— Brief Paper —

INTELLIGENT MODELING AND CONTROL OF WASHING MACHINE USING LOCALLY LINEAR NEURO-FUZZY (LLNF) MODELING AND MODIFIED BRAIN EMOTIONAL LEARNING BASED INTELLIGENT CONTROLLER (BELBIC)

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ABSTRACT

Intelligent control of home appliances has, in recent years, attracted much theoretical attention, as well as becoming a major factor for industrial and economic success and rapid market penetration. Washing Machines represent an important market. Intelligent control techniques are capable of providing useful means for both easier use and energy and water conservation. In this paper, the authors use two techniques that have successfully been used in other intelligent modeling and control applications. Firstly, the authors use a neuro-fuzzy locally linear model tree system for data driven modeling of the machine. Secondly, the authors use a neural computing technique, based on a mathematical model of amygdala and the limbic system, for emotional control of the washing machine. The obtained results indicate the applicability of the proposed techniques in this important business sector.

KeyWords: Washing machine, locally linear neuro-fuzzy modeling (LLNF), brain emotional learning.

I. INTRODUCTION

Biologically motivated intelligent control is the discipline in which control algorithms are developed by emulating certain characteristics of intelligent biological systems. It is quickly emerging as a technology that may open avenues for significant advances in many areas. Among the intelligent methods, Fuzzy logic control laws can be designed based on some knowledge or without any knowledge of the control system. In addition, an appropriate fuzzy logic controller can overcome the environmental variation during operation processes [1]. Due to these characteristics, many plants and processes use fuzzy logic control [2-7]. Several attempts have been made to model the emotional behavior of human brain [8-10]. In [9] the computational models of amygdala and context processing were introduced. Based on the cognitively motivated open loop model, a new controller architecture called BELBIC-Brain Emotional Learning Based Intelligent Controller-was introduced [11], and utilized in several industrial application and control purposes [12-16]. In this work, a new controller based brain emotional learning is introduced. This controller modifies the BELBIC introduced in [11]. One of the core problems of BELBIC in [11] was its large control signal which can be reduced impressively using this modified version.

The first new washing machine was introduced to market at the end of the eighteenth century. After that, several brands of washing machines came to market. In the 1980s and 1990s, improvements in washing machine technology came very fast. In [17,18], a new sensing device and motor was introduced for washing machines. The new method proposed remote sensing of pressure inside the wash load of domestic washing machines via a wireless data acquisition system [19]. Intelligent and fuzzy logic based controllers for washing machines were also successfully introduced since the 90s and quickly gained sizable market share [20]. Besides, many other works have been done in design and control of washing machine electromotors [21-23]. In 1990, the first fuzzy controller for a washing machine was introduced by Matsushita Company. They used fuzzy controllers for auto-adjusting of motor cycle

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versus amount and kind of dirt and cloth volume. In fact, the fuzzy control system had three inputs and one output, using optic sensors for measuring inputs [24]. Later, intelligent washing machines gained popularity all over the world. Hitachi washing machines used fuzzy controllers with amount of cloth and quality of cloth as inputs and automatically set the wash cycle for the best use of power and water [1]. In [25-27] a rather sophisticated finite element model of washing machine was presented. The System Identification approach, on the other hand, seeks to estimate the model of the washing machine based on observed input-output data. Several ways to describe a system and to estimate such descriptions exist. The procedure to determine the model of a dynamical system from observed input-output data involves three basic ingredients: 1. the input-output data 2. a set of candidate models (the model structure) 3. a criterion to select a particular model in the set, based on the information in the data (the identification method) [28]. In this paper, a lumped model for washing machines is introduced. The Locally Linear Model Tree (LoLiMoT) neuro-fuzzy algorithm [28-30] has been used for modeling the washing machine. Next, the brain emotional learning based intelligent controller (BELBIC) is applied to the model of washing machine. The results show the proposed controller has satisfactory control performance. This controller receives feedback from plant in its sensory inputs and punishments and awards from reward inputs. A cost function showed energy consumption is used to prepare the reward signal for controller, *i.e.*, as the cost increases, the reward input receives punishment, and vice versa. The rest of paper is as follows: in section II, the data used for identification of the washing machine is obtained. In section III, Locally Linear Neuro-Fuzzy (LLNF) modeling will be discussed. In section IV, a novel control method based on mammalian limbic emotional learning is proposed. The modeling of washing machine based previously extracted data with LLNF is implemented in section V, and finally, the proposed controller (BELBIC) is applied to washing machines in section VI.

II. EXTRACTING DATA

For extracting data, the real washing machine, simple model of washing machine was used. For obtaining data, the washing machine was operated in different conditions. Figures 1 ~ 4 shows a cross section of the data for fixed detergent and water volumes. Each data set was derived for a fixed heater temperature. In other words, in each regime it is assumed the heater temperature is constant and a step motor speed with different level is applied. The complete data, for different detergent levels and water volumes, was used for plant identification. Note that S, HT, D, WV, and WT are abbreviations of Speed, Heater Temperature, Detergent, Water Volume and Water Temperature, respectively. The range of inputs and output variables are as follows:

Table 1. Variation range.

Variable	range
Water Volume (liter)	0 ~ 20
Heater Temperature (°C)	15 ~ 70
Detergent	0 ~ 100%
Motor speed (rpm)	0 ~ 1500
Water temperature (°C)	0 ~ 70
Dirt (g/liter)	0 ~ 5.7
Wash time (min)	0 ~ 50

III. LOCALLY LINEAR NEURO-FUZZY IDENTIFICATION OF NONLINEAR SYSTEMS

The training algorithm LoLiMoT is found out to be rapid, precise, self tuned and more user friendly than other conventional methods for the training of neuro fuzzy networks which makes it more acceptable in online control applications [28-30]. The model based on this training algorithm is used in the following process control.

The network structure of a local linear neuro fuzzy model is depicted in Fig. 5. Each neuron realizes a Local Linear Model (LLM) and an associated validity function that determines the region of validity of the LLM. The network output is calculated as a weighted sum of the outputs of the local linear models, where the validity function is interpreted as the operating point dependent weighting factors. The validity functions are typically chosen as normalized Gaussians.

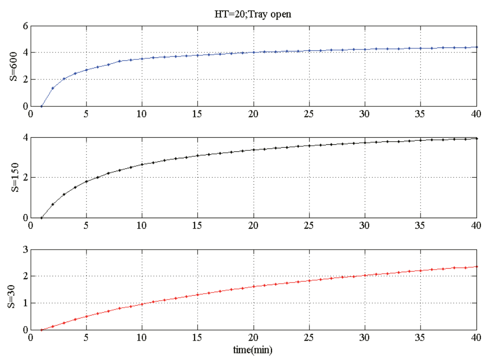

Fig. 1. Variation of dirt (g/liter) in washing machine at three different motor speeds at HT = 20.

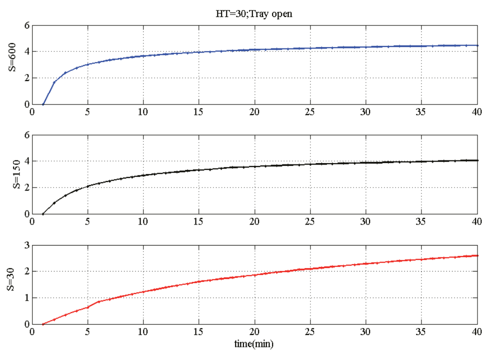

Fig. 2. Variation of dirt (g/liter) in washing machine at three different motor speeds at HT = 30.

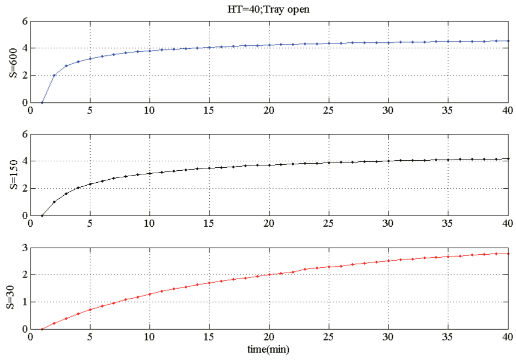

Fig. 3. Variation of dirt (g/liter) in washing machine at three different motor speeds at HT = 40.

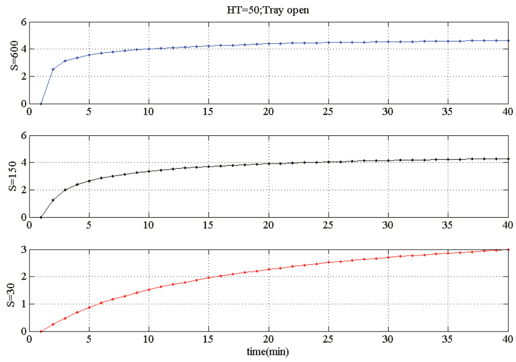

Fig. 4. Variation of dirt (g/liter) in washing machine at three different motor speeds at HT = 50.

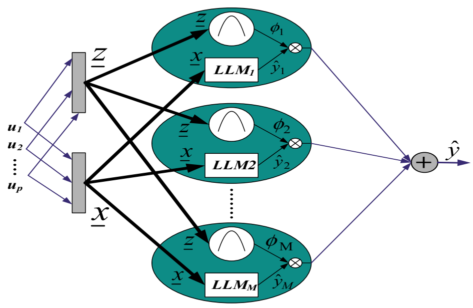

Fig. 5. Network structure of a local linear neuro-fuzzy model.

The local linear modeling approach is based on a divided-and-conquer strategy. A complex washing machine model is divided into a number of smaller and thus simpler sub-problems, which are solved independently by identifying simple linear models [28-30]. The most important factor for the success of such an approach is the division strategy for the original complex problem. This will be done by an algorithm named LoLiMoT (Locally Linear Model Tree).

LoLiMoT is an incremental tree-construction algorithm that partitions the input space by axis-orthogonal splits [28]. In each of the algorithm iterations, a new rule or local linear model is added to the model, and the validity functions that correspond to the actual partitioning of the input space are computed. In addition, the corresponding rule consequences are optimized by a local weighted least squares technique.

IV. MODIFIED BRAIN EMOTIONAL LEARNING BASED INTELLIGENT CONTROLLER (BELBIC)

There are many works that have been done for modeling of emotional learning. A recent work on a computational model of emotional learning in the brain by Morene and Balkenius [8,9] is used in this research introduced as a novel controller. In [11], a controller is introduced based on the Morene and Balkenius work called BELBIC. In this work, this controller is modified. The main drawback of BELBIC is its large control signal which is reduced greatly in this version. The main modification introduced with respect to the original version of BELBIC is the insertion of the terms S_i in Eqs. (3) and (4), and usage of thalamic inputs. This brings the model closer to what was originally proposed by Moren and Balkenius [8,9].

The proposed BELBIC is divided into two parts, very roughly corresponding to the amygdala and the obritofrontal cortex, respectively. The amygdaloidal part receives inputs from the thalamus and from cortical areas, while the orbital part receives inputs from the cortical areas and the amygdale only. The system also receives a reinforcing signal.

As shown in Fig. 6, there is one A node for every stimulus S, including one for the thalamic stimulus. There is also one O node for each of the stimuli except for the

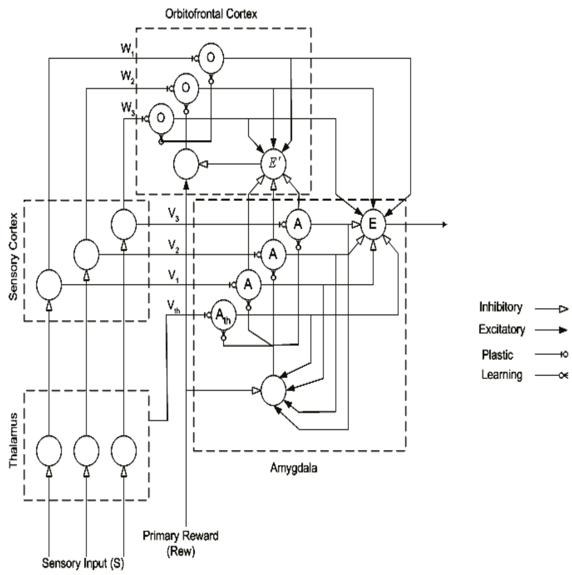

Fig. 6. A graphical depiction of the BELBIC. At the top is the primarily orbitofrontal part, at the bottom right is the amygdaloid part and at left are the thalamic and sensory cortical modules. The sensory inputs S enter the thalamic part, where a thalamic input to the amygdala is calculated as the maximum over all inputs. A primary reward signal R_w enters both the amygdaloid and orbitofrontal parts.

thalamic node. There is one output node in common for all outputs of the model, called E. The E node simply sums the outputs from the A nodes, then subtracts the inhibitory outputs from the O nodes. The result is the output from the model. The E' node is sums the outputs from A except A_{th} and then subtracts from inhibitory outputs from the O nodes. The BELBIC equations are as follow:

$$E = \sum_i A_i - \sum_i O_i \quad (\text{include } A_{th}) \tag{1}$$

$$E' = \sum_i A_i - \sum_i O_i \quad (\text{not include } A_{th}) \tag{2}$$

where

$$A_i = S_i V_i \tag{3}$$

$$O_i = S_i W_i \tag{4}$$

$$A_{th} = \max(S_i) \tag{5}$$

The learning rules in amygdale and orbitofrontal are as follow:

$$\Delta V_i = k_a \left(S_i \max(0, R_w - \sum_j A_j) \right) \tag{6}$$

$$\Delta W_i = k_0 \left(S_i (E' - R_w) \right) \tag{7}$$

where k_a, k_0, W_i, V_i, and R_w are adjusting terms for the learning factor of amygdale, the learning factor of orbitofrontal, amygdale gain, orbitofrontal gain, and the reinforcement signal respectively.

As is evident, the orbitofrontal learning rule is very similar to the amygdaloid rule. The only – but essential – difference is that the orbitofrontal connection weight can both increase and decrease as needed to track the required inhibition.

Note that since amygdala does not have the capability to unlearn any emotional response that it has learned, inhabitation of any inappropriate response is the duty of orbitofrontal cortex. In other words, this system works at two levels: the amygdaloidal part learns to predict and react to a given reinforcer. This subsystem can never unlearn a connection; once learned, it is permanent, giving the system the ability to retain emotional connections for as long as necessary. The orbitofrontal system tracks mismatches between the base systems predictions and the actual received reinforcer and learns to inhibit the system output in proportion to the mismatch.

The reinforcing signal R_w comes as a function of other signals which can be supposed to be a cost function validation, *i.e.* award and punishment are applied based on a predetermined cost function.

$$R_w = J(S_1, S_2, \ldots, S_n, E, PO_1, \ldots, PO_m) \tag{8}$$

Where PO_i is one of the outputs of plant.

In the same way, the sensory inputs must be a function of the plant outputs and the controller outputs as follows:

$$S_i = f(E, PO_1, \ldots, PO_m) \tag{9}$$

In Fig. 7 the block diagram of these control method is depicted.

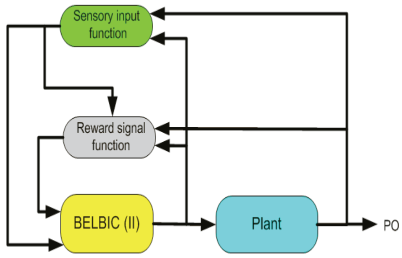

Fig. 7. Control system configuration using BELBIC.

V. IDENTIFICATION OF WASHING MACHINE

In this part, a Locally Linear Neuro Fuzzy Modeling (LLNF) method [28-30] is used to identify a washing machine based on the data which is extracted from a physical washing machine as discussed in Section II.

As shown in Fig. 8, the proposed model of washing machine has four inputs and two outputs. The inputs are motor speed, heater temperature, detergent and water volume, while the outputs are water temperature and cloth dirt.

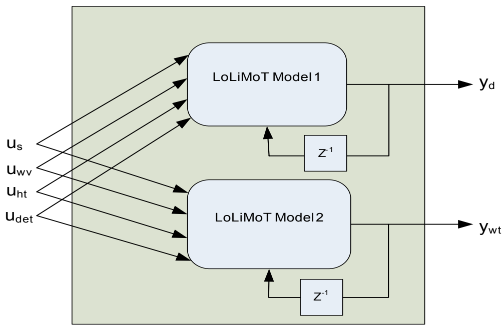

Fig. 8. Configuration of proposed washing machine.

An examination of the empirical data suggests first order models for the amount of cloth dirt dissolved in the washing machine water and water temperature as a minimal model.

$$\mathrm{dirt}(t) = f\left(\text{heater temperature, motor speed, } \mathrm{dirt}(t-1)\right) \tag{10}$$

In the case of locally linear identification, the most imperative concern is the number of neurons. It is desirable that the number of neurons be as small as possible. The number of neurons has been obtained based on sum of squared error curve. The number of outputs determines the number of Locally Linear Neuro-Fuzzy networks, so the proposed model of washing machine has two parallel LLNF networks. As shown in Fig. 9, the optimal number of neurons for the first LLNF network, which has dirt as its output, is about twenty. More neurons do not result in a significant reduction of error. Similarly, for the second LLNF network, which has the water temperature as its output, the number of neurons is 13 neurons. Next, using the Locally Linear Model Tree (LoLiMoT) algorithm, a model is fitted to the data. Below are the brief five basic steps to identify the washing machine model [28-30]:

1. Start with an initial model of washing machine.
2. Find worst Locally Linear Model that has maximum local loss function.
3. Check all hyper-rectangles to split (through).
   (3a) Construction of the multi-dimensional MSFs for both hyper-rectangles.
   (3b) Construction of all validity functions.
   (3c) Local estimation of the rule consequent parameters for both newly generated LLMs.
   (3d) Calculation of the loss functions for the current overall model.
4. Find best division (the best of the n_z alternatives checked in Step 3, and increment the number of LLMs: $M \rightarrow M + 1$).
5. Test for convergence.

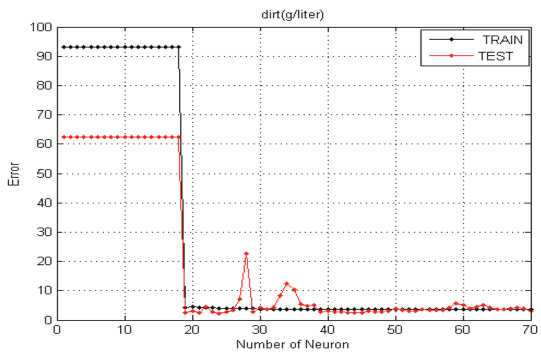

Fig. 9. The variation of sum square error of dirt.

VI. CONTROLLER DESIGN

Determination of water volume is dependant on the amount of clothes to be washed and is determined by inverse dynamic method. At first, a little water is let into washing tub, and the motor is powered on, thereby turning the rotor in the tub and causing the water and clothes to start rotating. This turns the motor into a dynamo, which generates a small amount of electrical power. The length of time during which power is generated in this way is measured, and the measurement is used as an indicator of the amount of cloth: A larger amount produces greater inertia, leading to longer generation time. Thus, the amount of water can be inferred from amount of clothes [21]. In this study, the researchers consider amount of cloth and thus water volume constant and assumed as 15 liters.

The performance of the BELBIC controller and identified washing machine model is examined through simulation studies using the SIMULINK toolbox of the MATLAB software. The proposed BELBIC controller for the washing machine has three sensory inputs and a reward signal. Three parallel BELBICs are applied on the washing machine model as a controller. The reward inputs of all three BELBICs are the same. As described in Section IV, the reward function's job is to provide punishment and reward for BELBIC, so it is expected that the reinforcement signal is large when the cost function is high and vice versa. The researchers consider a quadratic cost function which is a function of motor speed, heater temperature, detergent and dirt as follows:

$$J = w_1 E_s^2 + w_2 E_{ht}^2 + w_3 E_{\det}^2 + w_4 (PO_{\text{dirtss}} - PO_{\text{dirt}})^2 \tag{11}$$

where the steady state value PO_{dirtss} is an offline empirically determined value, and J is chosen to seek a suitable trade-off between achieving desired washing quality and avoiding excessive control efforts; the w_1, w_2, w_3, and w_4 are constant. The authors have used the following values for them:

$$w_1 = 0.002,\ w_2 = 0.01,\ w_3 = 0.001,\ w_4 = 0.1 \tag{12}$$

Note that the dirt is used as an indicator for wash time. In other words, we don't use dirt directly but we use its difference from its steady state value. The washing machine process ceases when $d(\text{dirt})/dt \cong 0$ or when dirt reaches its steady state value.

As discussed in Section IV, BELBIC receives other inputs called sensory inputs. In this work, three sensory inputs are used, each of which gets a feedback from plant outputs. The functions which were used for the sensory inputs are as follows:

$$S_1 = (PO_{\text{dirtss}} - PO_{\text{dirt}}) / PO_{\text{dirtss}} \tag{13}$$

$$S_2 = (PO_{\text{dirtss}} - PO_{\text{dirt}} + 0.1 PO_{\text{dirt}}^2) / PO_{\text{dirtss}} \tag{14}$$

$$S_3 = (PO_{\text{dirtss}} - PO_{\text{dirt}} + 0.3 PO_{\text{dirt}}^2) / PO_{\text{dirtss}} \tag{15}$$

In Figs. 10 ~ 19, the BELBIC and washing machine inputs and outputs are depicted for a washing cycle. As shown in Fig. 13, earlier in the washing machine cycle, the amount of reward is small due to the learning stage and small control efforts. However, in the post learning stage, the reward signal increases quickly to reduce the cost function. Figures 14 ~ 19 show inputs and outputs of the washing machine during a washing cycle. Note that the variation of inputs and outputs are dependant on the defined cost function. In addition, the energy consumption (cost function) of this controller is compared with a fuzzy controller similar to what is described in [21]. In Figs. 10 ~ 12, the sensory inputs of BELBIC are shown. Three membership labels, *i.e.* small, medium and large are used, and the fuzzy controller utilizes a Mamdani fuzzy interface. The results show that the proposed controller consumes 21% less

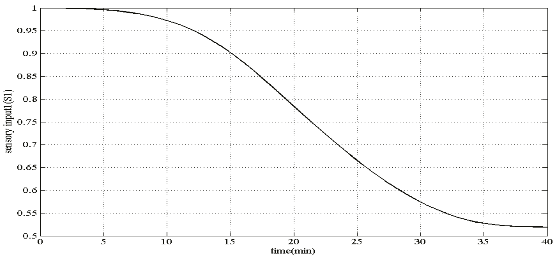

Fig. 10. The first sensory input of BELBIC controller in the washing cycle.

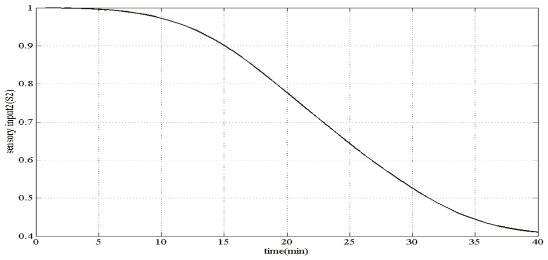

Fig. 11. The second sensory input of BELBIC controller in the washing cycle.

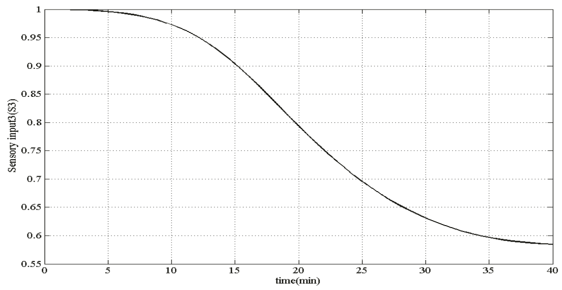

Fig. 12. The third sensory input of BELBIC controller in the washing cycle.

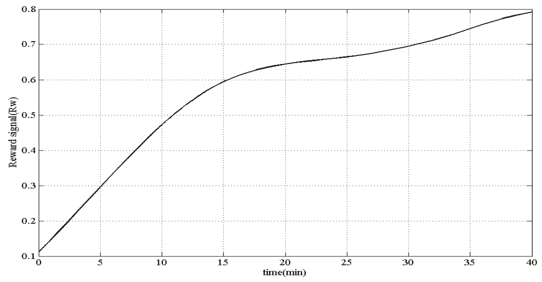

Fig. 13. Variation of Reward signal in the washing cycle.

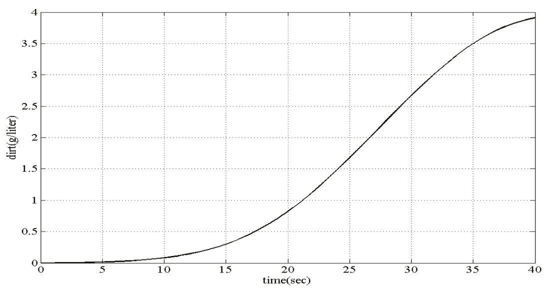

Fig. 14. Variation of dirt output in the washing cycle.

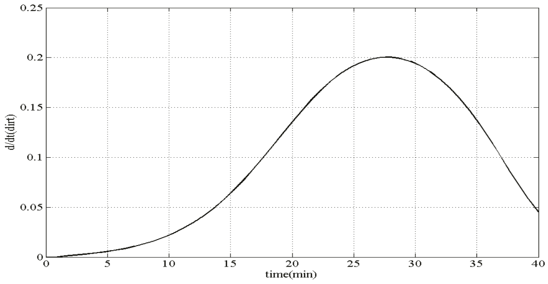

Fig. 15. Variation of $\dfrac{d(\text{dirt})}{dt}$ output in the washing cycle.

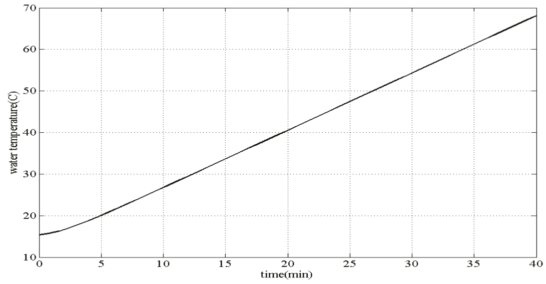

Fig. 16. Variation of water temperature output in the washing cycle.

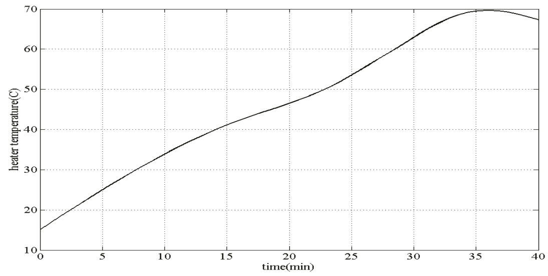

Fig. 17. Heater temperature variation in the washing cycle.

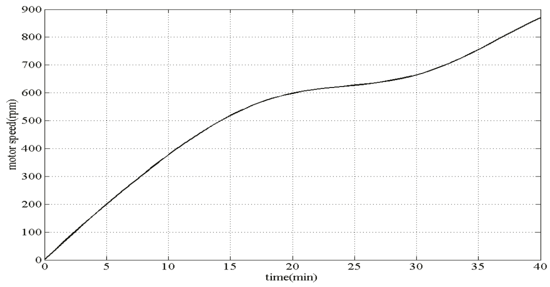

Fig. 18. Motor speed variation in the washing cycle.

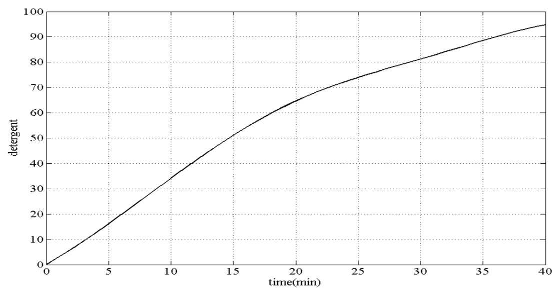

Fig. 19. Detergent variation in the washing cycle.

energy than the fuzzy controller. In Fig. 20, the variations of these two controllers are compared. It can be seen that in the beginning of washing process, the fuzzy controller leads to a smaller cost than BELBIC, but, after a while, the emotional learning helps BELBIC overcome the fuzzy controller and incur a smaller cost function.

For a more thorough investigation of the BELBIC behavior, its performance is examined in the Figs. 21 ~ 25 when an additive noise is inserted in washing machine output. As evident from Figs. 21 ~ 22, the outputs of the washing machine vary considerably smoothly. On the other hand, the inputs of the washing machine vary in order to reject the noise (Figs. 23 ~ 25).

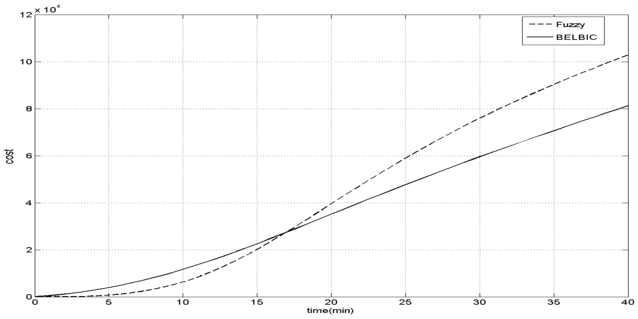

Fig. 20. Variation of cost function using BELBIC and fuzzy controller.

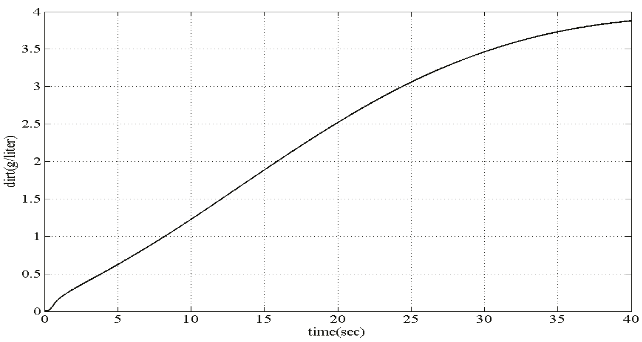

Fig. 21. Variation of dirt as the first output when washing machine is exposed to noise.

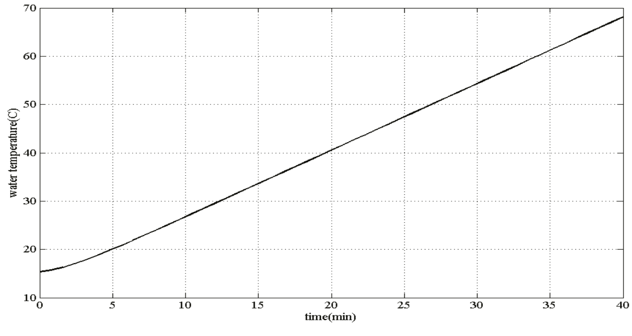

Fig. 22. Variation of water temperature as the second output when washing machine is exposed to noise.

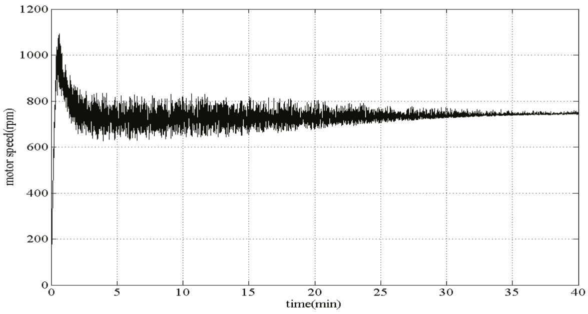

Fig. 23. Motor speed (washing machine input) variation when washing machine is exposed to noise.

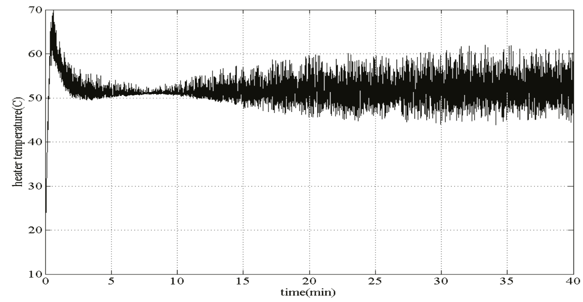

Fig. 24. Heater temperature (washing machine input) variation when washing machine is exposed to noise.

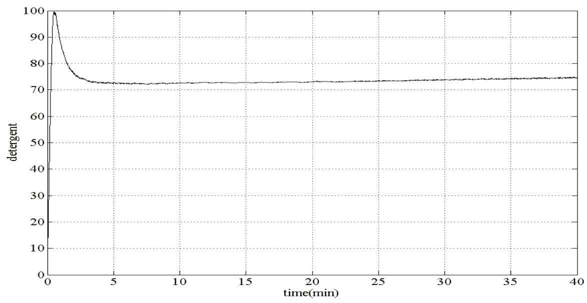

Fig. 25. Detergent (washing machine input) variation when washing machine is exposed to noise.

VII. CONCLUSIONS

In this paper, the washing machine was first identified by a Locally Linear Neuro-Fuzzy (LLNF) network based on data extracted from a washing machine operated in different regimes. Then, a novel controller, BELBIC, was proposed based on the emotional learning process in the mammalian brain. This controller was based on those parts of brain that are thought to play the most important roles in brain emotion processing: Thalamus, Sensory Cortex, Orbitofrontal Cortex and Amygdala. The proposed BELBIC and washing machine model were simulated, and the results were very satisfactory. Finally the energy consumption of this controller and another intelligent controller based on fuzzy expert rules were compared showing that further conservation of energy is achievable through using BELBIC.

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