or passive systems to control the internal RH. Control schemes built to deal with this issue have been described by Bouattoura et al. [1998], Amorim [1994], Guler and Burunkaya [2002] and Oliveira et al. [2006]. In fact, by controlling the relative humidity and air temperature values, one is actually also controlling the internal partial vapor pressure. This signal has an important role in the neonate water losses by skin and respiration.

So, from a control system point of view, an incubator is a system where temperature and RH signals (consequently, the partial vapor pressure signals) are the main controlled variables.

On the other hand, Hybrid systems are characterized by models involving an interactive combination of logic, dynamic and constraints [Labinaz et al., 1997, Bemporad and Morari, 1999]. This field has been the object of a rapid growth motivated by the need for developing control algorithms for several industrial applications which present hybrid properties.

In the present work, an actual pilot plant built to simulate the micro-clime found in neonate incubators is discussed. This plant contains actuators to change the internal temperature and humidity and sensors for monitoring the relevant signals. Two properties of this hygrothermal process can be associated with hybrid systems, in particular with the MLD - Mixed Logical Dynamical System [Bemporad and Morari, 1999]. They are: the input signal values belonging to a discrete set, and the system dynamic is characterized by piece-wise linear models.

In order to deal with the process operational characteristics, this paper proposes the use Model Based Predictive Control (MBPC) strategy [Camacho and Bordons, 1999], and describes a predictive scheme based on hybrid control concepts. Such scheme was first proposed by Oliveira et al. [2005]. Here, this work reviewed and, additionally, it is included real-time closed-loop control results.

An application of Laguerre basis [Heuberger et al., 2005] in the system identification procedure for the incubator is described , having the aim of predicting the system behavior and helping the control algorithm synthesis. Such modeling approach assumes a state-space realization and

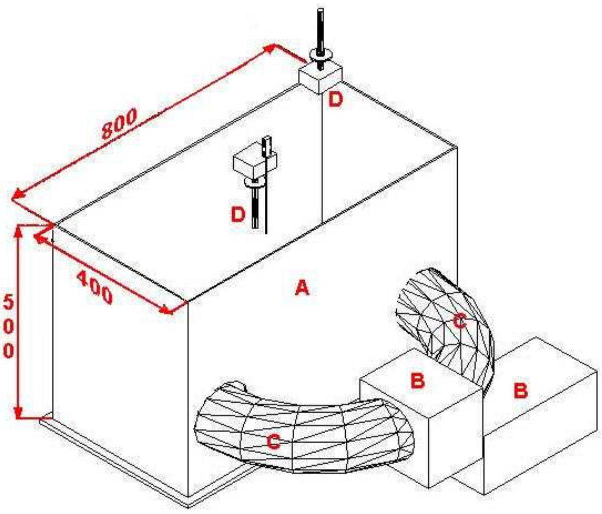


Fig. 1. Diagram with the main parts of the pilot plant

an advantage of in the piece-wise linear model case, is that the use of Laguerre basis with a constant pole smoothes the model transitions, since the state vector is the same for all models in set.

In the next section, details of the incubator prototype are presented, including the control problem statement. In Section 3, some important points related with orthonormal basis modeling are reviewed and, in Section 4, the control law for the incubator is described. Following, in Section 5, the system identification, using actual data, is performed and real-time examples illustrate the control algorithm performance. Finally, the conclusions are addressed.

## 2. PROCESS DESCRIPTION

In order to research issues related with hygrothermal process and to test the results discussed in this paper, a neonatal incubator prototype was constructed and the main points related with such equipment are mentioned in this section. The pilot plant has the following parts: an acrylic transparent box, a domestic heater, a fan and a humidifier. The heater and the humidifier are modified to allow external control in such a way that four power levels are available, that is: 0, 1, 2 and 3 (or off, low, medium and maximum). The humidifier is based on ultrasound, so water vapor is produced without heating generation and then mass transfer is obtained with low influence in the energy transfer. The fan is turned on. Ventilation ducts connect all the above-mentioned parts and allow air circulation inside the incubator. Fresh air supply is provided by the humidifier to guarantee some air renewal. Moreover, the pressure inside the incubator is slightly higher than the environment one. Due to these procedures, the thermal condition is, as far as possible, constant inside the incubator.

The process diagram is depicted in (Fig. 1). In this figure, the acrylic box is represented by $A$, the heating and humidifying devices by $B$, the fan is also in the position $B$, the ducts that form a closed circuit are represented by $C$ and the sensors are in the position $D$. Some orifices are placed in the incubator's side to promote air changes, simulating open spaces for catheters, ducts, wires, etc.

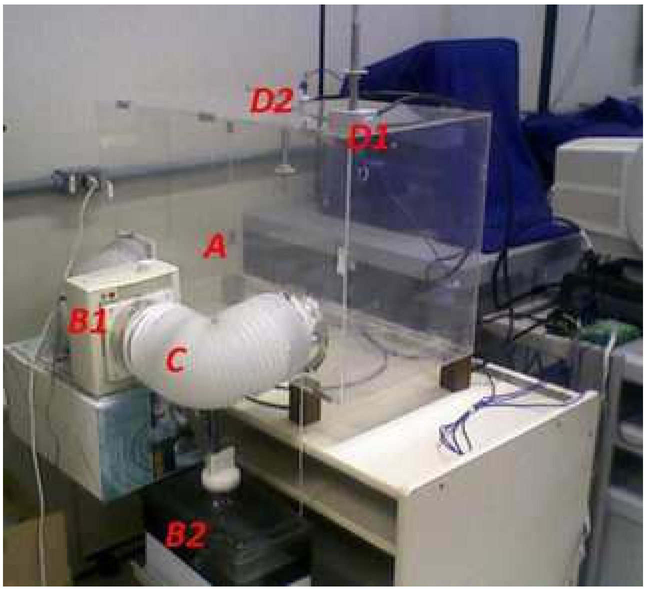


Fig. 2. The neonatal incubator prototype

Two sensors for internal and external temperature and RH measurements are available. The internal temperature measurement is based on T-type thermocouple. The sensors and the electronic device for the actuators, leading to changes in the process dynamics and delays, are the main modification in relation to the apparatus presented by Oliveira et al. [2005, 2006]. Figure 2 contains an incubator photograph. One can notice the acrylic box $A$, *i.e.*, the hygrothermal zone, the internal temperature and RH sensors $D_2$, the external temperature and RH sensors $D_1$, the heater $B_1$, the humidifier $B_2$ and the ventilation ducts $C$.

The environment for supervision and digital control is implemented by using the virtual instrumentation software LabView$^{TM}$, version 7.2, and National Instruments hardware PCI-6024/CB-68LP. The sampling frequency for temperature and RH signals is 2 Hz.

### *2.1 The control problem statement*

In this section, the incubator control problem is stated. The Brazilian technical norm [NBR, 1997] for neonate incubators indicates that the internal temperature set-point should be inside the interval [32,37] °C and the internal RH set-point should be inside the interval [40,60] %. The temperature signal's first overshoot should be less than 2°C.

Therefore, by using this guideline, the problem is, starting from the environmental conditions, to lead the incubator hygrothermal conditions close to 36.5°C and 60%. The partial vapor pressure value is correlated with temperature and RH values.

The available control signals for the heater and humidifier are integer numbers within the interval $[0, 3]$.

## 3. ORTHONORMAL BASIS FUNCTIONS FOR SYSTEM MODELING

A SISO linear causal and dynamic system can be described by its impulse response $h(k)$. If such system has finite memory, *i.e.*, $h(k)$ is absolutely integrable, it can be represented by a series of orthonormal functions, as follows:

$$h(k) = \sum_{i=1}^{\infty} c_i \phi_i(k) \tag{1}$$

where $\{ \phi_i(k) \}_{i=1}^{\infty}$ is a base constructed with orthonormal functions and $c_i$ is the $i$-th series coefficient. Assume that $\Phi_i(z)$ is the $\mathcal{Z}$ transform of $\phi_i(k)$ and $l_i(k)$ is the output of $\Phi_i(z)$ when the input signal is $u(k)$. By using these definitions, the model output $y(k)$, when the series is truncated at $n$ terms, is given by:

$$y(k) = \sum_{i=1}^{n} c_i l_i(k) = \boldsymbol{c}_{\mathrm{o}}^T \boldsymbol{l}_{\mathrm{o}}(k) \tag{2}$$

where the vectors $\boldsymbol{l}_{\mathrm{o}}(k)$ and $\boldsymbol{c}_{\mathrm{o}}$ are composed by the $l_i(k)$ signals and $c_i$ coefficients. This model is linear in the parameters, so a least square algorithm can be used to estimate the $c_i$ coefficients.

Although different orthonormal basis can be used in such a context, (see Heuberger et al. [2005], for instance), the present work is focused on the Laguerre basis since it represents a good tradeoff between the model quality and the *a priori* information required to build the basis. The model constructed with Laguerre basis (Laguerre Model) can be expressed as follows:

$$\boldsymbol{l}_{\mathrm{o}}(k+1) \;=\; A_{\mathrm{o}}\, \boldsymbol{l}_{\mathrm{o}}(k) + \boldsymbol{b}_{\mathrm{o}}\, u(k-\tau) \tag{3}$$

The matrix $A_{\mathrm{o}}$ and the vector $\boldsymbol{b}_{\mathrm{o}}$ have constant coefficients which depend on a *a priori* selected pole $p$, characterizing the Laguerre basis chosen to build the model. The size of such matrices is a function of the truncated series order $n$. $\tau$ is an approximate knowledge of the process time delay. It is assumed here that the model ($A$,$\boldsymbol{b}$,$\boldsymbol{c}$) is an state space representation of ($A_{\mathrm{o}}$,$\boldsymbol{b}_{\mathrm{o}}$,$\boldsymbol{c}_{\mathrm{o}}$) that incorporates, in the state vector $\boldsymbol{l}(k)$, the time delay $\tau$ samples.

The parametric identification properties of orthonormal based models, represented by (2) and (3), have been discussed by several authors in the literature (see, for instance, Heuberger et al. [2005] and references included). These work highlight some properties and advantages of such system modeling approach. Some of them, related with the present paper, are described below. A practical advantage is the low a priori information required in the identification procedure, only an approximation of the time delay and the dominant time constant is need. In the piece-wise linear model or multiple models case, the use of Laguerre basis with a constant pole smoothes the model transitions, since the state vector is the same for all models in set of valid models (the changes are present in the $c_i$ coefficients).

## 4. AN HYBRID APPROACH FOR MODEL PREDICTIVE CONTROL

Model predictive controllers (MPC) are defined by the following main steps: first, a model is used to compute the predicted process output. Next, a cost function related with the system closed loop performance is defined, and then, this cost function is minimized in relation to a set of future control signals. Finally, the first of these optimal control signals is applied to the process, *i.e.*, the receding horizon strategy. Several MPC algorithms have been proposed based on this scheme and the main difference between them is the strategy used to implement each step described above.

Before presenting the proposed control law, lets us briefly recall the cost function usually found in MBPC:

$$J_k = \sum_{j=1}^{N_{\mathrm{y}}} (\hat{y}(k+j|k) - w(k+j))^2 + \sum_{j=0}^{N_{\mathrm{u}}-1} \lambda \Delta u^2(k+j|k) \tag{4}$$

where $N_{\mathrm{y}}$ and $N_{\mathrm{u}}$ define the prediction and control horizon, respectively; $\lambda$ is a weighting factor in the control signal; $w(k)$ is the set-point signal, $u(k+j|k)$ is the optimal control signal at time $k+j$ computed at time $k$; $\Delta u(k) = u(k) - u(k-1)$ and $\hat{y}(k+j|k)$ is the process output prediction at time $k+j$, computed at time $k$, by using the process model. The control law is obtained by minimizing the cost function (4) in relation to $\Delta u(\cdot)$, as shown in following:

$$\begin{array}{l} \displaystyle\min_{\Delta u(k),\ldots,\Delta u(k+N_{\mathrm{u}}-1)} \quad J_k \\ \text{s.to} \\ \Delta u(k+j|k) = 0 \quad \forall\, j = N_{\mathrm{u}}, \ldots, N_{\mathrm{y}} \end{array} \tag{5}$$

Therefore, MBPC algorithms are primary defined by selecting a model to compute the predicted process output. Often, MBPC algorithms are implemented by assuming that the process can be modeled by a single linear model. However, there are many examples where such assumption does not apply. Here, it is assumed that the process dynamics have the following characteristics:

($i$) the input signal value are defined by a discrete set, *i.e.*,

$$u(k) \in \{u_c\}_{c=0}^{M-1} = \{\, u_0,\; u_1,\; u_2,\; \ldots,\; u_{M-1} \,\} \tag{6}$$

($ii$) the model dynamic depends on the input signal value.

$$G(z) = \begin{cases} \text{if} \quad u(k) = u_0 \quad \text{then} \quad G(z) = G_0(z) \\ \text{if} \quad u(k) = u_1 \quad \text{then} \quad G(z) = G_1(z) \\ \vdots \\ \text{if} \quad u(k) = u_{M-1} \quad \text{then} \quad G(z) = G_{M-1}(z) \end{cases} \tag{7}$$

These two characteristics are consistent with the definition of MLD (Mixed Logic and Dynamic) Hybrid Models. Following, an MBPC algorithm for such problem is proposed. It can be viewed as a hybrid predictive control algorithm. Although the proposed control solution is focused on the incubator described in the Section 2, it can be applied to any dynamic system having same characteristics.

The piece-wise linear model are constructed by using orthonormal basis functions models, having the same poles. Therefore, only one state transition equation is used:

$$\boldsymbol{l}(k+1) \;=\; A\, \boldsymbol{l}(k) + \boldsymbol{b}\, u(k-\tau) \tag{8}$$

and

$$y(k) = \begin{cases} \text{if} \quad u(k) = u_0 \quad \text{then} \quad y(k) = \boldsymbol{c}_0^T \boldsymbol{l}(k) \\ \text{if} \quad u(k) = u_1 \quad \text{then} \quad y(k) = \boldsymbol{c}_1^T \boldsymbol{l}(k) \\ \vdots \\ \text{if} \quad u(k) = u_{M-1} \quad \text{then} \quad y(k) = \boldsymbol{c}_{M-1}^T \boldsymbol{l}(k) \end{cases} \tag{9}$$

The model associated with the operation point $u_0 = 0$, *i.e*, $\boldsymbol{c}_0$, may vary at each sampling time and it is considered equal to the one used in the previous sampling time.

As described earlier, a $j$-step ahead output prediction equation is necessary in predictive control algorithms. By using the model (8) and (9) and assuming that only one control signal variation is used, which is equivalent to use a control horizon $N_\mathrm{u}$ equal to one in standard MBPC algorithms, one obtains a set of $M$ different values for the output prediction, as follows:

$$\begin{aligned}\hat{y}(k+j|k,c) = y(k) + \boldsymbol{c}_c^T S_{j-1} A \Delta \boldsymbol{l}(k) + \\ \boldsymbol{c}_c^T S_{j-1} \boldsymbol{b}\, \Delta u_{k,c} \quad \forall \quad c = 0, \ldots, M-1\end{aligned} \tag{10}$$

where: $S_j = \sum_{i=0}^{j} A^i$; $\boldsymbol{l}(k) = 0$ for $k \leq 0$; and $\Delta u_{k,c}$ is the incremental control signal, computed at the time instant $k$, It also belongs to a finite set, given by:

$$\begin{aligned}\{\Delta u_{k,c}\}_{c=0}^{M-1} = \{\, u_0 - u(k-1),\ u_1 - u(k-1),\ \ldots, \\ u_{M-1} - u(k-1)\,\}\end{aligned} \tag{11}$$

Therefore, each feasible $\Delta u_{k,c}$ is associated with one prediction equation, since there is a set finite set of feasible models. A set of feasible predictions values can be defined as follows, depending on the control signal applied at time instant $k$:

$$\{\, \hat{y}_c(k+j|k) : c = 0, 1, \ldots, M-1 \,\} \tag{12}$$

Based on this set, the following cost function is proposed:

$$J_{k,c} = \sum_{j=1}^{N_y} (\hat{y}_c(k+j|k) - w(k+j))^2 + \lambda \Delta u_{k,c}^2 \tag{13}$$

and the control law is equivalent to find the control signal $u(k) = u_c$, $c = 0, \ldots, M_1$, that minimizes the cost function (13), that is:

$$\min_{c \in [0,1,\ldots,M-1]} \quad J_{k,c} \tag{14}$$

Therefore, the optimal control value at the time instant $k$, that is, $u(k)$, is made equal to the $u_c$ related with the solution of problem (14), and is computed at each sampling time. Constraints in the control signal and control signal variation are handled by the feasible set of control values. As far as output constraints are concerned, the following inequations can be added to the control law (14):

$$\begin{aligned}y_{\min} \leq \hat{y}_c(k+j|k) \leq y_{\max} \\ \forall\, j = 1, \ldots, N_\mathrm{y} \quad \text{and} \quad c = 0, 1, \ldots, M-1\end{aligned} \tag{15}$$

In this equation, $y_{\min}$ and $y_{\max}$ define the output signal feasible bounds.

## 5. EXPERIMENTAL RESULTS

In this section, experimental closed-loop control results related with the use of the proposed hybrid predictive scheme in the incubator presented in Section 2 are presented. The section is divided in two parts. The first part describes the piece-wise model identification by using Laguerre basis structure. The second part contains the real-time control results.

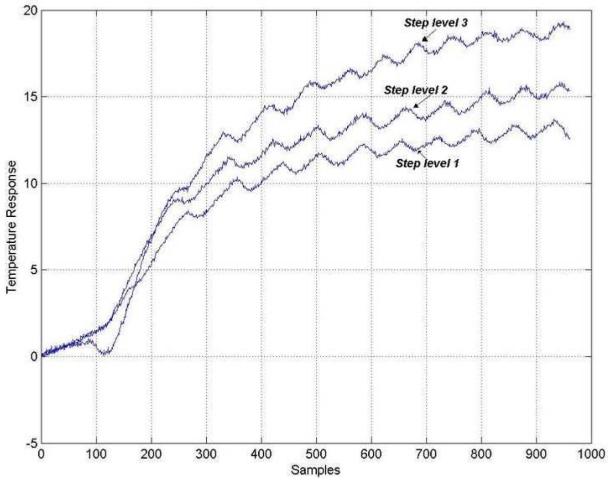


Fig. 3. Temperature signals for three input signals.

### *5.1 System Identification*

Now, an identification procedure is described and a set of linear temperature and RH models (see 7) is computed. The identification is based on open-loop step response signals for capturing the system behavior at each operating point. The data acquisition is performed with sampling time equal to 0.5 seconds. The values of the figures vertical axis of this section represent a variation in relation to the external temperature or RH values.

During the open loop temperature step response tests, an on-off closed loop control is active for maintaining the RH value close to 60%.

Although good results can be obtained by using a single linear model, the incubator discussed here is a non-linear process. Depending on the control signal intensity, it presents different open-loop behavior. Therefore, three step signals, having amplitude of 1, 2 and 3, are applied in the heater power. Fig. 3 contains the process behavior for each case (step at 60 seconds or sample 120). It can be notice that the process dynamic, mainly the gain, changes depending on the input signal. Moreover, the oscillations observed in the actual step response are due to the influence, on the temperature, of the on-off RH control-loop.

During the open loop temperature step response tests, an on-off closed loop control is active for maintaining the RH value close to 60%. By means of these step response experiments, temperature model time delay (see (2) and (3) ) can be obtained and it is approximately equal to 4.5 seconds.

The choice of a Laguerre basis pole is based on the system dominant time constant, and pole value used here is 0.99. This choice for the Laguerre pole indicates that the signals are over-sampled. However, due the large quantization in the input signal, such procedure has the aim of reducing the output signals oscillations.

The model parameters identified by using the three step type inputs are (see (9), with $M = 3$):

$$\begin{aligned}\{c_{1,i}\}_{i=1}^{6} = \{\ 0.7266,\ 0.0574,\ 0.1290, \ldots \\ -0.0263,\ 0.0829,\ -0.0260\}\end{aligned} \tag{16}$$

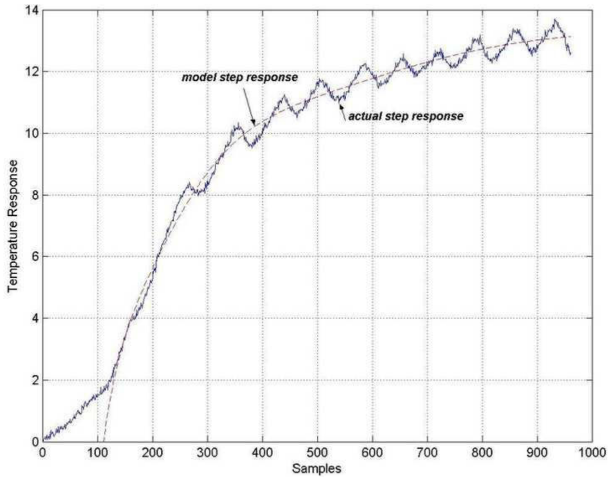


Fig. 4. Actual temperature and model step responses (amplitude 1).

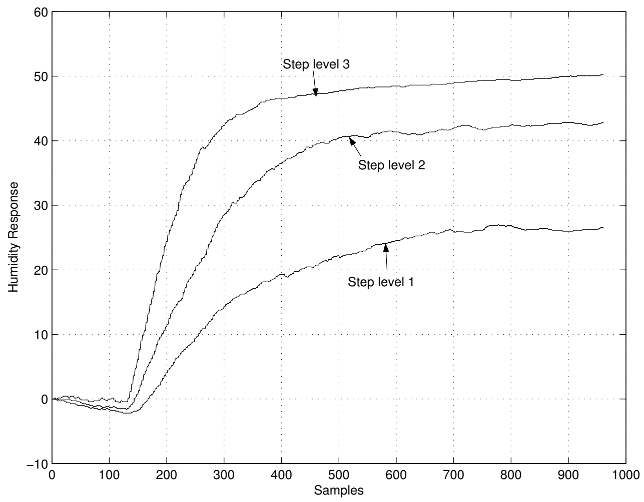


Fig. 5. RH signals for three input signals.

$$\{c_{2,i}\}_{i=1}^{6} = \{\ 0.4612,\ \ -0.0334,\ 0.1019, \ldots \\ -0.0043,\ 0.04510,\ 0.0052\} \tag{17}$$

$$\{c_{3,i}\}_{i=1}^{6} = \{\ 0.3243,\ 0.0560,\ 0.0359, \ldots \\ 0.0381,\ \ -0.0019,\ 0.0041\} \tag{18}$$

$c_{a,i}$ indicates the model parameter obtained with a step of amplitude $a$. The $k$-step ahead prediction (parallel-parallel structure) of a Laguerre model with $p = 0.99$ and $n = 6$ approximates the actual step response as shown in (Fig. 4). It can be notice that the curves (actual and model response) are very close to each other.

Following, the same procedure for RH are presented. During the open loop RH step response tests, an on-off closed loop control is active for maintaining the temperature value close to 36.5°C.

As discussed before, three local Laguerre models can be obtained by applying steps of magnitude 1, 2 and 3. Fig. 5 presents the process behavior for each case (step at 70 seconds or sample 140). Similar to the temperature case, here the process dynamic also changes depending on the input signal.

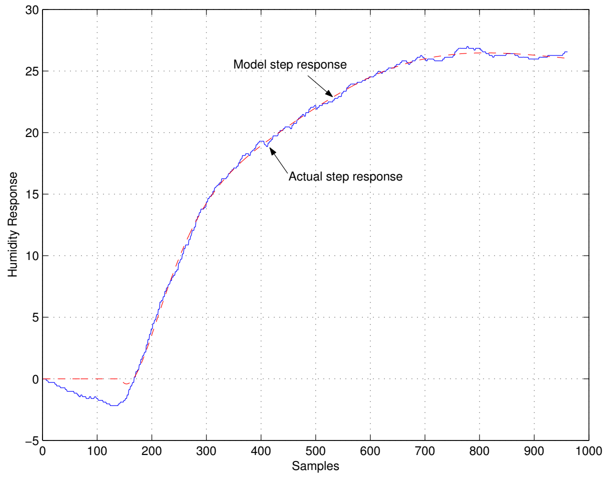


Fig. 6. Actual and model unit step responses

The choice of a Laguerre basis pole is also based on the system dominant time constant, and a pole value equal to 0.99 is obtained. The coefficients of the three identified models are:

$$\{c_{1,i}\}_{i=1}^{6} = \{\ 1.0141,\ 0.8960,\ \ -0.2271, \ldots \\ 0.3213,\ \ -0.2112,\ 0.0682\} \tag{19}$$

$$\{c_{2,i}\}_{i=1}^{6} = \{\ 1.0695,\ 0.5355,\ \ -0.1214, \ldots \\ 0.0169,\ 0.0365,\ 0.0198\} \tag{20}$$

$$\{c_{3,i}\}_{i=1}^{6} = \{\ 1.1755,\ 0.0525,\ 0.1454, \ldots \\ 0.1414,\ \ -0.0438,\ 0.0326\} \tag{21}$$

The $k$-step ahead prediction by using the Laguerre model with $p = 0.99$ and $n = 6$ approximates the actual step response as shown in (Fig. 6). It can be notice that the curves (actual and model response) are very close to each other.

### *5.2 Real-time Control Results*

The temperature and RH predictive controllers are constructed using the models identified in Section 5. The temperature and RH controller parameters are: $N_y = 30$, and $\lambda = 0$.

The performance of the predictive control strategies is given by (Fig. 7) and (Fig. 8). By means of these figures, it can be notice that the controllers are able to keep the internal hygrothermal conditions close to the desired value. The settling time for the temperature signal is small, mainly due to the fact that the external temperature was, at the time of the experiment, not too far from the desired one. Moreover, the predictive law presents no important overshoot. As far as the RH signal is concerned, the idea is to compensate, through humidification, the drop in the RH due to the internal heating. The settling time in the RH signal is close to the one observed for the temperature. Moreover, by improving the temperature and RH control, one can act on the partial vapor pressure (see Fig. 9), improving the thermal conditions for the neonate.

The controller disturbance rejection is analyzed by opening, during 10 seconds, the incubator at the time instant

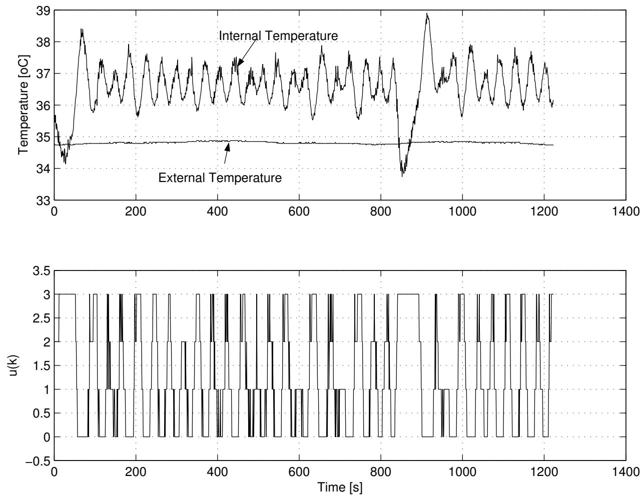


Fig. 7. Temperature control performance.

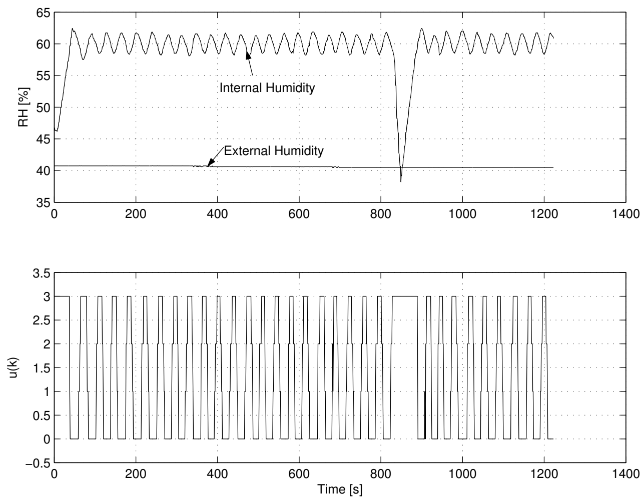


Fig. 8. RH control performance.

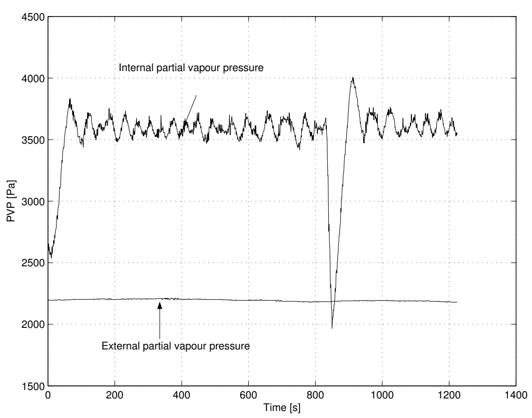


Fig. 9. Partial vapor pressure behavior.

840 seconds. By (Figs. 7), (8) and (9) one can observe that the steady state is obtained after few seconds.

These results show that the closed loop control behavior is quite good, validating the proposed hybrid predictive control algorithm scheme.

## 6. CONCLUSIONS

This work was focused on hygrothermal conditions control, represented by temperature, RH and partial vapor pressure signals, of neonatal incubators. In this context, a full scale pilot plant was used.

From the control point of view, such incubator presents some characteristics: the control signal belongs to a discrete set and the dynamic is described by a piece-wise linear model. These properties can include the incubator into the class of hybrid systems. Therefore, a predictive control law for such class of system was proposed. The control law is based on defining a set of feasible prediction equation and on finding the control signal that minimizes the prediction error. Such control law is also appropriated for hybrid systems having similar properties. The piece-wise linear model was constructed by using Laguerre functions.

By the using real-time experiments, it was shown that both techniques revealed to be appropriate for such context. The use of Laguerre functions provided accurate models based on small process information. The hybrid predictive control law provided a good closed-loop control performance.

## REFERENCES

M. F. Amorim. *Contribuition a la Conception et au Developpement d'un Nouvel Incubateur: Systeme de Controle d'Humidite et Monitorage Cardio-Respiratioire*. PhD thesis, Universite Technologie de Compiegne, 1994.

A. Bemporad and M. Morari. Control of systems integrating logic dynamics and constrains. *Automatica*, 35(2): 407–427, 1999.

D. Bouattoura, P. Villon, and G. Farges. Dynamic programming approach for newborn's incubator humidity control. *IEEE Trans. on Biomedical Engineering*, 45 (1):48–55, January 1998.

E. F. Camacho and C. Bordons. *Model Predictive Control*. Springer Verlag, 2 edition, 1999.

I. Guler and M. Burunkaya. Humidity control of an incubator using the microcontroller-based active humidifier system employing an ultrasonic nebulizer. *Journal of Medical Engineering & Technology*, 26(2):82–88, 2002.

P.S.C. Heuberger, P.M.J. Van den Hof, and B. Wahlberg, editors. *Modelling and Identification with Rational Orthogonal Basis Functions*. Springer Verlag, 2005.

G. Labinaz, M. M. Bayoumi, and K. Rudie. A survey of modeling and control of hybrid systems. *Annual Reviews in Control*, 21:79–92, 1997.

NBR. *Electro medical equipments, Part 2: Prescriptions for safety in neonate incubators (in Portuguese)*. Brazilian Technical Norms Association, Rio de Janeiro, NBR IEC 60601-2-19 edition, 1997.

G. H. C. Oliveira, M. F. Amorim, and K. Latawiec. Multiple model identification and control of neonate incubators using laguerre basis. In *Proc. of the IFAC World Congress*, Prague/Czech Republic, 2005.

G. H. C. Oliveira, M. F. Amorim, and C. Pacholok. A real-time predictive scheme for controlling hygrothermal conditions of neonate incubators. In *Proc. of the IFAC Symposium on Modelling and Control of Biomedical Systems*, Reims/France, 2006.