MULTIPLE MODEL IDENTIFICATION AND CONTROL OF NEONATE INCUBATORS USING LAGUERRE BASIS

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Abstract: This work is focused on temperature and humidity control problem of closed newborn incubators. Such incubator promotes a controlled micro-climate, with small heat transfer between the premature and the environment, leading to a healthful environment. In this context, a laboratory pilot plant (full scale) was built to evaluate control algorithms and this plant is presented here. Furthermore, some identification results based on the use of orthonormal basis functions are discussed and a control scheme is also proposed. This control law is based on multiple local models and predictive control ideas. Closed-loop control examples validates the proposed method.

Keywords: predictive control, multiple model control, system identification, orthonormal basis functions, neonatal incubators

1. INTRODUCTION

From many years, Incubators have been used to create a comfortable and healthful hygrothermal environment for neonates. The aim of such device is to keep the respiratory and transepidermal water losses to a minimum level and to increase the body heat storage.

The internal temperature of closed-type incubators can be completely controlled. This property avoids a fast fallen in the neonate's body temperature due to a large difference between the air and skin temperatures. An appropriate thermal environment decreases the rate of preterm infants morbidity and mortality. It has already been reported a reduction of 22% in such indexes by using incubators with temperature control (Perlstein *et al.* 1976).

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. Air RH values close to 65% prevents excessive body water loss and improves the maintenance of body temperature. The evaporation rate when the air is at 60% RH is approximately 40% lower than that observed at a lower relative humidity (eg, 40%) (Telliez *et al.* 2001). Therefore, some incubators have active or passive systems to control the internal humidity.

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Fig. 1. The neonatal incubator prototype.

In (Amorim 1994) (Bouattoura *et al.* 1998) (Guler and Burunkaya 2002), schemes built to deal with this issue are described.

All these above mentioned factors have great influence in the thermal balance between the neonate and its environment, so it is important to keep the micro-clime inside the incubator constant. From a control system point of view, an incubator is a system where the temperature and RH values are the main controlled variables. In the present work, an actual pilot plant built to simulate the micro-clime found in neonate incubators is presented. This plant contains actuators and sensors to control and monitor the relevant signals. An application of orthonormal basis function (OBF) (Wahlberg and Makila 1996) in the system identification procedure is described, the aim is to predict the system behavior and to obtain a model for the control algorithm synthesis. In order to deal with the process operational characteristics, this paper proposes algorithm based on the Model Based Predictive Control (MBPC) strategy (Clarke 1994) that uses the multiple model control concept (Murray-Smith and Johansen 1997). Models having the OBF structure are used to compute the prediction equations in the modified MBPC scheme.

In the next section, some details of the incubator prototype are presented. In Section 3, important points related with orthonormal basis modelling are reviewed. Following, the system identification procedure using actual data are performed. In Section 5, the control law is described and, in Section 6, simulation examples of temperature and RH closed-loop control illustrate the proposed algorithm performance. Finally, the conclusions are addressed.

2. PROCESS DESCRIPTION

In order to research issues related with incubators temperature and RH control and to test the results discussed in this paper, a neonatal incubator prototype was constructed as it is described in this section. The pilot plant has the following parts: an acrylic transparent box (50cm height $\times$ 80cm length $\times$ 40cm width); a domestic heater, a fan and a humidifier. The heater is modified to allow external control in such a way that four power levels are available, that is: 0, 1, 2, 3 (or off, low, medium, 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 (Guler and Burunkaya 2002). The humidifier is also modified to allow external control. The same structure is used, that is, four power levels are available. The fan is on all the time. Ventilation ducts connects 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. All these procedures makes the thermal conditions, as far as it is possible, constant inside the incubator.

The sensors are placed as follows: in the incubator center (10cm height, i.e., the neonatal approximately position) and in the incubator output air duct. The sensors located closed to the output air duct are those used for control purpose. The third temperature sensor is used for incubator outside measurements. Figure 1 contains an incubator photograph. In this photo, one can notice the acrylic box, the two inner temperature sensors and the two humidity sensors (two small black boxes), the electronic actuator device (it is below the acrylic box) and the ventilation ducts (they are behind the incubator). Some orifices are placed in the incubator's side to .

The software environment for supervision and digital control was implemented by using the virtual instrumentation software LabView / National Instruments. The temperature and RH signal's sampling frequency is 0.25 Hz.

3. ORTHONORMAL BASIS FUNCTION FOR SYSTEM MODELLING

A SISO linear causal dynamic system, with finite memory, can be described by its impulse response $h(k)$. If $h(k)$ has finite memory, 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 of 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 this definitions, the model output $y(k)$, when the series is truncated in n terms, is given by:

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

where the vectors $\boldsymbol{l}(k)$ and $\boldsymbol{c}$ are composed by the $l_i(k)$ signals and c_i coefficients.

Although different orthonormal basis can be used in such a context, the present work is focused on the Laguerre basis (Wahlberg and Makila 1996) since it represents a good tradeoff between the model quality and the *a priori* information required to build the basis. The model based on Laguerre basis (Laguerre Model) can be expressed by state equations as follows:

$$\boldsymbol{l}(k+1) \;=\; A\,\boldsymbol{l}(k) + \boldsymbol{b}\,u(k-\tau) \qquad (3)$$

The matrix A and the vector b have constant coefficients which depends only on the model order n and on the selected pole p, which characterizes the Laguerre basis. τ is an approximate knowledge of the time delay.

The parametric identification of model (2) have been discussed by several authors in the literature (see, for instance, (den Hof *et al.* 2000)). These works highlights some properties and advantages of such system modelling approach. Some of them, closely related with the present work, are described below. A quite 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 multiple models case, the use of Laguerre basis with a constant pole makes smooth the model transitions, since the state vector is the same for all models in set of valid models (the changes occurs only in the c_i coefficients). The complexity of the model can be changed by small changes in the model parameters, i.e, just augmenting the series terms. The main drawback of such structure is the lost of some physical insights such as the ones found in the poles and zeros of a transfer function representation.

4. MULTIPLE MODELS SYSTEM IDENTIFICATION

In this section, an identification procedure for the incubator described in Section 2 is performed and a set of linear models is computed. The humidifier is shut of during the temperature data acquisition experiments and RH initial value is 53%. However, during the humidity data acquisition, the internal temperature is kept close to 36.5°C, due to the presence of a standard PID controller.

By means of some step response experiments for temperature and RH, it can be notice that the process has time delay of approximately 2 sample times (8 seconds). Therefore, in this section, the model's structure is given by equations (2) and (3) with $\tau = 2$.

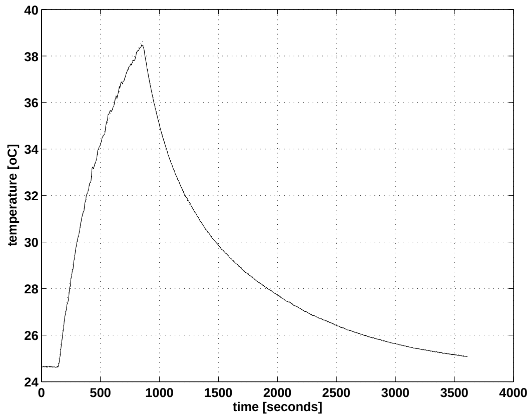

Fig. 2. Actual and model responses to a pulse input signal with magnitude 2.

The choice of a Laguerre basis pole is based on the system dominant time constant. It is made by measuring the system step response and by using a least square type algorithm to approximate the process with a first-order plus dead-time model (see (Bi *et al.* 1999)). For steps having amplitude of (1, 2 and 3), the identified continuous-time pole is (1.99×10^{-3}, 2.33×10^{-3} and 2.5×10^{-3}), which justifies the choice of 0.99 for the Laguerre basis pole. Although some interesting 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. Assume that a pulse shape input signal (magnitude 2) is applied to the system. The k-step ahead prediction of a Laguerre model with $p = 0.99$ and $n = 6$ approximates this pulse response as shown in Figure 2. The curves (actual and model response) are very close to each other and the MSE (Mean Square Error) of this approximation is 3.2245×10^{-3}. As a sake of comparison, the output signal of the first-order plus dead-time model used to calculate the Laguerre pole presents an MSE of 1.7797.

The coefficients of the above mentioned Laguerre model are:

$$\begin{aligned} \{c_i\}_{i=1}^{6} = \{&0.5961,\ 0.09045,\ 0.09278, \\ &0.02105,\ 0.006112,\ 0.004059\} \end{aligned} \qquad (4)$$

By means of the same procedure, but with input signals (pulse shape) having magnitude 1 and 3, one can obtain two others local linear Laguerre models (pole 0.99 and 6 functions). The unit step responses of each model are depicted in Figure 3. It can be notice that each model has different dynamics behavior (mainly in the gain), meaning that the process dynamic changes as a function of the input signal. The Laguerre coefficients of the two others models are given by:

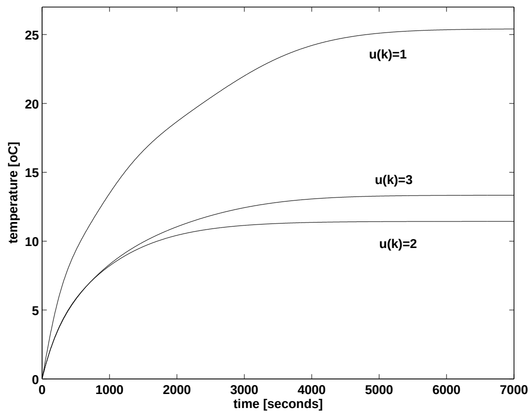

Fig. 3. Laguerre models response to a unit step.

$$\{c_i\}_{i=1}^{6} = \{0.9589,\ 0.2322,\ 0.2405,\ 0.1772,\ 0.07796,\ 0.1151\} \quad \text{(for magnitude 1)} \tag{5}$$

$$\{c_i\}_{i=1}^{6} = \{0.5959,\ 0.1170,\ 0.1264,\ 0.05595,\ 0.03289,\ 0.01728\} \quad \text{(for magnitude 3)} \tag{6}$$

In following, the same procedure for RH signal are presented. The choice of the Laguerre basis pole is also based on approximating the process with a first-order plus dead-time model, and one can obtains the value 0.96 for the pole equal. As discussed before, three local Laguerre models can be obtained by applying pulses of magnitude 1, 2 and 3. The k-step ahead prediction by using the Laguerre model with $p = 0.96$ and $n = 6$ approximates the actual level 2 pulse response as shown in Figure 4. The MSE between the actual and model responses is 3.03047×10^{-1}. The output of the first-order plus dead-time model used to calculated the Laguerre pole presents a MSE of 1.3477, so an improvement in the model approximation is obtained.

The Laguerre coefficients of the three identified models are given in following and its unit step responses are presented in Figure 5.

$$\{c_i\}_{i=1}^{6} = \{2.6674,\ 1.3863, -0.8263,\ 0.5674,\ -0.5333,\ 0.3074\} \quad \text{(for magnitude 1)} \tag{7}$$

$$\{c_i\}_{i=1}^{6} = \{3.6306,\ 0.5409, -0.3008,\ 0.2608,\ -0.1496,\ 0.1046\} \quad \text{(for magnitude 2)} \tag{8}$$

$$\{c_i\}_{i=1}^{6} = \{2.5873,\ 0.2080, -0.0439,\ 0.1299,\ -0.1082,\ 0.0560\} \quad \text{(for magnitude 3)} \tag{9}$$

5. AN APPROACH FOR PREDICTIVE CONTROL BASED ON MULTIPLE MODELS

Model based predictive controllers (MBPC) 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

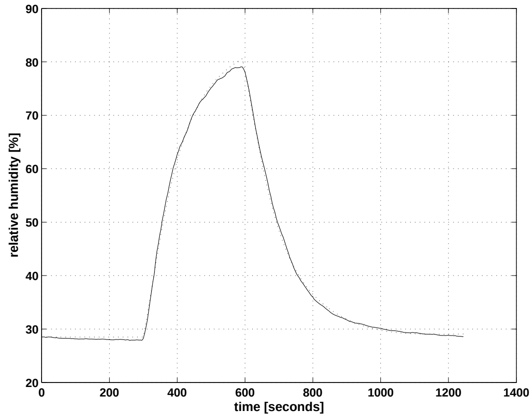

Fig. 4. Actual and model responses to a pulse input signal with magnitude 2.

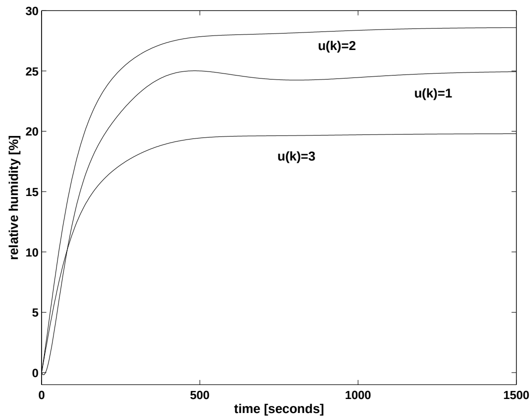

Fig. 5. Laguerre Models response to a unit step.

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 control signals is applied to the process, i.e. the receding horizon strategy.

Several MBPC algorithm have been proposed based on this scheme and the main difference is the strategy used to implement each step described above (Clarke 1994). On the other hand, multiple models based control has been receiving much attention since is represents an alternative to deal with complex process. The main idea is to decompose a complex control system into a finite set of feasible and simple (or treatable) control solutions, and then to integrate all these solutions into a specific control strategy (Murray-Smith and Johansen 1997). In this way, multiple local models can be viewed as a field of non linear identification and control.

Following, an MBPC algorithm is proposed. It is characterized by using multiple local Laguerre models, as the ones discussed in the previous section. This control solution is focused on the incubator problem described in the section 2, since the control signal is quantized in quite large steps.

Before presenting the control law, lets us recall the usual cost function of MBPC controllers:

$$J_k = \sum_{j=1}^{N_y} (\hat{y}(k+j|k) - w(k+j))^2 + \sum_{j=0}^{N_u-1} \lambda \Delta u^2(k+j|k) \tag{10}$$

where N_y and N_u define the prediction and control horizon, respectively; λ is a weighting in the control 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 model composed by equations (2) and (3). The control law is obtained by minimizing the cost function (10) in relation to $\Delta u(\cdot)$. In this scheme, the optimization problem has analytical solution. In the constrained case, the problem has numerical solution.

Here, it is assumed that the process are described by M local models, each one represented by I where $I = 0, 1, \ldots, M-1$. It is also assumed that each feasible value for $u(k)$ is associated with a local model (this is the case of the incubator described in this paper, see Section 2), i.e., $u(k) \in \{u_I\}_{I=0}^{M-1}$. Therefore, each feasible u_I is also associated with a different prediction equation, since there is a set of prediction equations related with the set of process local models, that is:

$$\{\, \hat{y}_I(k+j|k) : I = 0, 1, \ldots, M-1 \,\} \tag{11}$$

The model associated with the situation $u_I = 0$ varies in time and is considered equal to the one used in the previous sampling time.

Therefore, the cost function becomes:

$$J_{I,k} = \sum_{j=1}^{N_y} (\hat{y}_I(k+j|k) - w(k+j))^2 + \sum_{j=0}^{N_u-1} \lambda (\Delta u_I^2) \tag{12}$$

where $u_I = u(k-1) + \Delta u_I$. In this case, there is a finite set of feasible values of u_I and the optimal one should be found in this set. So, the control law is now given by:

$$I = \min_{I \in [0,1,\ldots,M-1]} J_{I,k} \quad \text{s.a} \quad \Delta u(k+j|k) = 0 \quad \forall\, j = N_u, \ldots, N_y \tag{13}$$

Therefore, at each sampling time k, an optimal u_I value related with the solution of problem (13) is computed and this value is made equal to the control signal $u(k)$. Constraints in the control signal and control signal increment are handled by the feasible set of $u(k)$ values. As for limitations in the output signal, a set of constraints can be added in problem (13) as it is usual in MBPC algorithm.

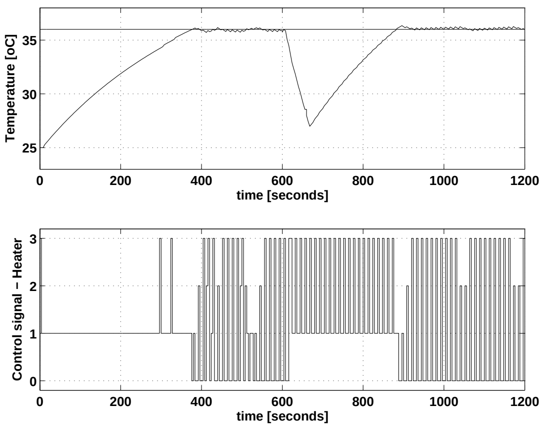

Fig. 6. Temperature controller performance.

6. SIMULATION CLOSED-LOOP CONTROL EXAMPLE

In this section, the temperature and RH control systems performance for the incubator described Section 2 are analyzed through a simulation example. The problem is to heat the incubator in order to keep the internal temperature around 36°C and to increase the internal RH until the 60% level. Available control signals for the heater and humidifier are integer numbers within the interval $[0, 3]$. Thus, as described before, three Laguerre models for the incubator temperature and RH can be identified (see equations (4) to (9)). Two sets of multiple local models are built using these models and are used in the MBPC law described in the previous section. The temperature controller parameters are: $N_1 = 1$, $N_y = 3$, $N_u = 1$ and $\lambda = 0$; and the RH controller parameters are: $N_1 = 1$, $N_y = 6$, $N_u = 1$ and $\lambda = 0$. The prediction horizon in the latter case is bigger than the former one due to the presence of slightly non-minimum phase behavior in one humidity model.

In order to evaluate the control laws in a simulation environment, the temperature and RH process dynamics are modelled by using a non-linear Hammerstein structure. The linear part of this structure is assumed equal to the linear Laguerre model computed by using the level 2 pulse data. The memoryless non-linear part is computed in such a way that the Hammerstein model has the same steady state gain of the three local models when the input is equal to the pulse level used in the identification phase. Therefore, the memoryless non-linear part of the Hammerstein temperature model is:

$$v(k) = 0.6946u^3(k-2) - 3.3068u^2(k-2) + 4.8351u(k-2) \tag{14}$$

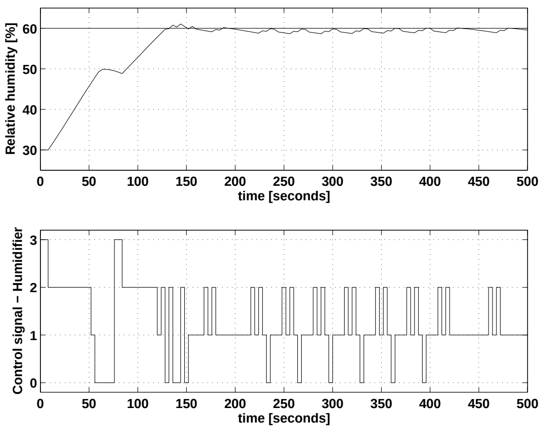

Fig. 7. RH controller performance.

where $v(k)$ is the signal that connects the output of the model non-linear part and the input of the model linear part. As for the RH model, one obtains:

$$v(k) = -0.2172u^3(k-2) + 0.7784u^2(k-2) + 0.3121u(k-2) \quad (15)$$

Figure 6 contains the temperature controller behavior. The situation described here is the heating phase from the environment temperature and the regulatory control around to 36°C. During 60 seconds after time 600 seconds, it is assumed that the incubator is opened for some reason and so the internal temperature fells down. It can be notice a good recovering to the steady state value. The main advantage of the proposed control law is the regulatory behavior, with small deviations around the steady state value (within [35.8,36.15]°C during the interval [400,600] seconds and within [35.9,36.25]°C after 950 seconds).

Figure 7 contains the RH controller behavior. The situation described here is the humidification phase from the external value and the regulatory control around 60%. The temperature control is adjusted at 36°C. It can also be notice that the control law is able to keep the internal humidity around the steady state value with small deviations around the steady state value (within the interval [58.7,60.1]% after 200 seconds).

The results show that both closed loop behavior are good, considering the actuator limitations, validating the control algorithm scheme.

7. CONCLUSIONS

This work has focused on temperature and RH control of neonatal incubators. In this context, a full scale pilot plant for tests was built and was presented here. In order to perform model based control synthesis, an identification procedure for the incubator was performed.

By defining a Laguerre basis, two sets of local linear models, i.e., temperature and RH models, were obtained. Therefore, a strategy that uses multiple models ideas and is based on the MBPC scheme was proposed. Simulation control examples were performed by assuming a Hammerstein structure for the process dynamics. The identification and control results illustrates the use and validity of such methods.

Although such control approach was proposed to the incubator problem, it could be applied to other process having similar characteristics. Future works will be focused on real-time control implementation.

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