ARTIFICIAL NEURAL NETWORKS IN THE ESTIMATION OF MEASURES OF TEMPERATURE AND HUMIDITY INSIDE A NEONATAL INCUBATOR

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Keywords: Artificial Neural Network, Neonatal Incubator, Temperature and Humidity Estimation.

Abstract: This paper seeks to estimate through Artificial Neural Networks the future behavior of temperature and humidity inside an incubator. This goal is motivated by the observation that the model-based predictive control is an interesting alternative for the generation of control signals of a neonatal incubator since: (i) it seeks to optimize a performance criterion that considers the future behavior of this controller, and (ii) restrictions may be imposed on future control signals. These two features can make more safe and comfortable the microclimate inside the device for the newborn: variables such as temperature and humidity can be better kept within the limits of technical standards such as the NBR IEC 601-2-19 and its amendment No. 1, NBR IEC 60601-2-19-2000. However, one predictive model of the process to be controlled must first be obtained. The obtained neural model has accuracy in predicting the incubator behavior one time step forward compatible with the technical standard, and it is ready to be applied in a predictive control structure.

1 INTRODUCTION

A neonatal incubator is an important electro-medical equipment used in a neonatal care unit to assist the care of premature infants or newborns with some kind of diseases (Barbosa and Oliveira, 2002). At Brazil, in 2007, approximately 50% of deaths of newborns under one year old occurred in the first 27 days after birth, according to the Brazilian Ministry of Health (Datasus Ministério da Saude, 2009), period during which the incubators are one of the most important tools to reduce the risks of mortality and diseases. The newborn incubator provides an ideal microclimate in order to minimize newborn's heat and water losses, which is vital for the survival of premature or critically ill infants, through the control of internal temperature and relative humidity (Barbosa and Oliveira, 2002).

Neonatal incubators as well as other electro-medical equipment suffer loss of calibration over time, compromising the control system and causing serious damage to the newborn or even resulting in the death of this (Barbosa and Oliveira, 2002; Arone, 1993; Farges et al., 1998). The Brazilian technical norm NBR IEC 601-2-19 and its amendment No. 1, NBR IEC 60601-2-19 2000, provide specifications over neonatal incubators to offer a safe environment to newborns. These requirements are verified by performing several tests which include the application of input signals to the temperature, humidity and air flow actuators, and recording and analyzing the temperature, humidity and air flow data in specific points inside the neonatal incubator (ABNT, 2000).

The optimal control of environments variables of the the neonatal incubator, provides a ideal microclimate to safety newborn development. From the viewpoint of control theory, the neonatal incubator can be seen as a TITO system, coupled, where the temperature and humidity are controlled variables.This system contains strong nonlinear characteristics, and its modeling through the phenomenological analysis of the process is a complex task.From models with a truer representation of the process, more efficient controllers can be designed (Camacho and Bordons, 2003), among controllers used in the non-linear processes, non-linear predictive controller, is an alternative. The predictive controller is strongly dependent on the plant model (Camacho and Bordons, 2003). The use of identification techniques for nonlinear systems is necessary to find an efficient model that represents the system behavior.

Based on the previous, this work proposes a model of behavior of the temperature and humidity at points specified by the standard (ABNT, 2000).This work

A. M. Albuquerque A., P. S. Braga A., C. Torrico B. and M. Almeida O..
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DOI: 10.5220/0003791502760281
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2012), pages 276-281
ISBN: 978-989-8425-89-8

Figure 1: Prototype of the incubator.

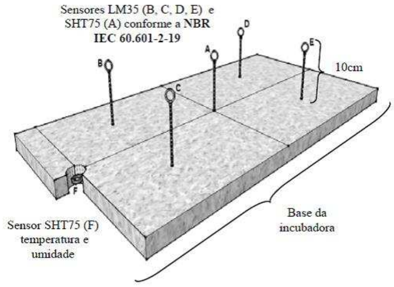

Figure 2: Spatial distribution of sensors inside the incubator.

uses artificial neural networks (Haykin, 2008) as a technique for the identification of nonlinear systems, to the identification of signals of temperature and humidity in the positions defined by the standard, as only a single temperature and humidity sensor installed in the exhaust air of the incubator. The model is intended to found its future use in a predictive controller, acting as the controller model and also inserting the restrictions provided by the standard output. This work is organized in the following topics: section 2 describes the prototype of the incubator used in the experiments. The section 3 discusses a review about artificial neural networks, in particular the multilayer perceptron architecture. The 5th section are shown the tests and the results obtained and the section 6 tells about the conclusions and final comments.

2 THE INCUBATOR PROTOTYPE

The incubator prototype built in the GPAR/DEE/UFC (Research Group in Robotics and Automation) research laboratory is shown in Figure 1.

The prototype is divided into two basic parts: the supporting structure with aluminum rods and wood planks and the acrylic dome with porthole windows similar to commercial models of incubators. In the supporting structure, just below the dome, is an acrylic duct forming an air circulation system of the incubator, where are installed a resistive heater and a cooler on opposite ends of the circuit. Below the air circulation system are the boards of control systems of heating, ventilation and relative humidity. Also below the ventilation system is located a commercial humidifier adapted in moisture control. The control system of the incubator can be divided into 3 subsystems of control: temperature control system, control system of moisture and ventilation system. The systems of control of temperature and humidity are connected to an acquisition board of National Instruments^{TM} (NI) to connect these two systems with Matlab^{TM} software. The ventilation system operates independent of the acquisition card, being that this was adjusted to maintain a constant ventilation speed of approximately 0.35 m/s, in accordance with the standard NBR IEC 601-2-19. The interior of the dome is thermally isolated through a cork board of 24mm thickness. Temperature and humidity sensors were installed in the interior of the dome following the provisions in standard NBR IEC 601-2-19 and in the air of the dome. Figure 2 shows the arrangement of sensors on the board of cork. The sensors at positions B, C, D, E, are temperature sensors LM35 (Semicondutors, 2000), while the sensors A and F are temperature and humidity of type SHT75 (Sensirion, 2010).

The sensors A, B, C, D and E remain inside the incubator during the tests, only being removed from the dome to the normal operation of incubator because sensors occupy the positions where the newborn is placed. The sensor F, which is not specified by the standard (ABNT, 2000), remains during the tests and the normal operation of the incubator. From measurements of the sensor F, performed during calibration, it is estimated a dynamic model of temperature and humidity in the interior of the dome. Through the model we intend to evaluate, during normal operation of the incubator, if there was deterioration in the calibration of the incubator. In the next section describes neural network used to perform the construction of the model of the signals of temperature and humidity.

3 MULTILAYER PERCEPTRON NEURAL NETWORK

In this paper, it is used a neural network MLP (Multilayer Perceptron) (Haykin, 2008) to estimate the signals of temperature and humidity in the interior of the dome's incubator. The MLP is formed by neurons distributed on layers that have high connectivity with layer neurons following in a feed forward configuration (Figure 3). The propagation of the signals takes

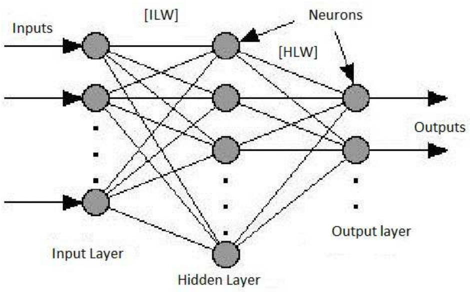

Figure 3: Multilayer perceptron network architecture, (Haykin, 2008) adapted.

place via the input layer to output layer, surrounding layers of neurons are connected to each other, the connection between two neurons i and j is weighted by a weight wij. Such parameters should be adjusted in sense to minimize the error between the value to be estimated (the training) and the MLP's output. It is shown below an algorithm to perform the adjustments (the backpropagation algorithm) (Haykin, 2008):

The backpropagation algorithm.

1. Initialize the weights with small values arbitrary or random.
2. Randomly choose an input pattern.
3. Propagate the signal through the network.
4. Calculate δ_i^l in the output layer.
   $\delta_i^l = g' \cdot (h_i^l) \cdot [d_i^u - y_i^l]$
   where h_i^l represents the net input to the $i_t h$ unit in the $I_t h$ layer, and g' is the derivative of the activation function.
5. Compute the deltas for the preceding layers by propagating the errors backwards;
   $\delta_i^l = g' \cdot (h_i^l) \sum_j^l w_{ij}^{j+1} \cdot \delta_i^l$
6. Update the weights using $\Delta w = \alpha \cdot \delta_i^l \cdot y_i^l$
7. Go to step 2 and repeat for the next pattern until the error in the output layer is below a prespecified threshold or a maximum number of interactions is reached.

(Haykin, 2008)

This algorithm can be divided into two steps: the propagation step forward and step of back propagation. In propagating forward, the training standards are presented the network with no change in the weights of the connections; the signals are calculated individually neuron by neuron, flowing of layer in layer to produce a result in the output layer. This result is then compared with the desired output, and the error is calculated. The second step is called back-propagation: the error is calculated from the output layer and back propagated by intervening layers until the input layer and the weights of the connections are modified as the error is propagated backward. Examples of training set are presented the network until it reached a stop criterion is satisfied. Two stop criteria normally used are (Haykin, 2008):

- The norm of the gradient vector of the error surface in relation to the vector of weights has a sufficiently small value.
- The minimum value for the mean quadratic error be reaching, choosing this criterion does not guarantee that the algorithm reaches this value.

4 THE PREDICTIVE CONTROL PROBLEM FORMULATION

The model-based predictive control reflects human behavior that it is thought to lead to the best predicted output over same limited horizon. To get this, on internal model of the process in question should be used. Hance a predictive control law has the following components:

1. The control low depends on predicted behavior and input/output.
2. The output prediction are computed using a process model and constraints mutualities.
3. The current input is determined by optimizing a predictive performance index subjected to input/output constraints.
4. The control input is updated at every sampling instant.(The receding horizon strategy)

According to (Rossiter, 2004), to solve the constraint optimization predictive control correspond to solve the following problem :

$$\begin{gathered} min_{\Delta U} \text{ J} \\ \text{s.t } C\Delta U - dk \end{gathered}$$

where ΔU is the control increments.

This is known as quadratic programming(QP) problem for witch solvers are easy to find (Rossiter, 2004). Its necessary to remember that:

$$d_k = \begin{bmatrix} \overline{\Delta U} \\ -\underline{\Delta U} \\ \overline{U} - Lu_{k-1} \\ -\underline{U} - Lu_{k-1} \\ \overline{Y} - QDU_{\leftarrow} - PY_{\leftarrow} \\ -\underline{Y} - QDU_{\leftarrow} - PY_{\leftarrow} \end{bmatrix}$$

Where $\overline{\Delta U}$ and $\underline{\Delta U}$ are the control increments maximum and minimum limits respectively. $\overline{Y}$ and $\underline{\mathrm{Y}}$ are

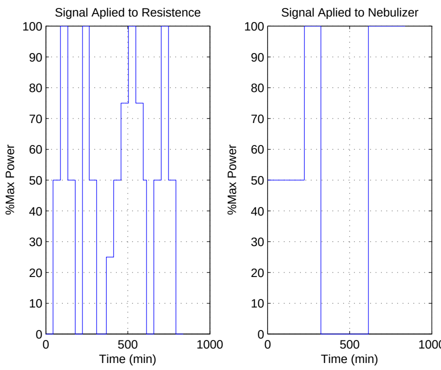

Figure 4: Signals applied to nebulizer and warm resistance.

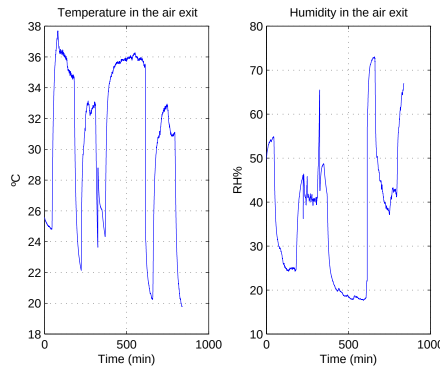

Figure 5: Signals measured of air exit temperature and humidity.

set of temperatures and humidity inside neonatal incubator. Whose models are inferred by proposed neural network.

$$Y = \begin{bmatrix} T_i \\ U \end{bmatrix}$$

where T_i with i=(A,B,C,D,E) is the standard temperature value according to figure 2 and U is standard humidity value.

5 EXPERIMENTAL RESULTS

For the MLP training, four experiments were made and the sensors' measures were stored.The figure 4 shown the signals applied in the warm resistance and nebulizer.The signal applied on the resistance is the percentage of duty cycle where the max duty represents a tension of 220V AC over the resistance and the signal applied to nebulizer represents the percentage flow of water vapor emitted by the nebulizer.

The data was acquired through an acquisition board of National Instruments^{TM} and Matlab^{TM}. Each experiment in the incubator prototype (Section 3) had mean duration of 210 minutes, with the sensors positioned in concordance the NBR IEC 60601-2-19. The dates of these four experiments were joined and reorganized randomly and 70% are used for training and 30% was used for validation of neural network. The signals of temperature and humidity in the air exit after the application of signal in the incubator's actuators is shown in figure 5. Network training is done off-line, ie, is performed with the data obtained in experiments carried out previously. The stopping criterion used for training the network, was to obtain a minimum mean square error or the execution of a total of 1000 epochs, whichever comes first. The value of the target MSE(Mean Square Error) was 0.001, however this target was never reached. The MLP network uses sigmoid activation functions in hidden layer neurons and linear function in output layer's neurons. After numerous tests with different number of neurons in the hidden layer, the 4-8-6 MLP had the best results when compared the performance index MSE. The mean learning time of the net was 120 seconds with one hundred epochs, after this number of epochs the performance index not change. The weights of neural network after the training are presented below:

$$ILW = \begin{bmatrix} 6,95 & 5,05 & 0,70 & 2,47 \\ -0,30 & 0,13 & -0,07 & -0,11 \\ 0,89 & -1,60 & -1,06 & 1,47 \\ 0,01 & -0,56 & 0,01 & 0,02 \\ -1,07 & -0,65 & 0,06 & 0,24 \\ -5,81 & -1,44 & 2,34 & 7,47 \\ -0,55 & -1,04 & -1,79 & -5,24 \\ -1,98 & -1,05 & -1,23 & 1,29 \end{bmatrix}$$

$$HLW^T = \begin{bmatrix} -0.13 & -0.45 & -0.52 & -0.30 & -0.36 & 0.33 \\ -4.25 & -6.96 & -3.58 & -3.74 & -9.44 & -0.98 \\ 0.22 & 0.26 & 0.28 & 0.21 & 0.14 & -0.05 \\ 0.44 & 0.45 & 0.49 & 0.46 & 0.46 & -1.76 \\ -0.81 & -0.76 & -0.82 & -0.83 & -0.71 & -0.07 \\ -0.05 & -0.05 & -0.03 & -0.05 & -0.02 & 0.14 \\ -0.18 & -0.23 & -0.25 & -0.20 & -0.10 & 0.22 \\ -0.15 & -0.14 & -0.21 & -0.17 & -0.03 & 0.04 \end{bmatrix}$$

Where *ILW* is the matrix weights of input layer and *HLW* is the matrix weights of hidden layer.

5.1 Results of training

In the Figure 6 shown the worst result of training of the temperature signal and the humidity signal. The inputs of the artificial neural network are the signal of temperature in the air exit (Sensor F - SHT75 - Figure 2), the signal of humidity in the air exit (Sensor F - SHT75 - Figure 2), the signal applied to the heating element and the signal applied in the nebulizer. The targets of the network are the signals of temperature measured in the positions A, B, C, D and E (shown in Figure 2 and the signal of humidity measured in position E. The mean square error was used as the performance index.

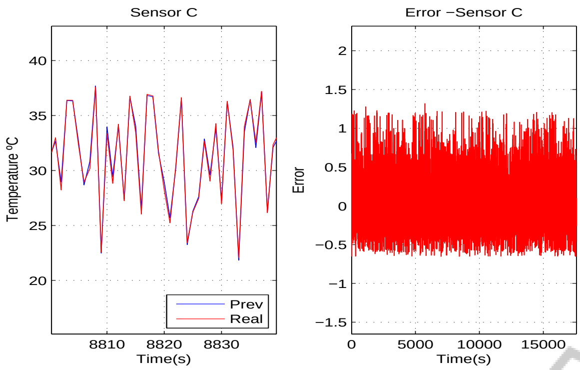

Figure 6: Comparisons, and error, between MLP outputs and the training data of temperature (worst case).

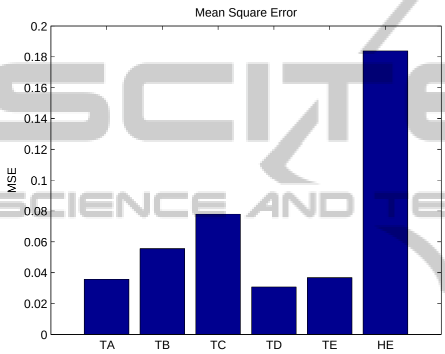

Figure 7: The mean squared error (MSE) between the signal of network and signal real for each sensor (training set).

Figure 7 summarizes the MLP performance with the mean squared error for each of the six considered sensor. The trained network successfully learned the mapping between the signals and desired output of the training set, as seen by low mean square error values that were in the order of 0.18.

5.2 Results of validation

The remaining 30% of data were used to validate the trained network. The mean squared error between network's outputs and the desired outputs are shown in Figure 8.

As one can be see, the mean squared error of the validation set shows values close to 0.08 for the temperature sensors, and the value of 0.16 for the humidity sensor. Figure 9 shows curves obtained with the validation set. Since the standard NBR IEC 60601-2-19 requires that the value of temperature do not varies above 0.5°C during one hour of service, and the value of relative humidity do not differ 10% of the defined by standard, the model errors in some points are above the standard requirements but the purpose of the model is just to give an indication that the sensor

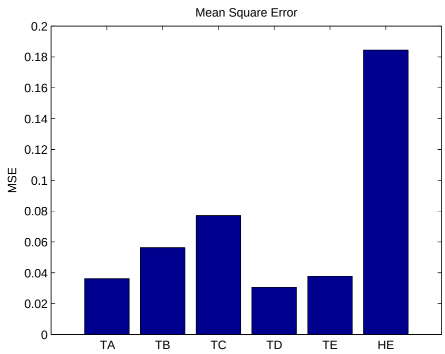

Figure 8: The mean squared error (MSE) between the signals of network and real signals for each sensor (validation set).

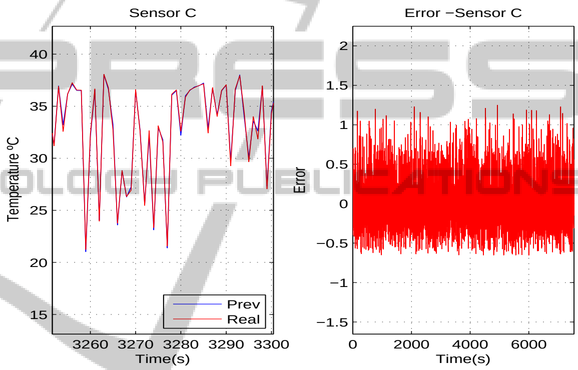

Figure 9: Comparisons, and error, between MLP outputs and the validation data of temperature (worst case)

measures the equipment are suffering a breakdown and that a more precise test calibration must be done. Therefore the model is useful to determine when the incubator is out of the norm prescriptions, alerting the operator which the equipment needs to be sent for maintenance.

6 CONCLUSIONS

The MLP network developed in this work, have success in the estimation of model of the temperature and humidity of the neonatal incubator, enabling a model where is possible formulate a predictive control problem with constraints to satisfy the standard specifications. As future work we intend to apply another neural network topologies (ex. RBF, SVM, SOM), and other non linear mapping techniques such Kalman filtering and NARMAX models in order to have a mapping of signals with greater accuracy, and the development of a prototype device that is attached to the incubator to check in real time with the models developed. As future work is required to develop a predictive controller to apply the model achieved in this article, and to study new topologies of neural networks to perform a comparative performance between the models estimated on these topologies in the application of predictive control.

ACKNOWLEDGEMENTS

The authors are thankful to FUNCAP (Fundação Cearense de Apoio ao Desenvolvimento Científico e Tecnológico) for the financial support.

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