Intelligent Control of Electrically Heated Micro Heat Exchanger with Locally Linear Neurofuzzy Identifier and Emotional Based Learning Controller

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Abstract:-In this paper, an intelligent controller is applied to electrically heated micro heat exchanger. First, the dynamics of the micro heat exchanger is identified using Locally Linear Model Tree (LOLIMOT) algorithm. Then, an intelligent controller based on brain emotional learning algorithm is applied to the identified model. Modeling emotions has attracted much attention in recent years, both in cognitive psychology and design of artificial systems. We apply the Brain Emotional Based Learning Intelligent Controller (BELBIC) to a highly nonlinear plant, micro heat exchanger. The performance of BELBIC is compared with that of classical controllers like PID.

Keywords:- Intelligent control, brain emotion based learning, locally linear networks, system identification, heat exchanger**.**

1 Introduction

Although industrial processes usually contain complex nonlinearities, most of the conventional control algorithms are based on a linear model of the process. Linear models such as step response and impulse response models derived from the convolution integral are preferred, because they can be identified in a straightforward manner from process test data. In addition, the goal for most of the applications is to maintain the system at a desired steady state, rather than moving rapidly between different operating points, so a precisely identified linear model is sufficiently accurate in the neighborhood of a single operating point. Even so, if the process is highly nonlinear and subject to large frequent disturbances a nonlinear model will be necessary to describe the behavior of the process.

Biologically motivated intelligent computing has in recent years been successfully applied to solving complex problems [1,2]. The process or plant to be controlled is often unknown and even after identification; its characteristics may change due to aging, wear and tear, etc. Furthermore, there are various noises and disturbances present in the system. New approaches where intelligence is not given to the system from outside, but is acquired by the system through learning, have proven much more successful [3,4]. Whether called emotional control or merely an analog version of reinforcement learning with critic (evaluative control) , the method is increasingly being utilized by control engineers, robotic designers and decision support systems developers and yielding excellent results [5-8]. Although, for a long time, emotion was considered as a negative factor hindering the rational decision making process, the important role of emotions in human cognitive activities is progressively being documented by psychologists [9,10].

In this paper, we will apply an intelligent controller to output temperature tracking problem in a electrically heated micro heat exchanger plant [11,12]. First, the nonlinear behavior of the process is identified using a Locally Linear Model Tree (LOLIMOT) network [13-16] and then Brain Emotional Learning Based Intelligent Controller is applied to the plant. Using the proposed strategy, the tracking problem of the temperature profile will be tackled. The performance of the proposed controller is compared with that of a PID controller, which simulation results show better match for BELBIC.

2 Electrically heated micro heat exchanger

Electrically heated micro heat exchangers have been developed to accelerate the fluid and gas heating in a reduced space [11,12]. This system consists of a diffusion bonded metal foil stack with many grooves, the heating element are placed between the foils (Fig. 1). In a small volume, powers to 15 kW can be converted. The advantages of this heat exchanger are

• Fluids and gas heated by electrical power and not by additional flow cycle
• Efficient transformation of electrical energy in thermal energy
• Fast temperature change of the media and temperature good fit for sensitive media
• Compact construction due to micro system technology
Also, the results of that are
• Production of 45 °C warm water by an electric power of 14 kW and a flow of about 6 l/min
• Complete evaporation of water with a flow of 5 l/h
• Heating of an air stream in only 1 millisecond from 25 °C to 850 °C with an electrical power of 400 W and a flow of 2000 l/h
Its characteristics is listed in below
• Heat transmission coefficient: 17500 W m-2 K-1 (for water)
• Yield higher than 90%
• Ultimate electric power: 15 kW
• Pressure drop: 100 mbar for 5 l/h water-flow
• Dimensions: 95 mm * 30 mm * 35 mm
For the identification of the plant, the input-output data is used. For this plant, the voltage in the system input and the output temperature is the output.

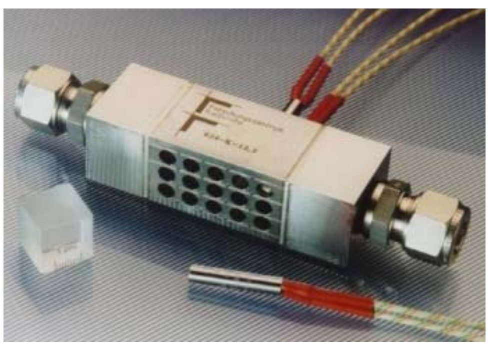

Fig. 1. Electrically heated micro heat exchanger.

3 Locally linear model tree identification of nonlinear systems

In the following, the modeling of nonlinear dynamic processes using LOLIMOT models is described. The network structure of a local linear neuro-fuzzy model [13,14] is depicted in Fig. 2. Each neuron realizes a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The validity functions form a partition of unity, i.e., they are normalized such that

$$\sum_{i=1}^{M} \varphi_i(\underline{z}) = 1 \qquad (1)$$

for any model input $\underline{z}$.

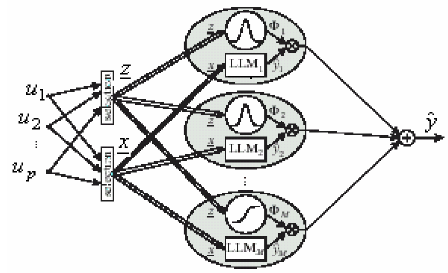

Fig. 2. Network structure of a local linear neurofuzzy model with *M* neurons for *nx* LLM inputs *x* and *nz* validity function inputs *z*.

The output of the model is calculated as

$$\hat{y} = \sum_{i=1}^{M} (w_{i,o} + w_{i,1}x_1 + \ldots + w_{i,n_x}x_{n_x})\varphi_i(\underline{z}) \qquad (2)$$

where the local linear models depend on $\underline{x} = [x_1, \ldots, x_{n_x}]^T$ and the validity functions depend on $\underline{z} = [z_1, \ldots, z_{n_z}]^T$. Thus, the network output is calculated as a weighted sum of the outputs of the local linear models where the $\varphi_i(.)$ are interpreted as the operating point dependent weighting factors. The network interpolates between different Locally Linear Models (LLMs) with the validity functions. The weights w_{ij} are linear network parameters.
The validity functions are typically chosen as normalized Gaussians. If these Gaussians are furthermore axis- orthogonal the validity functions are

$$\varphi_i(\underline{z}) = \frac{\mu_i(\underline{z})}{\sum_{j=1}^{M} \mu_j(\underline{z})} \qquad (3)$$

with

$$\mu_i(\underline{z}) = \exp\left(-\frac{1}{2}\left(\frac{(z_1 - c_{i,1})^2}{\sigma_{i,1}^2} + \ldots + \frac{(z_{n_z} - c_{i,n_z})^2}{\sigma_{i,n_z}^2}\right)\right) \qquad (4)$$

The centers and standard deviations are *nonlinear* network parameters.
In the fuzzy system interpretation each neuron represents one rule. The validity functions represent the rule premise and the LLMs represent the rule consequents. One-dimensional Gaussian membership functions

$$\mu_{i,j}(z_j) = \exp\left(-\frac{1}{2}\left(\frac{(z_j - c_{i,j})^2}{\sigma_{i,j}^2}\right)\right) \qquad (5)$$

can be combined by a t-norm (conjunction) realized with the product operator to form the multidimensional membership functions in (3).

Brain emotional based learning intelligent controller (BELBIC)

Motivated by the success in functional modeling of emotions in control engineering applications [17-19], the main purpose of this research is to use a structural model based on the limbic system of mammalian brain, for decision making and control engineering applications. We have adopted a network model developed by Moren and Balkenius [21], as a computational model that mimics amygdala, orbitofrontal cortex, thalamus, sensory input cortex and generally, those parts of the brain thought responsible for processing emotions. There are two approaches to intelligent and cognitive control. In the indirect approach, the intelligent system is utilized for tuning the parameters of the controller. We have adopted the second, so called direct approach, where the intelligent system, in our case the computational model termed BELBIC, is used as the controller block. The model is illustrated in Fig. 4. BELBIC is essentially an action generation mechanism based on sensory inputs and emotional cues. In general, these can be vector valued, although in the benchmark discussed in this paper for the sake of illustration, one sensory input and one emotional signal (stress) have been considered. The emotional learning occurs mainly in amygdala. The learning rule of amygdala is given in formula (6).

$$\Delta G_a = k_1.\max(0, EC - A) \qquad (6)$$

where G_a is the gain in amygdala connection, k_1 is the learning step in amygdala and EC and A are the values of emotional cue function and amygdala output at each time. The term $\max$ in the formula (6) is for making the learning changes monotonic, implying that the amygdala gain can never be decreased. This rule is for modeling the incapability of unlearning the emotion signal (and consequently, emotional action), previously learned in the amygdala [7,21]. Similarly, the learning rule in orbitofrontal cortex is shown in formula (7).

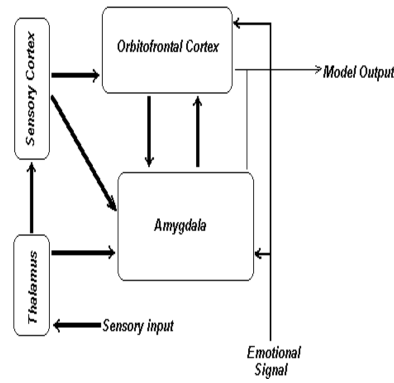

Fig. 4. The abstract structure of BELBIC

$$\Delta G_o = k_2.(MO - EC) \qquad (7)$$

where G_o is the gain in orbitofrontal connection, k_2 is the learning step in orbitofrontal cortex and MO is the output of the whole model, where it can be calculated as formula (8):

$$MO = A - O \qquad (8)$$

in which, O represents the output of orbitofrontal cortex. In fact, by receiving the sensory input S, the model calculates the internal signals of amygdala and orbitofrontal cortex by the relations in (9) and (10) and eventually yields the output.

$$A = G_a.S \qquad (9)$$

$$O = G_o.S \qquad (10)$$

Since amygdala does not have the capability to unlearn any emotional response that it ever learned, inhibition of any inappropriate response is the duty of orbitofrontal cortex.

Controllers based on emotional learning have shown very good robustness and uncertainty handling properties [17,18], while being simple and easily implementable. To utilize our version of the Moren-Balkenius model as a controller, we note that it essentially converts two sets of inputs into the decision signal as its output. We have implemented a closed loop configuration using this block (termed BELBIC) in the feed forward loop of the total system in an appropriate manner so that the input signals have the proper interpretations. The block implicitly implemented the critic, the learning algorithm and the action selection mechanism used in functional implementations of emotionally based (or generally reinforcement learning based) controllers, all at the same time [17-20]. The structure of the control circuit we implemented in our study is illustrated in Fig. 5. The functions we used in emotional cue and sensory input blocks are given in (11) and (12),

$$EC = W_1.e + W_2.CO + W_3.PO + W_4.\dot{e} \quad (11)$$

$$SI = W_5.e + W_6.\dot{e} + W_7.\int edt \quad (12)$$

where EC, CO, SI and PO are emotional cue, controller output, sensory input and plant output and the W_1 through W_7 are the gains must tuned for designing a satisfactory controller.

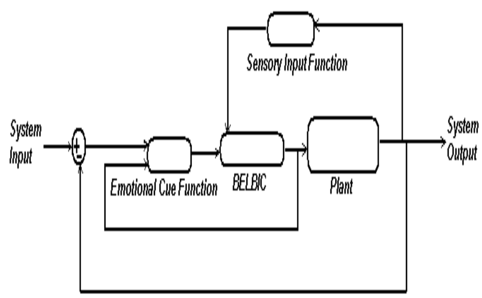

Fig. 5. Control system configuration using BELBIC

Simulation results

In this section, the simulation results of the output voltage tracking problem using BELBIC with LOLIMOT identifier will be presented. The input voltage profile for identification of the plant is depicted in Fig. 6. Using LOLIMOT algorithm, the identified output temperature as well as the actual values is depicted in Fig. 7. In the same figure, the error between the identified and actual values is shown. As it can be seen, the error is not considerable and the system is identified satisfactory. Now, we can apply BELBIC to the identified plant.

The closed-loop system response using BELBIC is shown in Fig. 8. In order to investigate the performance of BELBIC, we will provide another simulation using conventional PID controller. Using trail and error algorithm, the best values for PID controller in which the closed-loop system is stable and has almost satisfactory performance is adopted .

$$\text{PID Controller} \Rightarrow k_p + \frac{k_i}{s} + k_d s$$

The closed-loop system response using PID controller with above parameters is shown in Fig. 9. Comparing Fig. 8 with Fig. 9, we can see that the performance of the system using BELBIC is much better than that of PID controller. The system response using BELBIC is faster without any considerable overshoot on this highly nonlinear ,non minimum phase system.

Also BELBIC controller did not make acontrol effort much more than PID controller with the same undershoot and less overshoot in the reponse of plant.(Fig. 10 &11)

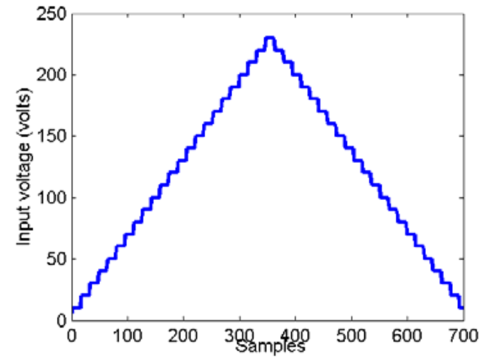

Fig. 6. Input voltage for system identification.

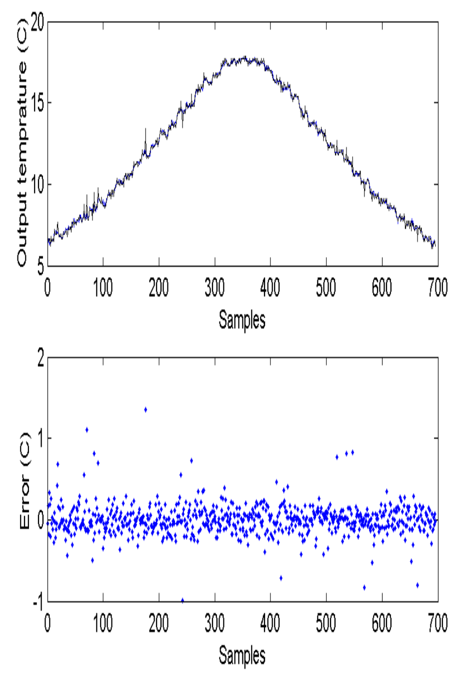

Fig. 7. The identified and actual output temperature with error between theses two values.

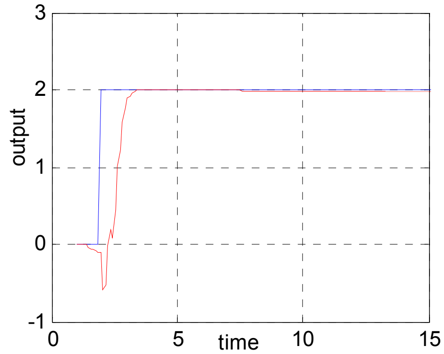

Fig. 8. Closed-loop system response using BELBIC with LOLIMOT identifier.

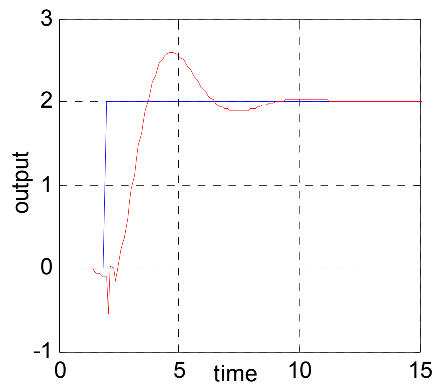

Fig. 9. Closed-loop system response using PID with LOLIMOT identifier.

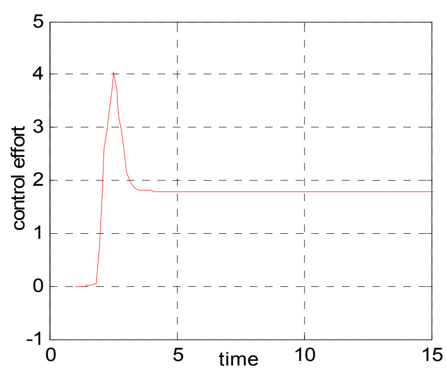

Fig. 10. Control signal of BELBIC controller

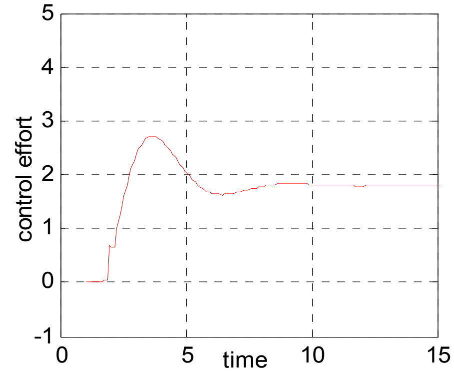

Fig.11. Control signal of PID controller

Conclusion

A Brain Emotional Based Learning Intelligent Controller (BELBIC) was applied to electrically heated micro heat exchanger, which is a highly nonlinear plant. To this end, the dynamics of the system was identified using Locally Linear Model Tree (LOLIMOT) algorithm. Then, BELBIC was applied to the system to tackle the output temperature tracking problem. The closed-loop system performance using BELBIC was compared with that of PID controller, which the result of BELBIC was much better that PID controller. BELBIC could settle faster with less distortion.

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