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Applying brain emotional learning algorithm for multivariable control of HVAC systems

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Abstract. In this paper, we apply a modified version of Brain Emotional Learning (BEL) controller for Heating, Ventilating and Air Conditioning (HVAC) control system whose multivariable, nonlinear and non-minimum phase nature makes the task difficult. The proposed biologically-motivated algorithm achieves robust and satisfactory performance even though there are more than one control inputs to the plant, which may be used to get the desired performance. The response time is also very fast despite the fact that the control strategy is based on satisficing decision making. The proposed strategy is very flexible and alternative performance specifications can easily be enforced via defining proper emotional cues. Simulation results reveal the effectiveness of the approach.

Nomenclature

A	Amygdala nodal output
C_p	Specific heat of air
f	Volumetric flow rate of air
gpm	Flow rate of chilled water
h_{fg}	Enthalpy of water vapor
h_w	Enthalpy of liquid water
M_o	Moisture load
MO	BEL model output
OC	Orbitofrontal Cortex nodal output
Q_o	Sensible heat load
SI	Sensory Input
T_2	Temperature of supply air
T_3	Temperature of thermal space
T_o	Temperature of outdoor air
V	Amygdala adaptive gain
V_{he}	Volume of heat exchanger
V_s	Volume of thermal space
W	Orbitofrontal Cortex adaptive gain
W_3	Humidity ratio of thermal space
W_o	Humidity ratio of outdoor air
W_s	Humidity ratio of supply air
α	Amygdala learning rate
β	Orbitofrontal Cortex learning rate
ρ	Air mass density

1. Introduction

HVAC (Heating, Ventilating and Air Conditioning) systems are one of the most challenging plants in the field of process control. The energy consumed by HVAC equipments constitutes 50% of the total world energy consumption [1]. HVAC systems include all the air conditioning systems used for cooling or heating the closed environments. In designing the HVAC systems, the objectives are usually controlling the temperature and percentage of humidity.

The literature review in this field shows different works to fully or partially achieve the objectives. For

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many years, PID and Direct Digital Controllers have been used to control the temperature [2–5]. In reference [6] a tuning method for a digital controller based on relay feedback and pole placement strategies is described. Different intelligent methods have also been used for control and identification of HVAC systems [7–12]. Implementing optimal and robust controllers for nonlinear HVAC systems have also been described in references [13–15]. Also, Zaheeruddin introduces a suboptimal controller for these systems [16].

In previous works, we also dealt with this problem with new approaches. For the purposes of control and minimization of actuator repositioning by different methods the reader is referred to [17,18]. Feedback linearization and Backstepping methods are also used for the purposes of disturbance decoupling and regulation [19]. For the same purpose and in the case where disturbances are not available, a load estimator is designed in a more recent work [20].

Although many strategies have been used to improve the performance of these systems, there are yet so many unsolved problems with these systems. The purpose of this paper is to suggest another control approach, based on a modified version of Brain Emotional Learning (BEL) algorithm, to achieve faster response with reduced overshoot.

Basically, BEL is an action selection algorithm based on a computational model of emotional processing in the brain [21]. The idea that emotions are important elements in intelligent performance of machines and systems has gained considerable interest in recent years [22,23], and led to new designs in control engineering [24,25]. The increasing appreciation of the roles of emotion is not confined to artificial intelligence, computation, control, and communication systems. Increased theorization in the crucial importance of emotions is also evident in disciplines like cognitive science and psychology [26,27].

A main motivation of this study is to extend the applicability of the approach to more complex control tasks involving unknown plant delays or non-minimum-phase input-output relationships. Indeed, we see that the essentially static learning model in the previous applications of BEL proves inadequate [28] and we have to introduce delay elements, which we suspected from neuro-anatomical considerations, so as to deal with the complexities of the given task. In the subsequent sections, we discuss the HVAC system, the proposed control algorithm and its application in HVAC control system by simulations.

2. Modeling

In this section, we describe the HVAC system studied in this paper and the BEL control algorithm:

2.1. HVAC mathematical model

Literature review shows several models considered for HVAC systems. For examples in reference [17], a linear first order model of the system with a time delay is considered. In [14], a nonlinear SISO model is used for simulations. In some other works a bilinear model is considered for presenting the temperature [13], humidity or both of them [1]. It is obvious that the humidity and temperature factors are important in providing a well-conditioned air. In this study, we used the model given in [1], which is a Multi Input-Multi Output HVAC system and presents both factors of temperature and humidity as it seems to present more practical model of a single-zone HVAC system. The system has delayed behavior which is represented via linearized first-order time delay model [17]. Furthermore, one of the I/O channels of the system has a right half plane zero, i.e. it is a non-minimum-phase system [18].

To be more practical, the present work considers the actuators dynamics, as well. The mathematical model of the system, without actuators dynamics, is represented via formulas given in Eqs (1)–(6):

$$\dot{\mathbf{x}} = \mathbf{f}_1 \mathbf{x} u_1 + \mathbf{g}_1 u + \mathbf{p}_1 \boldsymbol{\omega}, \tag{1}$$

$$\mathbf{f}_1 = \begin{bmatrix} -a_1 60 & a_2 60 & a_1 60 \\ 0 & -a_1 60 & 0 \\ b_1 45 & -b_3 45 & -b_1 60 \end{bmatrix}, \quad \mathbf{p}_1 = \begin{bmatrix} a_3 & -a_3 h_{fg} \\ 0 & a_4 \\ 0 & 0 \end{bmatrix}, \tag{2}$$

$$\mathbf{g}_1 = \begin{bmatrix} -a_2 60 W_s & 0 \\ a_1 60 W_s & 0 \\ -b_3 60(.25Wo - W_s) & 6000 b_2 \\ \quad +b_1 15 T_o & \end{bmatrix}, \tag{3}$$

$$y_1 = x_1,\ y_2 = x_2. \tag{4}$$

where x is the state vector, u and y are the input and output vectors and ω is the disturbance vector which consists of heat and humidity loads [1].

The parameters used in the above formulas are defined as follow:

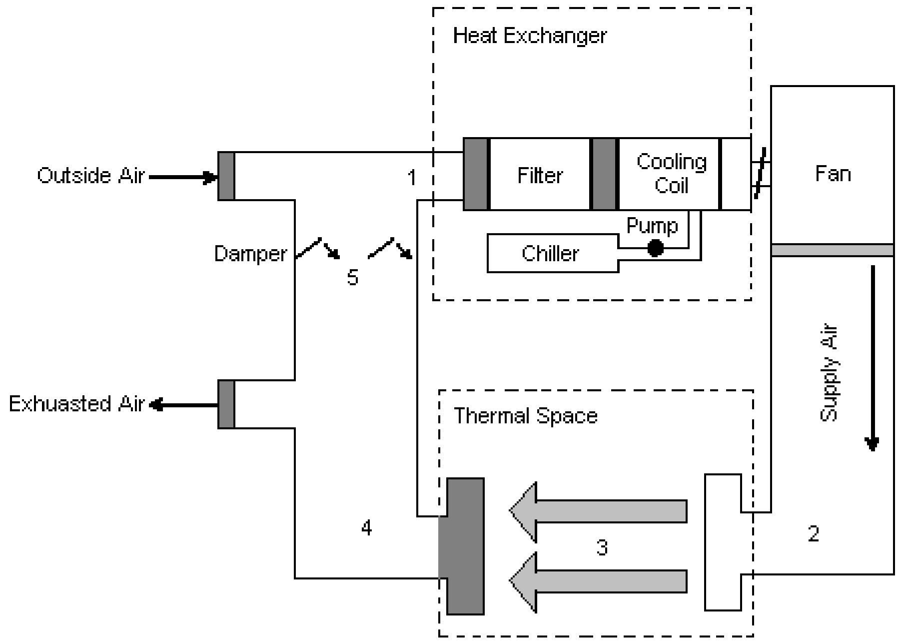

Fig. 1. The model of a single-zone VAV HVAC system.

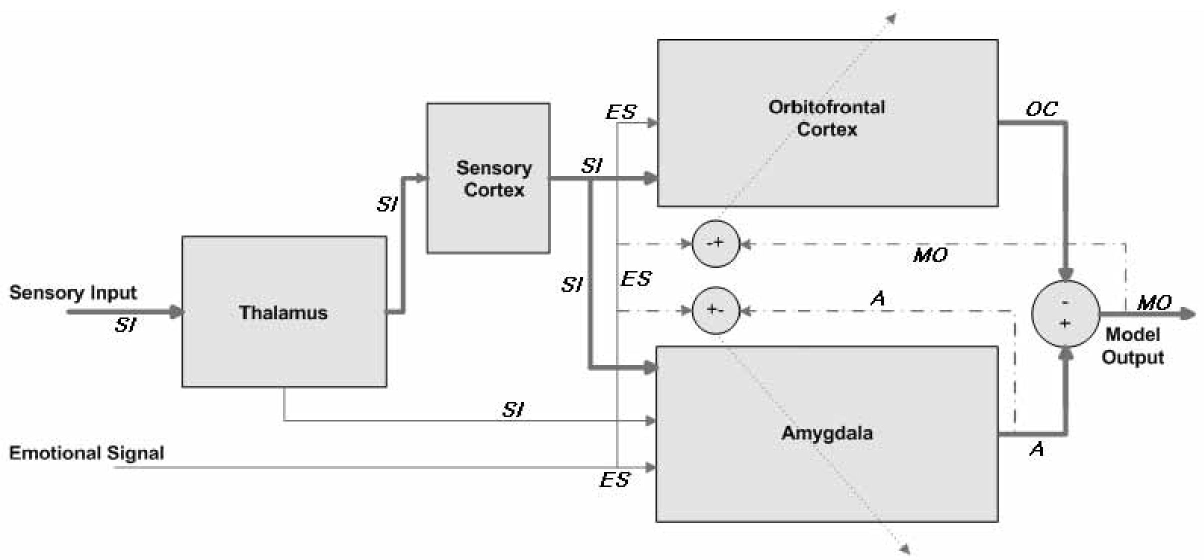

Fig. 2. Block diagram of the simplified limbic model (BEL).

$$x = \begin{bmatrix} T_3 \\ W_3 \\ T_2 \end{bmatrix} \quad a = \begin{bmatrix} 1/V_s \\ h_{fg}/C_pV_s \\ 1/\rho C_pV_s \\ 1/\rho V_s \end{bmatrix} \quad u = \begin{bmatrix} f \\ gpm \end{bmatrix}$$
$$\omega = \begin{bmatrix} Q_0 \\ M_0 \end{bmatrix} \quad b = \begin{bmatrix} 1/V_{he} \\ 1/\rho C_pV_{he} \\ h_w/C_pV_{he} \end{bmatrix}. \tag{5}$$

where a and b are the vectors of a_is and b_is, respectively. Table 1 shows numerical values of the parameters of the system:

The following assumptions are made in the modeling process [1]:

1. VAV (Variable Air Volume) system with variable chilled water flow rate

Table 1
Numerical values for system parameters

$\rho = 0.074$ lb/ft^3	$C_p = 0.24$ Btu/lb.$^\circ$F	$V_s = 58464$ ft^3	$T_o = 85^\circ$F	$M_o = 166.06$ lb/hr
$V_{he} = 60.75$ ft^3	$W_s = 0.007$ lb/lb	$W_o = 0.0018$ lb/lb	$Q_o = 289897$	$\tau = 0.008$hr, $k = 5$

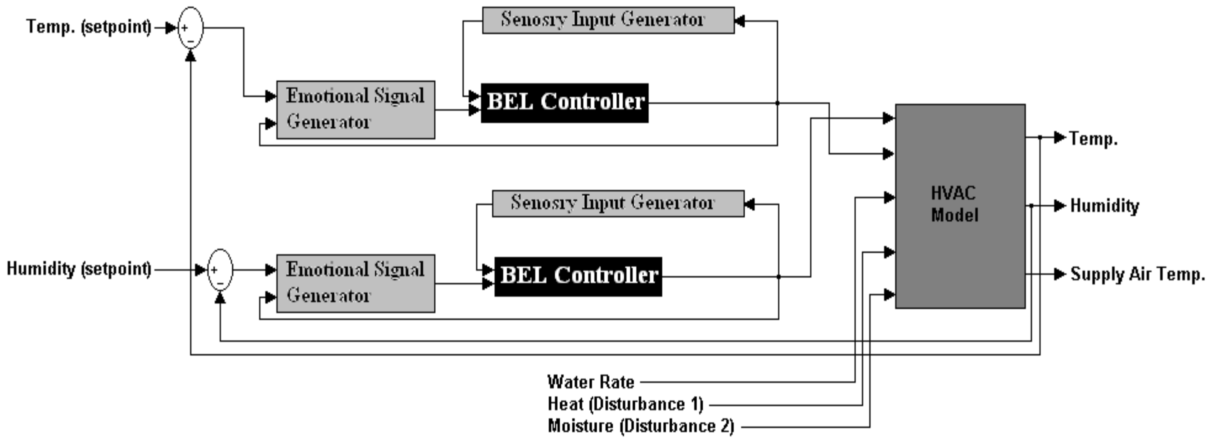

Fig. 3. Control block diagram with two BEL controllers.

2. Constant ratio of (total to fresh) air flow rate:

$$r = f/f_0 = 4 \quad (6)$$

3. Ideal gas behavior and perfect mixing
4. Constant pressure, negligible thermal storage
5. Negligible infiltration, exfiltration, and transient effects in the flow splitter and mixer.

The control signal in this model is implemented to liquid valves and as described in [29], the valve dynamic model can be considered as follows:

$$z(s) = \Psi(s)/(1 + \tau s), \quad (7)$$

in which $\Psi(s)$ is the valve inherent characteristic, τ is its time constant and z_s is the flow rate of liquid enters the valve.

According to the discussion in [29], by modeling the characteristics of a linear valve as $\Psi(s) = ku(s)$, with a constant k, the valve transfer function can be written as:

$$G(s) = z(s) \Big/ u(s) = k/(1 + \tau s), \quad (8)$$

where $u(s)$ and $z(s)$ are respectively the control signal to the actuator and the input signal to the plant.

The schematic structure of the HVAC system is given in Fig. 1.

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

2.2. BEL control algorithm

BEL (Brain Emotional Learning) is a learning algorithm based on the emotional learning in mammalians [28]. Motivated by the success in functional modeling of emotions in control engineering applications [24,30,31], a structural model based on the limbic system of mammalian brain is developed for application in decision-making and control systems [28].

The key elements of the limbic system, and its related cortical and subcortical areas, which are considered for the model are the Amygdala, the Orbitofrontal Cortex, the Sensory Cortex and the Thalamus. From the aforementioned components, the first two play a key role in the processing of emotions while the other two largely (though not entirely) function as preprocessors of sensory input.

In particular, the task of the thalamus is to provide a non-optimal but fast response to stimuli. This capability is often simulated by passing the maximum signal, over all sensory signals, to the Amygdala [32–34]. The main task of the sensory cortex in biological systems is to appropriately distribute the incoming sensory signals through the Amygdala and the Orbitofrontal Cortex, where in this study it is modeled as a computational delay [32].

The fundamental idea behind decision-making based on emotional learning, following [21,32] is to generate the action (output), which minimizes an emotional stress (or maximizes an emotional reward), while the

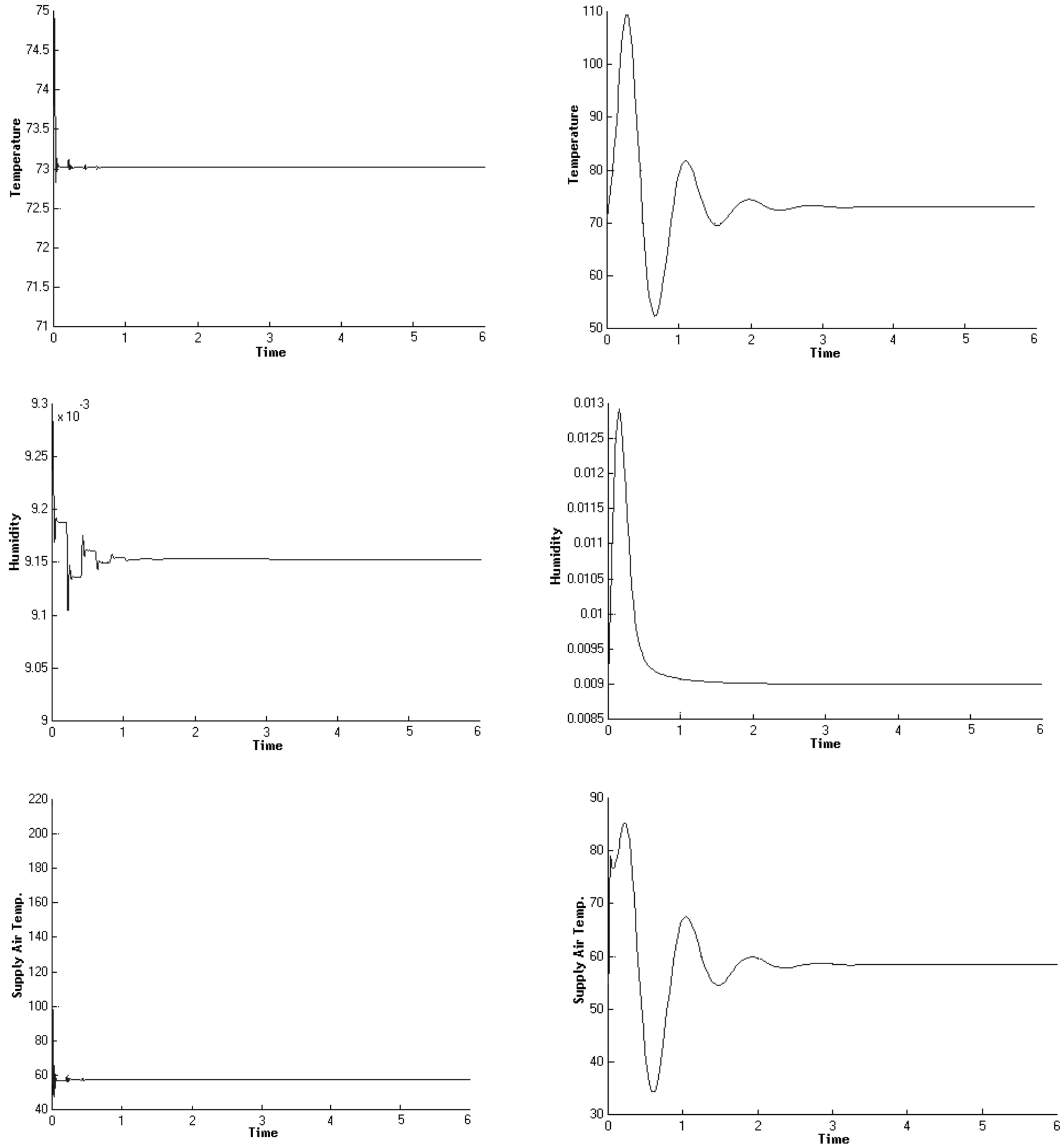

Fig. 4. Responses of the HVAC system with two controllers (Left: BEL, Right: PID).

system is receiving different sets of sensory signals. The sensory inputs received by the system represent the situation the system is currently experiencing, and the emotional signals reflect the degree of satisfaction with the performance of the system.

Based on these mechanisms, Fig. 2 shows the schematics of the model of the Brain Emotional Learning (BEL) algorithm.

The main learning of this system occurs within the Amygdala and the Orbitofrontal Cortex components which are illustrated in Fig. 2 by dotted lines over these components. The output of the model, , is generated as the difference between all the excitatory Amygdala and inhibitory Orbitofrontal Cortex nodal outputs as

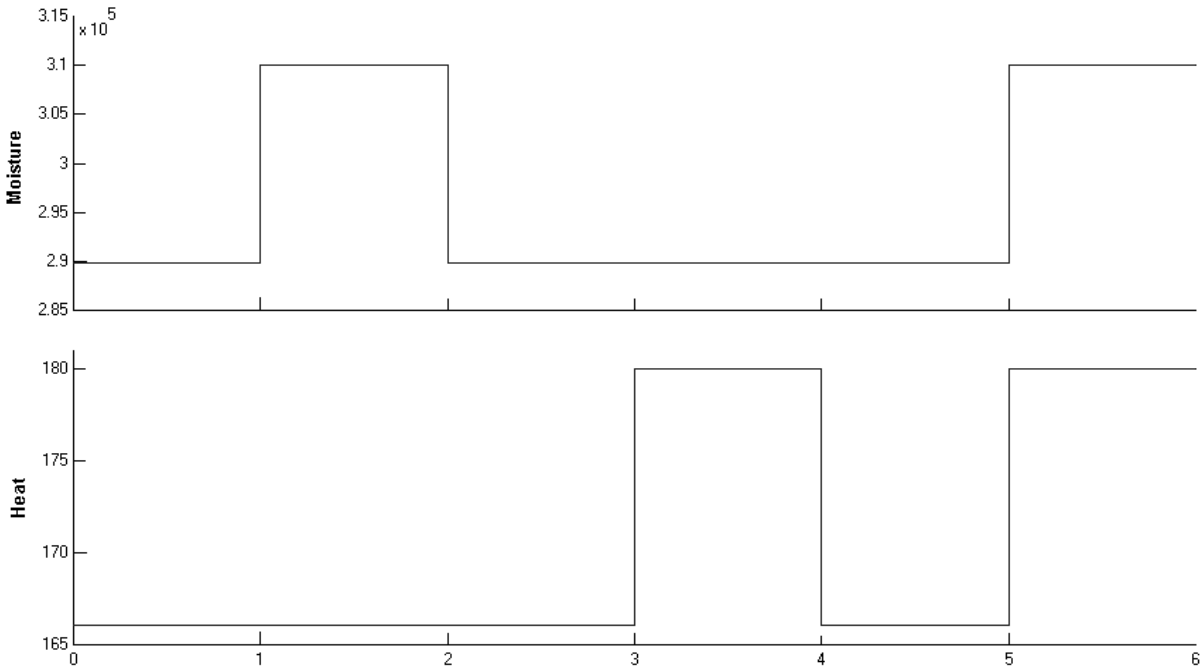

Fig. 5. The heat and moisture disturbance signals.

follows:

$$MO = \sum_i A_i - \sum_i OC_i. \tag{9}$$

For each sensory input received by the model, SI_i, there is one corresponding Amygdala node, A_i, and one corresponding Orbitofrontal Cortex node, OC_i, which generate the nodal Amygdala and Orbitofrontal Cortex outputs. These outputs are generated by multiplying the sensory input signal by the Amygdala and the Orbitofrontal Cortex as given by:

$$A_i = V_i.SI_i, \tag{10}$$

$$OC_i = W_i.SI_i. \tag{11}$$

In the above, V_i and W_i are the adaptive gains of the Amygdala and the Orbitofrontal Cortex, respectively. The Amygdala and the Orbitofrontal Cortex learning processes occur through their internal weights update rule as:

$$\Delta V_i = \alpha.SI_i.\max\left(0, ES - \sum_i A_i\right), \tag{12}$$

$$\Delta W_i = \beta.SI_i.(MO - ES), \tag{13}$$

where ES and MO are the emotional signal and the model output, respectively.

As it is observed in Fig. 2, except for the signal going from Thalamus to the Amygdala, the Amygdala and the Orbitofrontal Cortex are both receiving the same set of signals, while the Orbitofrontal Cortex also receives a signal from the Amygdala. A fundamental characteristic of the model is the fact that the motivation to respond and the response itself are different [36]. This is inspired by the biology where the task of the Amygdala is to learn the associations between the sensory and the emotional input and to reflect them at the output [37].

As it is realized from the Amygdala learning rule stated above, the adaptation trend is monotonic [38]. Whether the experienced association is favorable or unfavorable, the Amygdala captures the essence of this association and tends to function on the basis of the new experience in the future. This is however mitigated by the fact that the final action generated by the limbic system is further controlled by the Orbitofrontal Cortex, which generates inhibitory signals to counter or augment the signal generated by the Amygdala [39]. The functional effect is to block the Amygdala response when it is acting based on an *inappropriate* association.

In this connection, we also need to point out the role of the thalamus. The shortcut path from thalamus to the Amygdala improves the speed and fault tolerance properties of the model, because it bypasses the more time-consuming sensory cortex processing while also en-

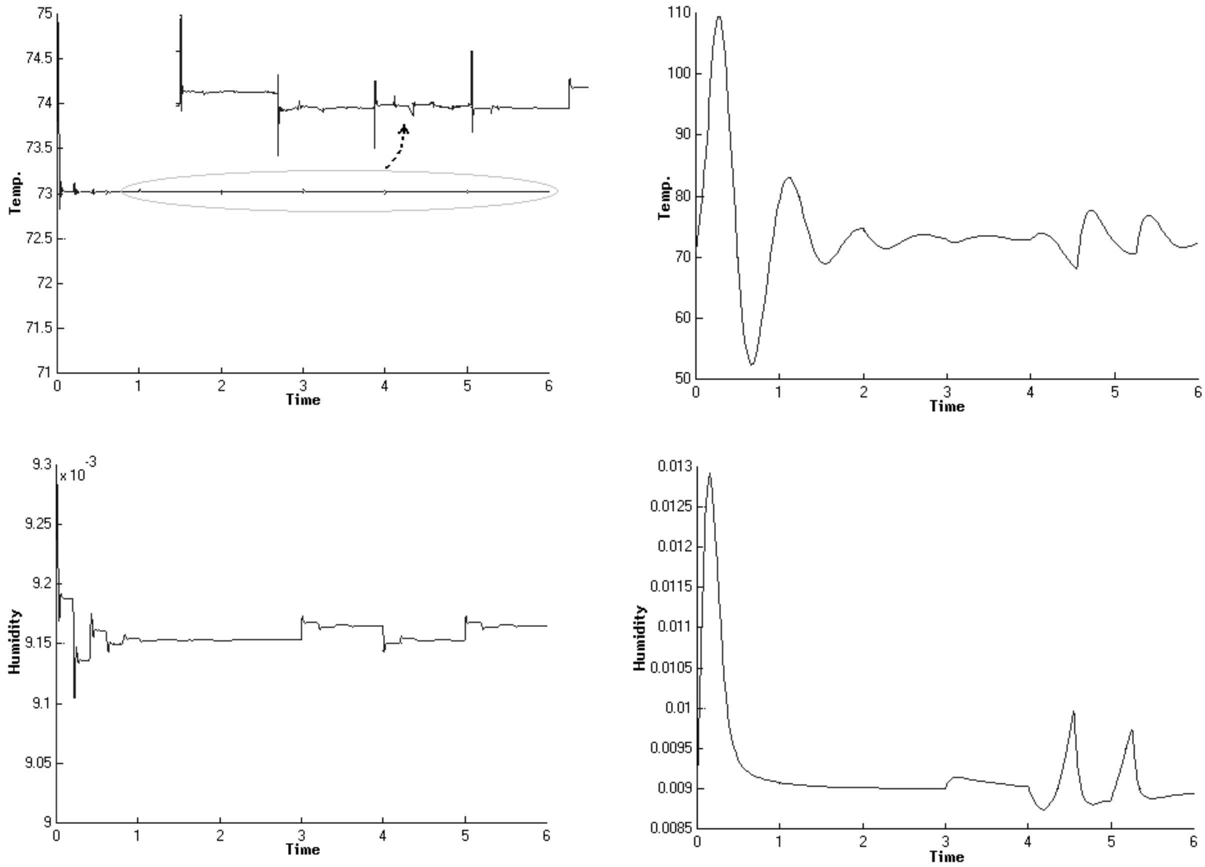

Fig. 6. Responses of the HVAC system with two controllers under disturbed inputs (Left: BEL, Right: PID).

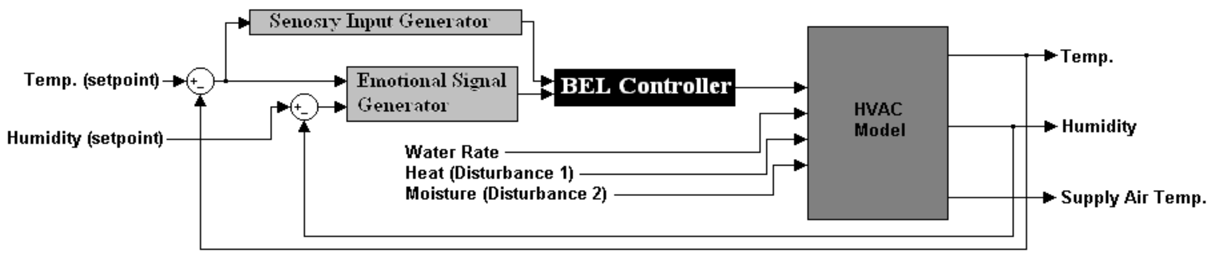

Fig. 7. Control block diagram with one BEL controller.

ables the model to generate a fast (albeit non-optimum) action, called *Satisfactory Decision*, even when the Sensory Cortex does not work perfectly (largely if it is overwhelmed by the sheer number of contradictory sensory signals). This signal effectively carries as much information contained within the multiple sensory inputs as possible. In this model of thalamus, the maximum over the sensory inputs is invoked as the signal from thalamus to Amygdala [21,32].

From a biological standpoint, the emotional signal is a generic, internally generated signal which can represent various reinforcing inputs from Thalamus, Hypothalamus and parts of the Basal Ganglia. The same issue is applicable when the model is simulated in an artificial environment. The emotional signal can be generated differently to reflect various objective functions.

Utilizing BEL algorithm in different applications confirms its performance as an action selection mechanism [28,40].

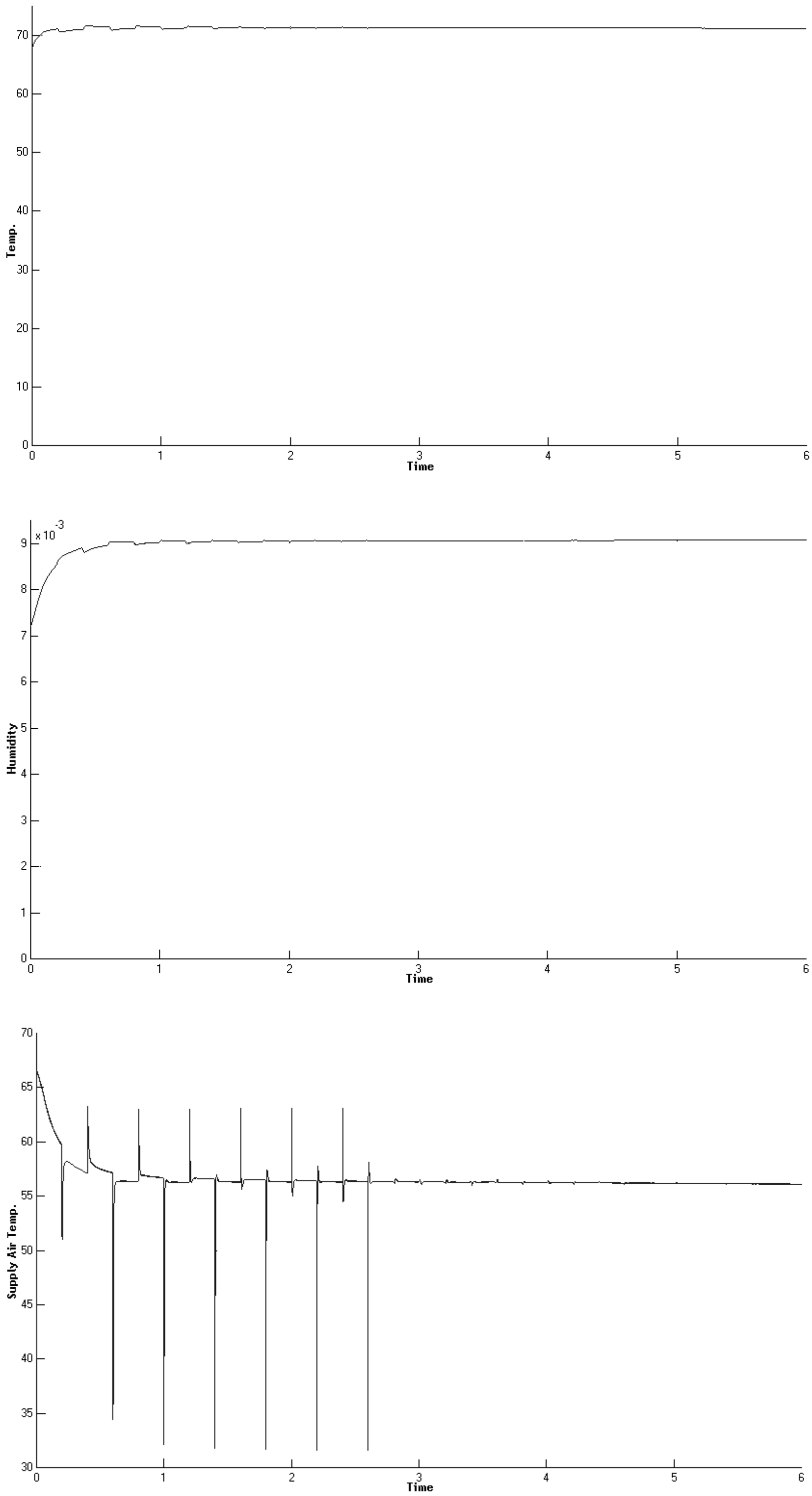

Fig. 8. Response of the HVAC system with one BEL controller.

Emotions can, therefore, be viewed as case-based guides to decision making, helping select those actions proven more likely to result in satisfaction of goals and intentions. Of course, emotions can only be approximate and quick guide not a deliberative reasoning carried out with full awareness, consciousness, volition and intentionality. But by the same token they are less dependent on the existence of fairly accurate mental representation of the environment and upon resources for carrying out involved deliberations.

3. Applying the BEL algorithm to the HVAC system

In this section, we describe the procedures for applying the BEL algorithm to control the HVAC system. The BEL model used in this study is basically the same as the original model given in [28] but it includes the additional delay elements in Orbitofrontal and Sensory Cortices in order to induce dynamic behavior.

There is no prior knowledge assumed on the plant delays and so the time delays in BEL do not have explicit relationship with possible plant delays. The delays in BEL merely help distribute the reward dynamically, without attempting to find the optimal credit assignment schema. The biological plausibility of this modification stems from the fact that delayed signal has been known to occur in the Orbitofrontal and Sensory Cortices [21]. The actual plant model involves four inputs and three outputs, of which two inputs can be manipulated for achieving desired performance levels. Our initial attempt to consider a 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. The successful results are achieved by using two individual BEL controllers in order to obtain the design goals, as given in Fig. 3.

It is desired to track temperature and humidity to their respecting set point levels of 73°F and 0.009 lb./lb., while maintaining the supply air temperature within the range of 40°F to 100°F. The responses of the BEL and PID controllers as well as their time-domain performance indices are given in the Fig. 4 and Table 2, respectively.

It is realized that regarding the settling time, the responses of the BEL controllers are much faster compared to those of PID controllers.

Due to the learning capability of BEL controllers, it is expected to be more robust with respect to changes. Now, we are examining the robustness of these controllers with respect to external disturbances. To do that, we add disturbances to the heat and moisture signals. The disturbed signals are given in the Fig. 5, where there are some deterioration in the time intervals, 1–2, 3–4 and 5–6 seconds. The responses of the BEL controllers and of the PID controllers are given in the Fig. 6. The reader is referred to Appendix A for the PID design procedure.

The figure demonstrates that the Temperature output of the system is barely affected with the BEL controllers whereas that of the PID ones is totally disturbed. The variations in the Humidity output of the system are also less with the BEL controllers while those of the PID controllers show noticeable variations in the disturbance periods. It is to be mentioned that reduced level of control effort can be alternatively considered as an explicit design goal to be minimized.

The next implementation is the control block diagram of Fig. 7, where one BEL controller is used to control the HVAC system. To do this, we have to prioritize the different criteria via using appropriate weights in generating the emotional signal. Therefore, the acceptable level of control effort is now achieved implicitly, because the combined emotional signal demonstrated little sensitivity to any extra objective for reduced control effort, unless we associate unacceptably high priority to control effort reduction which impairs achieving other control goals. The responses of the system with single BEL controller are shown in Fig. 8. Generally, the single controller proved much more difficult to fine-tune than the double controller block diagram of Fig. 3.

4. Conclusion

In this paper, we showed the applicability of a biologically-motivated control system for adaptive set point control and disturbance rejection of an 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 the control theoretic viewpoint. The presented BEL controller possessed fast tracking and robustness properties.

The flexibility of the controller also means that it is possible to pursue further objectives, e.g. trading off between response speed and smoothness of control ef-

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

	S-S Error(Temp-Humi)	Rise Time(Temp-Humi)	POS(Temp-Humi)
BEL	0.02%–1.67%	0.004–0.002	02.70–01.42
PID	0.00%–0.00%	0.009–0.002	49.96–43.33

fort, as well as steady state and transient characteristics of the responses, or utilizing it in a PI configuration. The comparison with a PID controller is only meant to signify the extent of the goal overfulfillment and does not imply that no other intelligent and adaptive controller can perform as well. Also it should be noted that neither of the controllers is designed based on any optimum tuning algorithms. A further objective of the paper was to show the advantages associated with emotional control.

Generally, system theory has been preoccupied by modeling rational decision making. It is usually prescribed even for human decision makers by folk psychology and management, to avoid making decisions based on emotions. However, it should be noted that emotive faculties would not have survived the evolutionary changes were they negative factors in decision making. On the other hand, it can be argued that emotion signals can be very powerful tools for decision making with bounded rationality when there are uncertainties and/or limitations on computational resources [25–27,41]. Functional models for emotional control have been reported successful [24,30]. In this study, an emotional algorithm is adopted for application in control systems which demonstrated satisfactory results.

To summarize, the main contributions presented in this paper are firstly to develop a flexible solution to the HVAC control problem with satisfactory performance, and secondly to extend the applicability of the BEL controller to complex and demanding control tasks. It should, however, be noted that no claim to guaranteed stability, robustness, or optimality is made in this study. Guaranteed stability is perhaps the main research challenge in the coming decade for intelligent and even adaptive/nonlinear control systems in general, and reinforcement learning based control systems in particular. Some steps towards the achievement of this goal can be seen in. The same can be said about guaranteed robustness. Claim to good adaptivity and robust performance however could be made because of the model-free and learning nature of the proposed control system and the fact that actions are guided by implicit perception of their desirability as experienced in the past. The performance of the controlled system is not sensitive to the validity of any given or identified model, but is responsive to changes in environmental conditions as well as deviations between expectations and realized outcomes.

The fact that emotional decision making relies upon cues and assessed desirabilities rather than optimization of objective functions, means that satisficing rather than optimality is the driving paradigm. Emotionally led decisions are not random, irrational or chaotic. They merely encompass a different rationality based on assessments of past outcomes rather than deliberation and reasoning about optimality of future outcomes given the model. As to the real-time realizability of the proposed control system and its generality with respect to plant variations, the approximate nature of the emotional cues and the fact that they are learned and adapted to environmental variations and not dependent on lengthy and model-based deliberations mean that these properties can be more easily achieved by BEL than by conventional controllers.

In assessing the proposed methodology it should be stressed that alternative design goals can be added, replaced and compromised, because it suffices to implement them as rewards with no need to be concerned with their differentiability, or the solvability of the resulting Bellman-Hamilton-Jacobi equation and the associated computational burden.

Appendix A

Design of PID Controller

The HVAC plant can be considered as a first order system with time delays. So the parameters of such approximation can be calculated according to the step response of each I/O channel, by methods such as “Process-Reaction Curve” [29]. After the system is being identified, the parameters of the PID controller can be tuned with conventional methods such as those given in [29,42]. It is important to notice that the plant considered in this study is MIMO, but it has some properties, which can be used for designing the individual controllers for two I/O channels [18]. The relationship for each PID controller is as follows:

$$u = k_p e(t) + k_1 \int e(t)dt + k_d \dot{e}(t). \qquad (14)$$

In this paper, the PID gains are designed by Cohen-Coon method [29,42], which gives the best results. Other methods such as Ziegler-Nichols [29,42], Internal Model Control [35], Haalman and Pole Placement [42] are also tried but are not found as effective as the Cohen-Coon method.

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