Robust Control of Nonlinear HVAC Systems via Emotional Critic Based Intelligent Controller

BEHZAD MOSHIRI FARZAN RASHIDI

Center of Excellence for Control and Intelligent Processing, Department of Electrical and Computer Engineering, University of Tehran
Tehran, Iran

Abstract- In this paper, the idea of emotional critic based fuzzy controller is generalized in order to control of nonlinear, MIMO HVAC System. The proposed methodology is composed of a set of neurofuzzy controllers, the weights of which are adapted according to emotional signals created by a block called fuzzy critic. Our proposed solution, can achieve very robust and satisfactory performance even though there were only two controlled input processes to the plant which could be used to get the desired performance levels. The response time was also very fast despite the fact that the control strategy was based on bounded rationality. The proposed strategy is very flexible and alternative performance specifications can easily be enforced via defining proper emotional cues.

Keywords: Neural Network- Fuzzy Logic- Neuro-Fuzzy Controller- Nonlinear HVAC System

1 Introduction

The HVAC (Heating, Ventilation, and Air Conditioning) problem is a difficult control problem receiving much attention in recent and past research. The present methods for control are satisfactory in most cases, but there is significant room for improvement, both in terms of human comfort and particularly energy savings. HVAC systems are highly nonlinear with widely varying dynamics at different operating points. It is difficult, if not impossible, to construct LTI models of the system which exhibit dynamics similar to the physical plant dynamics. Such systems also incur highly variable gains at different operating points. The different components of an HVAC system, (heating coils, fans, dampers, etc) are highly interactive and cannot be modeled as isolated units [1]. HVAC systems depend heavily on unpredictable scheduling; changes in weather conditions and unpredictable human activities contribute to the difficulty of the HVAC problem. Traditional adaptive control techniques are often ineffective, because these techniques make assumptions about the underlying dynamics of the system and the form of the system.

The problem of HVAC control can be posed from two different points of view. In the first, one aims at reaching an optimum consumption of energy. In the second, that is more common in HVAC control, the goal is keeping moisture, temperature, pressure and other air conditions in an acceptable range. Several different control and intelligent strategies have been developed in recent years to achieve the stated goals fully or partially. Among them, PID controllers [2,3], DDC methods [4,5], optimal [11,12,13], nonlinear [13] and robust [14,15] control strategies, and neural and/or fuzzy [6,7,8,9,10,16] approaches are to be mentioned. We have also dealt with this problem and provided novel solutions in [18,19,20,21,22]. The purpose of this paper is to suggest another control approach, based on a modified version of Context Based

Reinforcement Learning (CBRL) [23], to achieve faster response with reduced overshoot and rise time. A main motivation was to assess the extent of applicability of our non model-based and heuristic approach to more complex control tasks involving unknown plant delays or non-minimum-phase input-output relationships. In the subsequent sections, we discuss the HVAC system, our proposed controller, and its application in the closed loop control system, simulation and some concluding remarks.

2 HVAC System

In HVAC systems, a central air supply provides air at a controlled temperature and flow rate for use in heating (or cooling) a space. A heating (or cooling) coil is used in the central air supply for heating (or cooling) the discharged air. The temperature of the discharged air is controlled by regulating the rate at which hot (or chilled) water flows through its heating (or cooling) coil(s). The flow rate of the discharged air is regulated to maintain a predetermined static air pressure within the temperature controlled space. Typically, the space within a building is divided into smaller zones, allowing the temperature within each zone to be maintained independently of the others. Each zone contains a reheat (and/or cooling) coil which is used to moderate the final temperature of the air discharged into the zone.

A characteristic of today's HVAC systems is the use of centralized hot (or chilled) water supplies in servicing multiple central air supplies. Such an HVAC interconnection (architecture) restricts the controller design and impacts the performance of the resulting system. A full MIMO controller requires control of the temperature and flow rates of both the air and water owing through the heating coil. Consequently, independent air and water supplies would be required for each coil. Such a system represents a major shift from current HVAC design paradigms.

For simulation of HVAC systems, some different models have been proposed and considered. In [18,19] a linear first order model of the system with a time delay is put forward, while the nonlinearity of the HVAC systems is considered in [17]. In this paper, we used the model developed in [1], since it aims at controlling the temperature and humidity of the Variable Air Volume (VAV) HAVC system, however SISO bilinear model of the HVAC system for controlling the temperature has been given in [13]. Below, we describe the mathematical structure of a MIMO HVAC model used throughout this paper. The state space equations governing the model are as follows:

$$\dot{x}_1 = u_1\alpha_1 60(x_3 - x_1) - u_1\alpha_2 60(W_s - x_2) + \alpha_3(Q_o - h_{fg}M_o) \tag{1}$$

$$\dot{x}_2 = u_1\alpha_1 60(W_s - x_2) + \alpha_4 M_o \tag{2}$$

$$\dot{x}_3 = u_1\beta_1 60(-x_3 + x_1) + u_1\beta_1 15(T_o - x_1) - u_1\beta_3 60(0.25W_o + 0.75x_2 - W_s) \tag{3}$$

$$y_1 = x_1 \tag{4}$$

$$y_2 = x_2 \tag{5}$$

In which the parameters are:

$$u_1 = f, u_2 = gpm, x_1 = T_3, x_2 = W_3, x_3 = T_2 \tag{6}$$

$$\alpha_1 = 1/V_s, \alpha_2 = h_{fg}/C_pV_s, \alpha_3 = 1/\rho C_pV_s, \alpha_4 = 1/\rho V_s, \beta_1 = 1/V_{he}, \tag{7}$$

$$\beta_2 = 1/\rho C_pV_{he}, \beta_3 = h_w/C_pV_{he} \tag{8}$$

And the numerical values are given in table 1.

$\rho = .074\ lb/ft^3$	$C_p = .24\ Btu/lb.°F$
$V_s = 58464\ ft^3$	$T_o = 85°F$
$M_o = 166.06\ lb/hr$	$V_{he} = 60.75\ ft^3$
$W_s = .007\ lb/lb$	$W_o = .0018\ lb/lb$
$Q_o = 289897$	$\tau = .008\ hr, k = 5$

Table1: Numerical Values for system parameters

Also, the actuator's transfer function can be considered as:

$G_{act}(S) = k/(1+\tau S)$

In which k and τ are the actuator's gain and time constant. The schematic structure of the HVAC system is given in figure 1.

The system has delayed behavior which is represented via linearized, first order and time delay system. Furthermore, the model represents a MIMO system in which one of the I/O channels has a right half plane zero, meaning that it is non-minimum-phase.

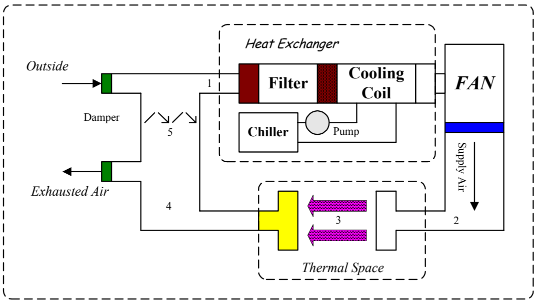

Figure1- Model of the HVAC system

3 Neuro-Fuzzy Controiller

A Block diagram representation of ECBFC is shown in Fig.2. As it can be seen, it is composed of two main parts:

A: Neurofuzzy controller: which provides the control signal for the plant.
B: Critic: which provides the emotional signal according to the control situation and updates the weights of the neurofuzzy controller.

3.1. Design of the neurofuzzy controller

The neurofuzzy controller applied is a standard Sugeno fuzzy controller composed of four layers. In the first layer, all inputs are mapped into the range of [-1, +1]. In the second layer, the fuzzification process is performed using gaussian membership functions with five labels for each input. In layer 3, decision-making is done using Max-Product law and defuzzification is carried out in the fourth layer in order to calculate the proper control input using Takagi-Sugeno relationship:

$$y = \frac{\sum_{i=1}^{n} u_i (a_i x_1 + b_i x_2 + c_i)}{\sum_{i=1}^{n} u_i} \qquad (9)$$

Where x_1 and x_2 are inputs to the controller, u_i, n, and y are the ith input of the fourth layer, number of rules in the third layer, and output of the control system, respectively and a_i, b_i, c_i are parameters to be determined via learning.

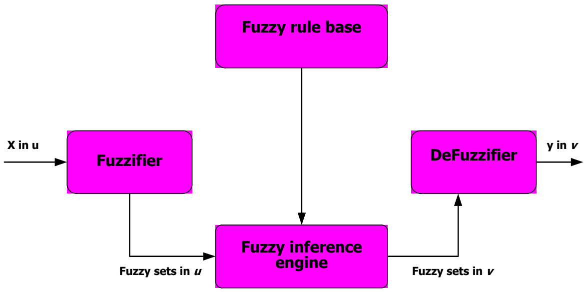

Figure 1.B- The Structure of Fuzzy Controller

3.2. Design of the Critic

The critic block applied here has the same structure of a fuzzy PD controller. Inputs of the critic are e and $\dot{e}$ (error and the rate of change of error). Fuzzification and defuzzification are performed by gaussian membership functions with 5 labels for each input and 7 labels for the output; deduction is performed by Max-Product law and for defuzzification the centroid law is used (Due to the important role of the critic, the number of the labels are increased to achieve a better performance). The rule base for fuzzy critic is shown in Fig.3.

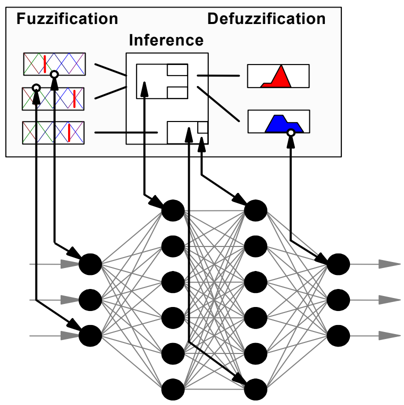

Figure 2- Block Diagram of Neuro-Fuzzy Controller

The aim of the control system is the minimization of the sum of squared emotional signals. Accordingly, first we describe the error function E as follows:

$$E = \sum_{j=1}^{m} K_j (\tfrac{1}{2} r_j^2) \qquad (10)$$

where r_j 's are the output signals of each critic, Kj 's the corresponding output weights and m is the total number of outputs.
For the adjustment of controllers' weights the steepest descent method is used:

$$\Delta\omega_i = -\eta_i \frac{\partial E}{\partial \omega_i} \qquad (i = 1,2,\ldots,n) \qquad (11)$$

Where η_i is the learning rate of the corresponding neurofuzzy controller and n is the total number of controllers. In order to calculate the RHS of (11), the chain rule is used:

$$\frac{\partial E}{\partial \omega_i} = \sum_{j=1}^{m} \frac{\partial E}{\partial r_j} \cdot \frac{\partial r_j}{\partial y_j} \cdot \frac{\partial y_j}{\partial u_i} \cdot \frac{\partial u_i}{\partial \omega_i} \qquad (12)$$

From (10), we have,

$$\frac{\partial E}{\partial r_j} = K_j \cdot r_j \qquad (j = 1,2,\ldots,m) \qquad (13)$$

Also,

$$\frac{\partial y_j}{\partial u_i} = J_{ji} \qquad (14)$$

where J_{ji} is the element located at the ith column and jth row of the Jacobian matrix. Taking

$$e_j = y_{refj} - y_j \qquad j=1,2,\ldots, m \qquad (15)$$

where e_j is the error produced in the tracking of jth output and y_{refj} is the reference input (in case number of outputs is greater than the number of inputs, some of y_{refj}'s are taken as zero as it will be cleared by the inverted pendulum example). Now we have

$$\frac{\partial r_j}{\partial y_j} = -\frac{\partial r_j}{\partial e_j} \qquad (16)$$

Since with the incrimination of error, r will also be incremented and on the other hand, on-line calculation of $\frac{\partial r_j}{\partial e_j}$ is accompanied with measurement errors, thus producing unreliable results, only the sign of it (+1) is used in our calculations.

From (10) to (16), $\Delta\omega_i$ will be calculated as follows:

$$\Delta\omega_i = \eta_i \sum_{j=1}^{m} K_j . r_j . J_{ji} \cdot \frac{\partial u_i}{\partial \omega_i} \qquad (17)$$

Equation (17) is used for updating the learning parameters a_{il}'s, b_{il}'s and c_{il}'s in (9), which is straightforward.

e → Δe↓	NL	NS	ZE	PS	PL
PL	ZE	PS	PM	PL	PL
PS	NS	ZE	PS	PM	PL
ZE	NM	NS	ZE	PS	PM
NS	NL	NM	NS	ZE	PS
NL	NL	NL	NM	NS	ZE

PL: Positive Large PM: Positive Medium PS: Positive Small ZE: Zero	NS: Negative Small NM: Negative Medium NL: Negative Large

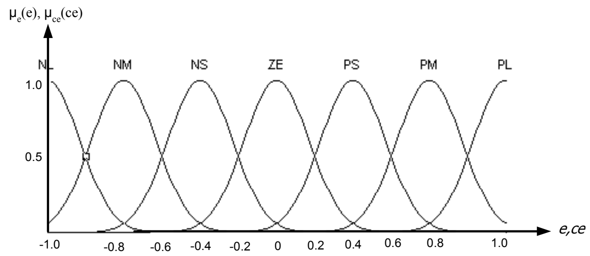

Figure 3- Rule and fuzzy sets of the critic

4 Simulation Results

In this section, we describe the circuits we have used for controlling the HVAC plant. We have, of course, assumed no prior knowledge of the plant delays and the time delays introduced in ECBFC has no special relationship with possible plant delays. The delays in ECBFC merely help distribute reward, dynamically without attempting to find the optimal credit assignment schema. The actual plant model involves four input and three output processes, of which two inputs can be manipulated for achieving desired performance levels. Our initial attempt to consider an SISO problem in which temperature set point tracking was the main goal proved futile, because the rest of the system could not be regarded as disturbances and unmodeled dynamics. The response speed caused the other outputs increase beyond acceptable levels. Next, we tried to achieve the design goals via two separate ECBFC agents (Fig. 4). We wished to track temperature and humidity to their respecting set point levels of 73°F and 0.009, while maintaining the supply air temperature within the range of 40°F to 100°F. This proved very satisfactory (Fig. 5). The performance levels achieved via the two alternative approaches are outlined in table 2.

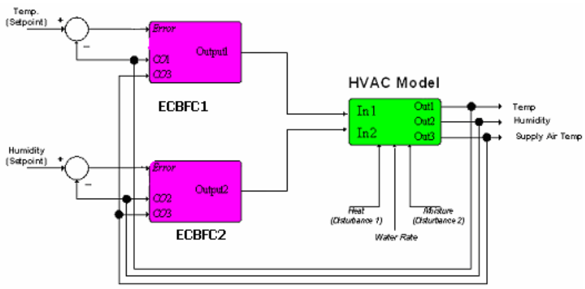

Figure4- Control circuit with two controllers

We examined the robustness of these controllers with respect to external disturbances. To do that, we fed the plant with time-variable heat and moisture disturbance signals in the form given in figure 6. The response of the two ECBFC controllers is given in the figure 7.

5. Conclusion

In this paper, we showed the applicability ECBFC to the fulfillment of complex tasks of adaptive set point tracking and disturbance rejection of a HVAC system. The control of the non-minimum phase, multivariable, nonlinear and nonlinearizable plant with constraints on its supply air temperature is indeed a demanding task from control theoretic viewpoint. The controller presented in this paper possessed excellent tracking speed and robustness properties. The results presented in this paper are an important step toward showing the utility of ECBFC in carrying out real world and complex control tasks.

6 References

[1] Serrano, B. A., Velez-Reyes, M., 1999, "Nonlinear Control of A Heating, Ventilation and Air Conditioning Systems with Thermal Load Estimation" IEEE Transaction on Control Systems Technology, Volume 7, (1)

[2] Fargus, R. S., Chapman, C., 1997, "Implementation of Commercial PI-Neural Controller for Building Services" IEE, Savoy Place

[3] Geng, G., Geary, G. M., 1993, "On Performance and Tuning of PID Controllers in HVAC Systems" Conference on Control Application

[4] Hartman, T. B., 1993, "*Direct Digital Controls for HVAC Systems*" MC Graw-Hill

[5] Newman, H. M., 1994, "*Direct Digital Controls for Building Systems*" John Wiley

[6] Miller, R. C., Seem, J. E., 1991, "Comparison of Artificial Neural Network with Traditional Methods of Predicting Return Time from Night or Weekend Setback" ASHRAE Transaction, Volume 97

[7] Hepworth, S. J., Dexter, A. L., 1994, "Neural Control of Nonlinear HVAC Plant" Conference on Control Application

[8] Osman, A., Mitchell, J. W., Klein, S. A., 1996, "Application of General Regression Neural Network in HVAC Process Identification and Control" ASHRAE Transaction, Volume 102

[9] Curtiss, P. S., Kreider, J. F., Branenuehl, M. J., 1994, "Local and Global Control of Commercial Building HVAC Systems Using Artificial Neural Networks", ACC

[10] Farzan Rashidi and et.al, "Emotional Temporal Difference Learning Based Intelligent Controller", Accepted at CCA03 IEEE, 2003

[11] Zaheeruddin, M., 1992 “Optimal Control of A Single Zone Environment Space” Building and Environment
[12] Zaheeruddin, M., 1993, “The Design and Simulation of A Sub-Optimal Controller for Space Heating” ASHRAE Transaction, Volume 99
[13] Tigrek, T., Dasgupta, S., Smith, T. F., 2002, “Nonlinear Optimal Control of HVAC Systems” Proceedings of IFAC

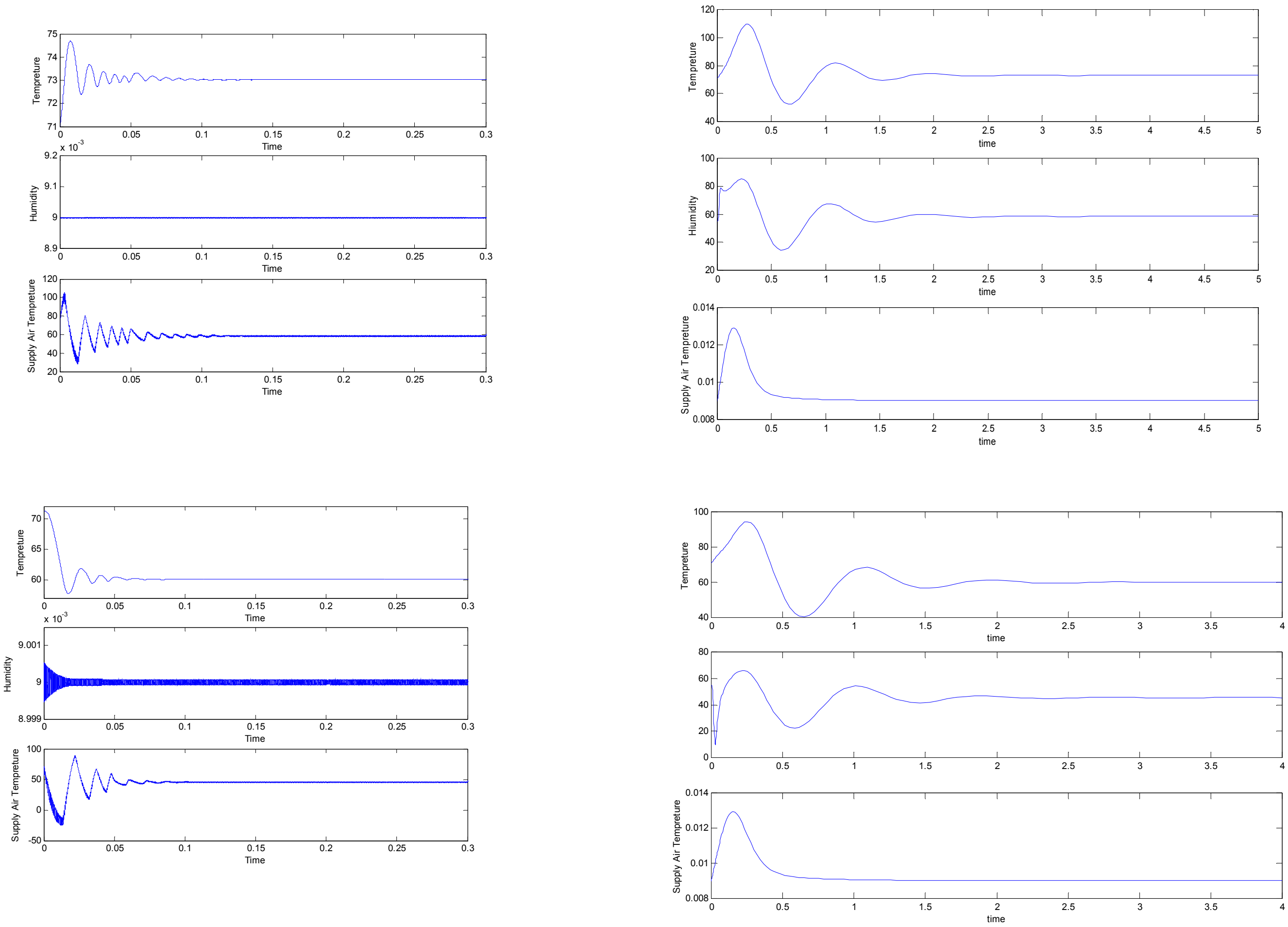

Figure 5- HVAC system responses with two controllers (Left: ECBFC, Right: PID)

	S-SError(Temp-Humi)	RiseTime(Temp-Humi)	POS(Temp-Humi)
Neuro-Fuzzy Controller	0.01%-0.00%	0.001-0.0002	01.90- 0.00
PID	0.00%-0.00%	0.009-0.002	49.96-43.33

Table 2- Performance characteristics of HVAC system with two PID and CBRL controllers

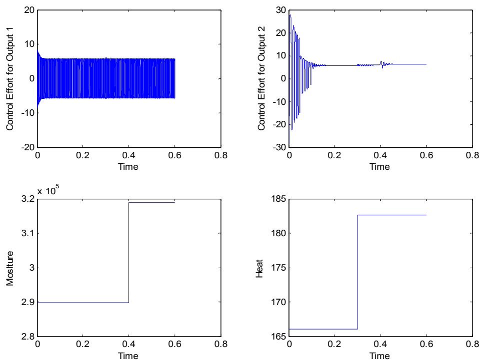

Figure 6- The heat and moisture disturbance signals for robustness consideration

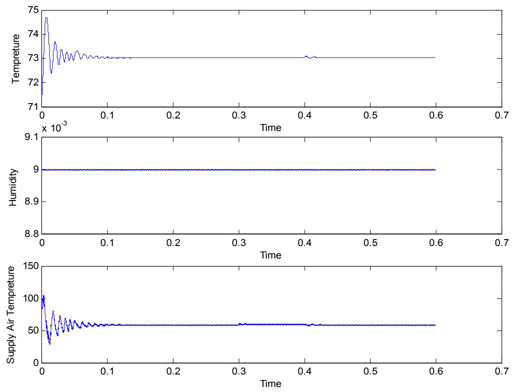

Figure 7- HVAC system responses of the two controllers with the presence of disturbance variations

Nomenclature

h_w	Enthalpy of liquid water	W_o	Humidity ratio of outdoor air
h_{fg}	Enthalpy of water vapor	V_{he}	Volume of heat exchanger
W_s	Humidity ratio of supply air	W_3	Humidity ratio of thermal space
C_p	Specific heat of air	T_o	Temperature of outdoor air
M_o	Moisture load	Q_o	Sensible heat load
T_2	Temperature of supply air	T_3	Temperature of thermal space
V_s	Volume of thermal space	ρ	Air mass density
f	Volumetric flow rate of air	gpm	Flow rate of chilled water