

# **A Review of Emotional Learning And It's Utilization in Control Engineering**

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## **Abstract**

*In mammals, brain Limbic System is responsible for emotional process. An important part of motor learning as well as attention is formed by the system. Brain Emotional Learning (BEL) process of mammals has been mathematically modeled. Based on the model, a controller architecture called Brain Emotional Learning Based Intelligent Controller (BELBIC) has been developed. Emotional Learning is a powerful methodology in real time control and decision systems due to low computational complexity and fast training where the gradient based methods and evolutionary algorithms are hard to be applied because of their high computational complexity. In this paper, the emotional processes and the Limbic System will be reviewed. In addition, the utilization of BELBIC model in variety of applications of control system will be examined. The results of simulations demonstrate control systems based on BELBIC have good performances.*

**Keywords:** *Limbic System, Emotional Learning, BELBIC, Control System*

## **1 Introduction**

The design of intelligent systems has received considerable attentions in recent years. Control techniques based on Artificial Neural Networks [1], Fuzzy Control [2] and Genetic Algorithms [3] are among them. Emotional Learning is a psychologically motivated algorithm which is a family of intelligent algorithms [4].

Recently, biologically motivated intelligent computing has been successfully employed for solving different types of problems [5, 6, 7, 8, 9]. The greatest different of an intelligent system from a traditional one is the capability of learning. A common attribute of the learning process is the adaptation of the system parameters to better tackle the changing environment. An evaluation mechanism is necessary that any learning algorithm assesses the operating condition of the system. One type of evaluation is based on emotional cues, which evaluate the impact of the external stimuli on the ability of the system both to function effectively in the short term and to maintain its long term prospects for survival [10]. Emotional learning is one of the learning strategies based on emotional evaluations. In mammalian brains, this learning process occurs in the brain Limbic System [11].

Moren and Balkenius [12, 13] presented a neurologically inspired computational model of the Amygdala and the Orbitofrontal Cortex in the Limbic System. Based on this model, a control algorithm called Brain Emotional Learning Based Intelligent Controller (BELBIC) has been suggested [14]. There are two approaches of applying the brain emotional learning model into control systems, direct approach and indirect approach. The former uses BEL model as the controller block, while the latter utilizes BEL model to tune the controller parameters.

In [10], the model was adapted for applications in control systems and the applicability of the model is verified by simulating it in controlling different systems with increasing complexity. The results of designing a BEL and a PID controller showed that the responses of the BEL controller were faster with lower overshoot when compared with the PID responses. In addition, the robustness of the BEL controller with respect to changes in the system parameters and the input disturbances was much more robust to these variations rather than the PID controllers.

In real time control and decision systems, Emotional Learning is a powerful methodology due to its simplicity, low computational complexity and fast training where the gradient based methods and evolutionary algorithms are hard to be applied because of their high computational complexity [15, 16, 17, 18, 19, 20].

Lately, many engineering systems are proposed by BELBIC such as power system [21], active queue management [22], washing machine [23], aerospace launch vehicle [24], interior permanent magnet synchronous motor system [25], micro-heat exchanger [26], flight simulation servo system [27], delayed systems [28] and other uncertain nonlinear systems [29]. The BELBIC has been designed for SISO<sup>1</sup> applications and for MIMO<sup>2</sup> systems, we must employ each controller for generating one control output [10, 30, 31]. The relevant researches have indicated that BELBIC has a good robustness and performance. Particularly, it is

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<sup>1</sup> Single Input Single Output

<sup>2</sup> Multi Input Multi Output

very powerful in disturbance handling and robust with respect to parameter changes because of its appropriate learning ability [14].

In this paper, we introduced an intelligent controller, BELBIC, based on mammalian limbic Emotional Learning algorithms. The performance of BELBIC in several applications is demonstrated. Taking into account the short introduction given in Section 1 above, this paper, furthermore, tries to have a look into the following sections: In section 2, the architecture of the Limbic System is briefly reviewed. The problem formulations will be explained in section 3. In section 4, Brain Emotional Learning Based Intelligent Controller will be described. Control system applications are illustrated in section 5 and finally in section 6, summary and conclusion are presented.

## 2 Architecture of the Limbic System

The Limbic System, as part of the mammalian creatures' brain, is mainly in charge of the emotional processes. The Limbic System located in the cerebral cortex consists mainly of following components: Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Cortex, Hypothalamus, Hippocampus and some other less important areas.

In this section, we try to describe briefly these main components and their tasks. Fig. 1 illustrates the anatomy of the main components of Limbic System [32]. The first sign of affective conditioning of the system appears in Amygdala which is a small almond-shaped in sub-cortical area. This component is placed in a way to communicate with all other Sensory Cortices and areas within the Limbic System.

The Amygdala connections to/from other components are illustrated in Fig. 2 [13]. The studies show that a stimulus and its emotional consequences are associated in the Amygdala area [33, 34]. In this region, highly analyzed stimuli in the Sensory Cortices, as well as coarsely categorized stimuli in the Thalamus are associated with an emotional value.

In a reciprocal connection, the Orbitofrontal Cortex, as of another component of the brain system, interacts with the Amygdala. The main interrelated function of this component is: *Working Memory, Preparatory Set and Inhibitory Control* [35]. The current and recent past events are represented in the *Working Memory*. The Preparatory Set is the priming of other structures in anticipation of impending action. Inhibitory Control is the selective suppression of areas that may be inappropriate in the current situation. More specifically, the Orbitofrontal Cortex takes action in omission of the expected reward or punishment and control the extinction of the learning in the Amygdala [34].

Another component in this area is Thalamus which lies next to the basal ganglia. It is a non-homogeneous sub-cortical structure and a way-station between cortical structures and sub-cortical. Moreover, various parts of the Thalamus also relay the majority of sensory information from the peripheral sensory systems to the Sensory Cortices [36]. Particularly, the Thalamic Sensory Inputs going to the Amygdala are believed to mediate inherently emotionally charged stimuli as well

as coarsely resolved stimuli in general [37]. The Thalamus signal going to the Amygdala evades the processes involved in the Sensory Cortex and other components of the system. Therefore, Amygdala receives a non-optimal but fast stimulus from the Thalamus which among the input stimuli is often known as a characteristic signal [36].

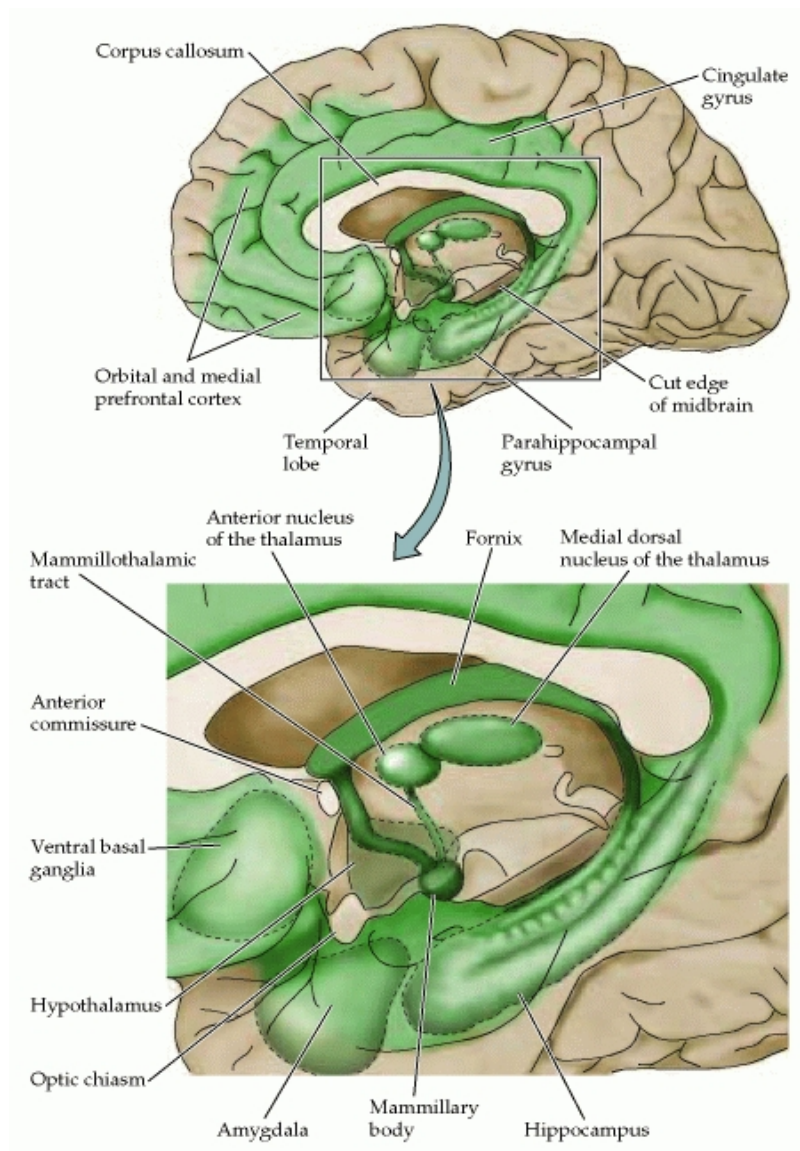


Fig. 1: The major brain structures associated with the Limbic System [32]

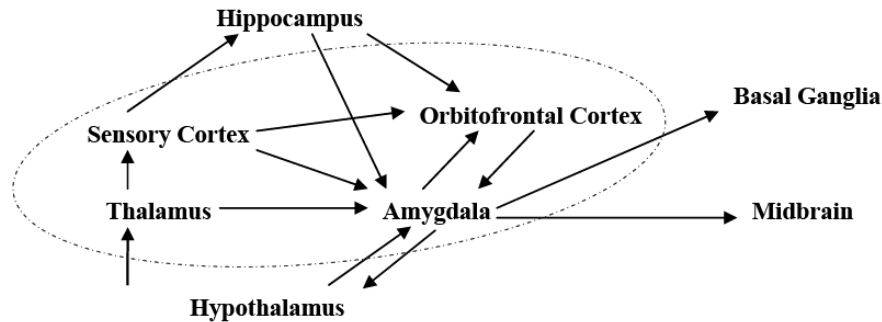


Fig. 2: Connections of the Amygdala with other components of the Limbic System [13]

The next component is the Sensory Cortex close to the Thalamus which receives its input from the latter one. In fact, Sensory Cortex processes the information from the sensory areas. The Sensory Cortex sends highly analyzed input to the Amygdala and Orbitofrontal [33, 34, 38]. Generally, the mammals use these areas of their Limbic System for higher perceptual processing.

Below the Thalamus, lies another component named Hypothalamus which is apparently in charge of regulation of the endocrine system, the autonomous nervous system and primary behavioral surviving states [39]. The lateral region of Hypothalamus is connected to various regions of the Amygdala and vice versa. The connections are believed to have a major role in motivational control of the Structures within the Hypothalamus [40].

Furthermore, one of the most complex and twisting components of the Limbic System is Hippocampus which is located in the same area as the Amygdala. Its main role is the mapping of the environment based on environmental cue. The Hippocampus has other functions such as spatial navigation, laying down of the long-term memory and formation of the contextual representations [41].

In addition to the components mentioned here above, there are other components which have specific role in the Limbic System. To that extent, components such as Basal Ganglia, Globus Pallidus, Substantia Nigra, Subthalamic Nucleus and Periamygdaloid Cortex could be mentioned. Since in this paper, biological description of the Limbic System is not under focus, it has been tried to avoid detailed and comprehensive explanation of each component. We deal with the key characteristics components in the System.

### 3 Problem Formulations

Moren and Balkenius [12, 13] developed a computational model that mimics Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Input Cortex and generally

those parts of the brain thought responsible for processing emotions. Fig. 3 shows the computational model of emotional learning [12]. The model is divided into two parts: the Amygdala and the Orbitofrontal cortex. The Amygdala part receives inputs from the Thalamus and from cortical areas, while the Orbitofrontal cortex obtains inputs from the cortical areas and the Amygdala. The system also receives a reinforcing signal (Primary Reward) which has been left unspecified, as it is still uncertain from where it comes.

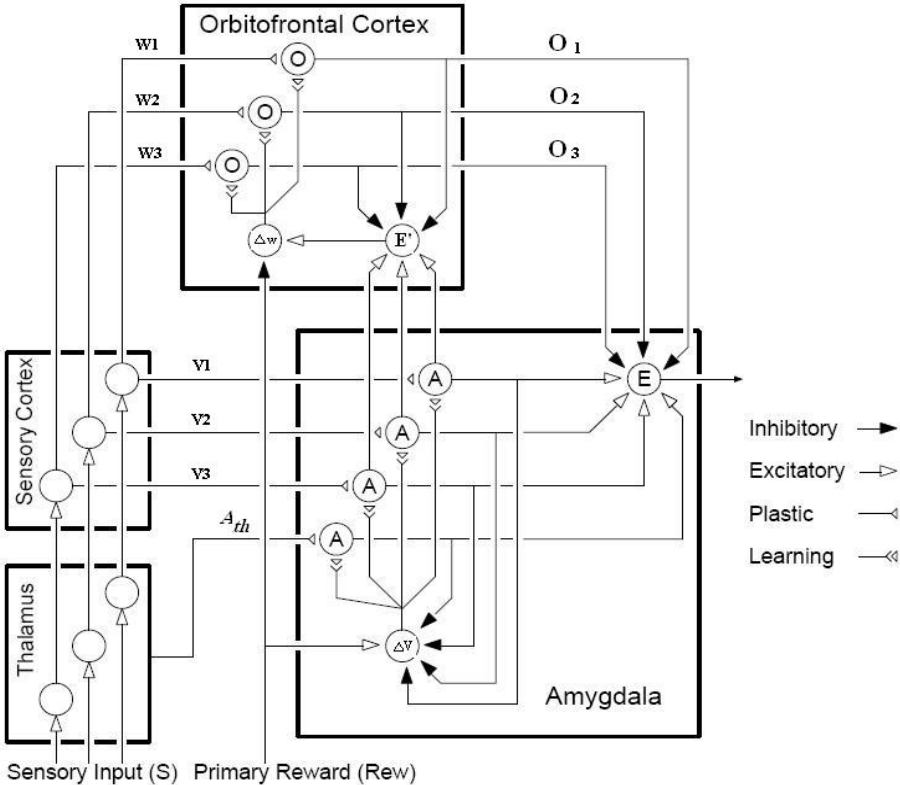


Fig. 3: Graphical depiction of the Brain Emotional Learning (BEL) process [12]

The vector  $S$  shows stimuli inputs to the system. There is one  $A$  node for each stimulus  $S$ .  $A_{th}$  is another input to the Amygdala part which is the maximum of stimuli inputs( $S$ ):

$$A_{th} = \max (S_i) \tag{1}$$

There is a plastic connection weight  $V$  for each  $A$  node. The output of each node obtains by multiplying any input with the weight  $V$ .

$$A_i = S_i V_i \quad (2)$$

The  $V_i$  is adjusted proportionally to the difference between the activation of the  $A$  nodes and the reinforcement signal  $Rew$ . The  $\alpha$  term is a constant used to adjust the learning speed:

$$\Delta V_i = \alpha (S_i \max(0, Rew - \sum_j A_j)) \quad (3)$$

The weights  $V$  cannot decrease. It is good reasons for this design choice because once an emotional reaction is learned, this should be permanent and cannot be unlearned. It is the task of the Orbitofrontal part to inhibit this reaction when it is inappropriate. The Orbitofrontal learning rule is very similar to the Amygdala rule but the Orbitofrontal connection weight can both increase and decrease. The  $O$  nodes behave analogously, with a connection weight  $W$  employed to the input signal to create an output.

$$O_i = S_i W_i \quad (4)$$

$\beta$  is another learning rate constant.  $\Delta W_i$  is calculated as:

$$\Delta W_i = \beta (S_i (E' - Rew)) \quad (5)$$

The  $E$  node simply sums the outputs from the  $A$  nodes and then subtracts the inhibitory outputs from the  $O$  nodes. The result is the output from the model. The  $A$  nodes give outputs proportionally to their contribution in predicting the reward  $Rew$ , while the  $O$  nodes inhibit the output of  $E$  as necessary. The  $E'$  node is sums of the outputs from  $A$  except  $A_{th}$  and then subtract from inhibitory outputs from the  $O$  nodes.

$$E = \sum_i A_i - \sum_i O_i \text{ (including } A_{th}) \quad (6)$$

$$E' = \sum_i A_i - \sum_i O_i \text{ (not including } A_{th}) \quad (7)$$

## 4 Brain Emotional Learning Based Intelligent Controller

Based on the cognitively motivated open loop model, BELBIC- Brain Emotional Learning Based Intelligent Controller- was introduced by Lucas et al [14]. The intelligent controller has been utilized by several industrial applications and control purposes [23, 42]. The model of Fig. 3 is illustrated as control blocks in

Fig. 4 [14]. The BELBIC is essentially an action generation mechanism based on sensory inputs and emotional cues (Reward signals). The BELBIC equations are the mentioned formulas of (1) - (7).

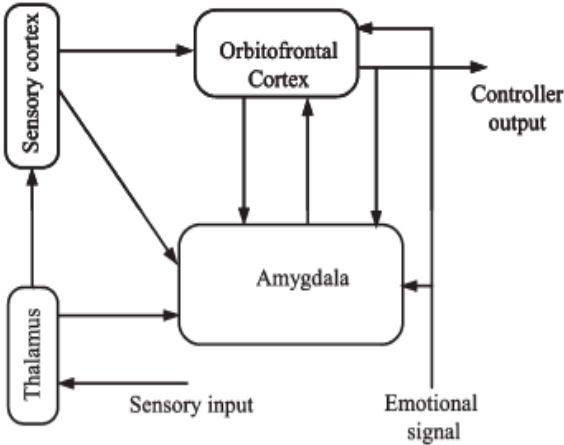


Fig. 4: Basic block structure of emotional controller [14].

Fig. 5 demonstrates a reasonable candidate for embedding the BELBIC model within a typical feedback control block diagram [14]. The implemented functions in emotional cue and sensory input blocks should be defined for each application [14].

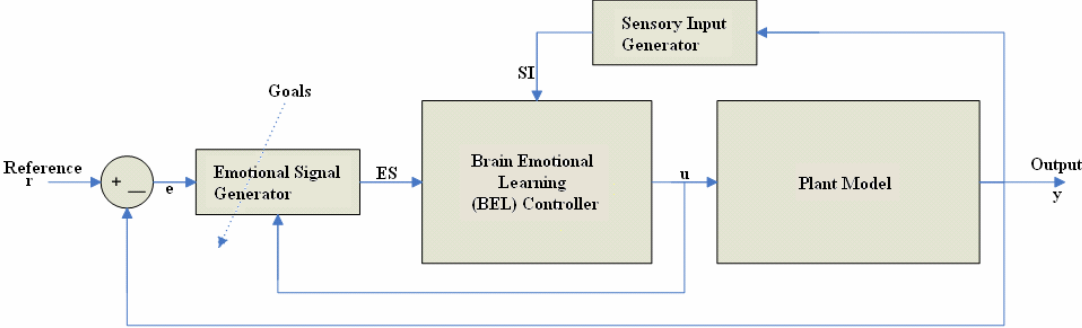


Fig. 5: Control system configuration using BELBIC [14]

### 5 Control System Applications

The rationale for using emotional learning in control engineering has been previously established [9, 43]. The main issue in using the model for different



applications is defining the sensory and emotional signals in such a way that properly represent the state and objectives of the system. Some of researchers have developed intelligent systems based on BELBIC which in this section some of the designed applications are briefly introduced and the results of simulation are demonstrated in some applications.

Rouhani and co-workers [26] used BELBIC in a neuro-fuzzy model of micro-heat exchanger. First, a locally linear learning algorithm called Locally Linear Mode Tree (LoLiMoT) was applied to build the neuro-fuzzy model. Then, the BELBIC based on PID control was adopted for the micro-heat exchanger plant. The performance of presented controller was compared with classic PID controller. Fig. 6 and Fig. 7 show the closed-loop system response using BELBIC and PID controller respectively. As shown the performance of the system using BELBIC is much better than that of PID controller.

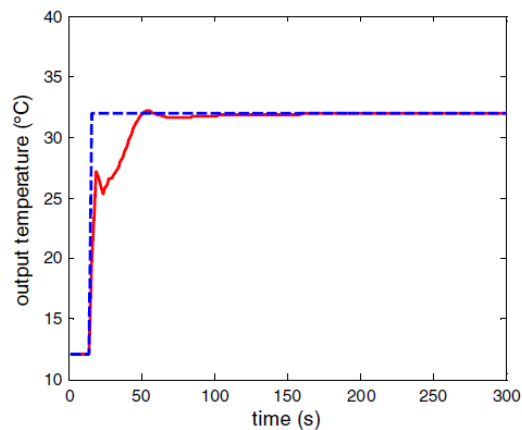


Fig. 6: Closed-loop system response using BELBIC with LoLiMoT identifier [26]

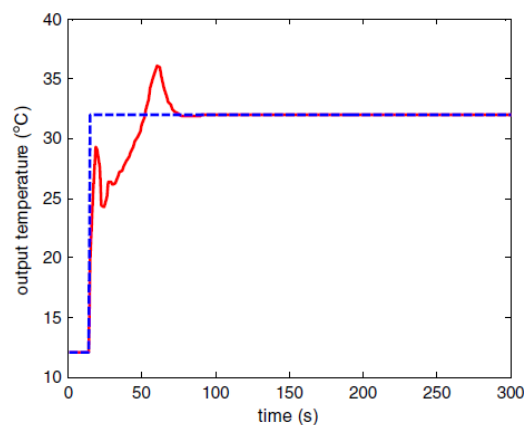


Fig. 7: Closed-loop system response using PID with LoLiMoT identifier [26]

Lucas et al. [23] modified BELBIC and proposed an intelligent control of washing machine using Locally Linear Neuro-Fuzzy (LLNF). They employed two techniques: First, they applied a neuro-fuzzy locally linear model tree system for data driven modeling of the machine. Then, they used the modified BELBIC model. In this version, they reduced the large control signal which was the main disadvantage of BELBIC. The model was simulated and the results were compared with another intelligent controller based on fuzzy expert rules. The results showed that the proposed controller consumes 21% less energy than the fuzzy controller.

In [44], a method of dynamic power management based on BELBIC has been introduced. The proposed learning algorithm predicted idle times around  $T_{BE}$ . Break Even Time ( $T_{BE}$ ) is an important parameter in dynamic power management algorithms.  $T_{BE}$  is the time whether the system is off or on. Table 1 demonstrates the result of normalized power consumption of all algorithms. As seen BELBIC has the lowest power consumption among the others.

Table 1: Normalized power consumption of all approaches [44]

<b>Algorithm</b>	<b>Power Consumption</b>
Timeout	1
Lshop	0.84
AT0	0.96
AT1	0.81
Competitive	0.86
Exponential	0.75
Probability	0.80
Anfis	0.74
BELBIC	0.71

Rahman and co-workers [45] implemented an Interior Permanent-Magnet Synchronous Motor (IPMSM) drives based on BELBIC for the first time. To validate this emotional controller and, hence, established the effectiveness of the proposed BELBIC scheme, the performances of the IPMSM drive based on the proposed control scheme were investigated both in simulation and experimental investigations at different operating conditions. The speed control loop of the drive system was also designed, simulated, and experimentally implemented with an industry standard proportional–integral–derivative (PID) controller to compare the performances of those obtained from the proposed emotional-controller-based drive system. To make a fair judgment, the PID controller was tuned at rated conditions to give the quick and smooth response (settling time and undershoot/overshoot). Digital simulations had been carried out using Matlab/Simulink. The proposed emotional controller had four gains which gave good freedom for choosing desired responses in terms of overshoot, settling time, steady-state error and smoothness. This made the emotional controller effective and flexible in high-performance drive applications. Moreover, it was strongly felt

that an algorithm for optimum tuning of the emotional controller could make it so much more efficient.

In [46] a controller based on BELBIC for a PWR nuclear reactor during load following operation has been designed. For inputs, a neuro fuzzy system with power error and its derivative were applied. The controller could simulate an expert operation in reality and learning rules were very simple and its independence from the system model. In addition, the computational speed was high. The simulation was performed on the presented reactor model using Matlab software to evaluate the performance of the controller. The reactor power tracks the demand power with no overshoot and oscillation and maximum control rod was reduced considerably. Besides, this work showed that the emotional controller can control the reactor in any state when the reactor core parameters change.

Gholipour et al. [47] utilized the BELBIC to provide an intelligent predictor for geomagnetic activity index:  $Kp$  which is mainly applied in warning and alert systems for satellites. The proposed learning algorithm inherently emphasized to learn the behavior of system during geomagnetic sub-storms, which are more important for satellites and space missions. Fig. 8 shows the predicted and observed values by BEL based predictor. According to Fig. 8 the prediction errors of low  $Kp$  indices are not so high to be able to significantly increase the probability of false detections in alert systems. In comparison with the results of other methods, the prediction accuracy of high  $Kp$  values and the rate of correct warning messages issued on the basis of these predictions are satisfactorily good.

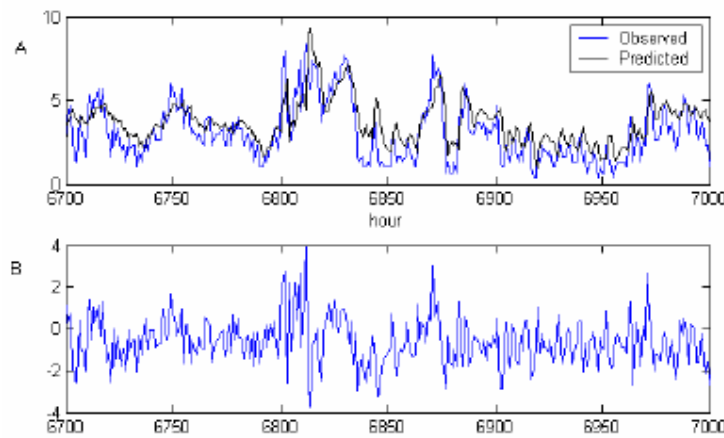


Fig. 8: Prediction of  $Kp$  index by BEL algorithm; (A): Observed and Predicted values, (B): prediction error [41]

Jafarzadeh et al. [30] proposed an intelligent autopilot for a 2-DOF helicopter model based on BELBIC. The majority of previous systems were based on the

linearization model or through several linearization techniques for helicopter that made the proposed controls unreliable. The designed model used a BELBIC controller and feedback linearization technique to a nonlinear model of a helicopter. In this method, the states of the system have been separated into two parts, and each part has been controlled by one of the control inputs. The performance of the two mentioned controllers simulated the in Simulink. The simulation results of controller system by BELBIC controller and feedback linearization controller have been demonstrated in the Fig. 9, and in Fig. 10, the control inputs of the system has been shown.

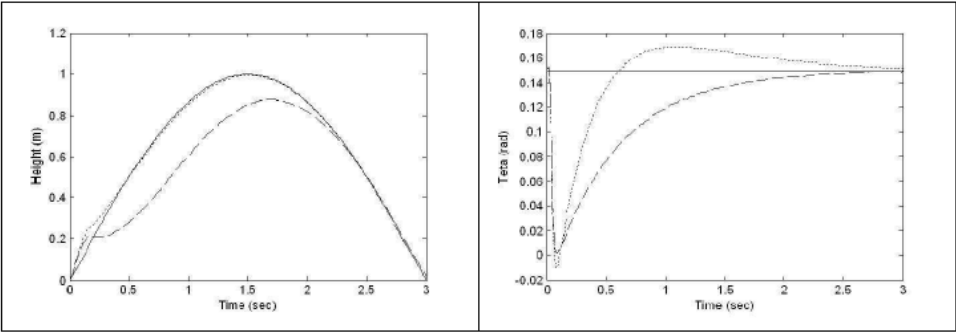


Fig. 9: Height (left) and Collective rotor blade angle (right) of helicopter (Solid: set point, Dashed: feedback linearization, Dotted: BELBIC) [30]

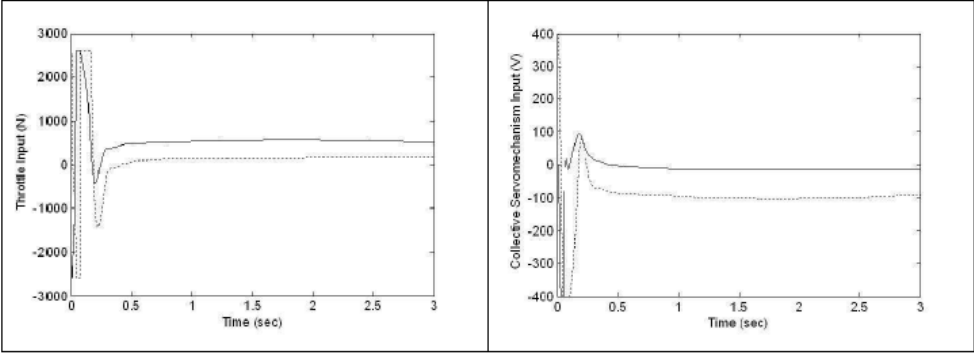


Fig. 10: First (left) and second (right) control input of helicopter (Solid: feedback linearization, Dotted: BELBIC) [30]

It can be seen from these simulations that the tracking performance of BELBIC controller for the height is better than Feedback linearization controller, but in the sense of steady state the performance of both controllers is satisfactory. However, stability guarantee is an important drawback for this controller.

In [31] an intelligent control based on BELBIC has been introduced for speed and flux control of an induction motor. It was a novel and simple model of induction motor drives control which controlled motor speed and flux accurately, without needing to use any conventional controllers and independent of motor parameters. In order to evaluate this emotional controller, digital computer simulations have been performed using Matlab/Simulink. The results showed that the emotional controller had some gains, which gave good freedom for choosing desired responses in terms of overshoot, settling time, steady state error and smoothness. These made the controller effective and flexible in high performance applications. Moreover, Simple structure, fast auto learning and high tracking potency of BELBIC have been made to present a new control plant that is independent of motor parameters and controls speed and flux simultaneously.

Jafarzadeh et al [48] designed a PID and BELBIC controllers for path tracking of a vehicle used in automated highway systems. In path tracking problem the car should follow a moving point. A modified BELBIC controller had been applied to a sixth order model of the vehicle which should track any normal path. A model with the coupling terms between steering angle and traction force was considered in order to avoid unstable situations. The task also has been done using PID controllers. The performance of the two mentioned controllers for vehicle in a normal path has been demonstrated in Fig. 11.

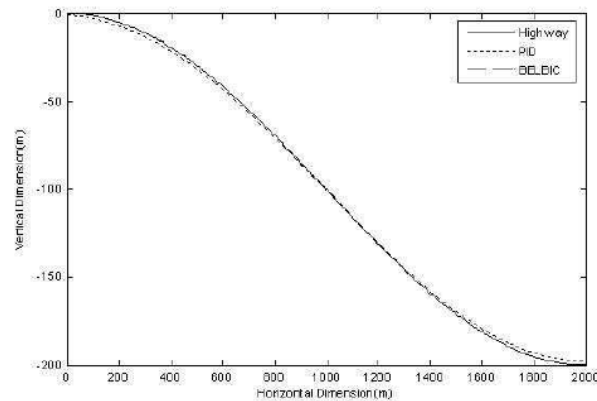


Fig. 11: Highway and vehicle controlled by PID and BELBIC [48]

As shown in Fig. 11 the vehicle tracked the highway perfectly when is controlled by BELBIC. The BELBIC controlled vehicle's trajectory and highway are not distinguishable in Fig. 11. It can be seen from these simulations that the tracking performance of BELBIC controller is better than PID controller.

During landing, aircrafts have to face low-altitude wind shear that can be fatal. Most commercial aircrafts currently have optimal automatic landing systems, but they are activated only if well-specified wind speed limitations are met. The reason is that these autolandings systems are not designed to work in the presence

of strong with gusts. Lucas and co-workers [49] applied a modified version of BELBIC to the autoland system which multivariable and non-minimum phase nature made the task difficult. As the essential elements used in previous utilization of BELBIC [50] proved inadequate, they used another model, which included delay elements to handle the non-minimum-phase behavior [14]. By comparing the results with the results derived from using a high-gain controller, the proposed solution could achieve robust and satisfactory performance.

## 6 Summary and Conclusion

In this paper, the main components of Limbic System which are involved in emotional processes were described. They are mainly known as the Amygdala-Orbitofrontal Cortex system. A computational model of the limbic system based on these concepts was discussed. The model is used in the design of an intelligent controller called BELBIC-Brain Emotional Learning Based Intelligent Controller. Moreover, the utilization of BELBIC in different applications of control was demonstrated. The results showed that BELBIC has satisfactory control performance.

Although, the idea of using BELBIC for engineering applications and control systems having advantages such as low computational complexity and fast training, it can be said that different aspects of this problem are still in their infancy stages. For future works, there are several suggestions that can be done for improvement of this study. To that extent, the current computational models of the Limbic System are simplified forms. Furthermore, in reality, some other components function in the real Limbic System which can affect on the emotional learning, but they are not considered in the current models. Moreover, BELBIC structure has been designed for SISO systems, but in applications where the system is MIMO, several different controllers each to generate one control output must be used. Therefore, in case MIMO system is employed a new controller needs to be designed. In addition, for each application, we need to obtain suitable design parameters. In other words, current design procedure of the BELBIC does not have a systematic routine. Thus, it is very useful to design a self-tuning algorithm to determine the gains of the controller and corresponding weights in the emotional and sensory signals.

## References

- [1] K. S. Narendra, K. Parthasarathy, "Identification and control of dynamical systems using neural networks", *IEEE Trans. on Neural Networks*, Vol. 1, NO. 1, (1990), pp. 4-27.
- [2] T. M. Takagi, M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control", *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 15, No. 1, (1985), pp. 122-132.
- [3] R. J. Wai, J. D. Lee and K. H. Su, "Supervisory enhanced genetic algorithm control for indirect field-oriented induction motor drive", *Proceedings IEEE*

- International Joint Conference on Neural Networks*, Vol. 2, (2004), pp. 1239-1244.
- [4] H. Zhang, S. Liu and S. Y. Yang, "An emotion-based behavior coordination approach to autonomous mobile robots", *Proceedings of the International Conference on Sensing, Computing and Automation*, Vol. 1, (2006), pp. 249-254.
- [5] M. Sipper and M. Tomassini, "Convergence to Uniformity in A Cellular Automaton via Local Co-evolution", *International Journal of Modern Physics*, 8, No. 5, (1997), pp. 1013-1024.
- [6] C. Lucas, D. Shahmirzadi and M. Biglarbegian, "Co-evolutionary Approach to Graph-Coloring Problem", *Technical Journal of Amirkabir University of Technology*, Vol. 14, NO.54, (2003), pp. 363-369.
- [7] S. Hofmeyr and S. Forrest, "Architecture for an Artificial Immune System", *Journal of Evolutionary Computation*, Vol. 7, No. 1, (2000), pp. 45-48.
- [8] J. Chen, E. Antipov, B. Lemieux, W. Cedeno and D. H. Wood, "DNA Computing Implementing Genetic Algorithms", *Workshop on Evolution As Computation*, Piscataway, New Jersey, (1999), pp. 39-49.
- [9] M. Fatourehchi, C. Lucas and A. Khakisedigh, "Reducing Control Effort by Means of Emotional Learning", *Proceedings of 19th Iranian Conference on Electrical Engineering*, Tehran, Iran, (2001), pp. 41.1-41.8.
- [10] D. Shahmirzadi, *Computational Modeling Of The Brain Limbic System And Its Application In Control Engineering*, Master dissertation, Texas A&M University, U.S.A. , (2005).
- [11] S. Maren, "Long-Term Potentiation in the Amygdala: A Mechanism for Emotional Learning and Memory", *Trends in Neurosciences*, Vol. 22, No. 12, (1999), pp. 561-567.
- [12] J. Moren, C. Balkenius, "A Computational Model of Emotional Learning in the Amygdala", *Cybernetics and Systems*, Vol. 32, No. 6, (2000), pp. 611-636.
- [13] J. Moren, *Emotion and Learning – A Computational Model of the Amygdala*, PhD dissertation, Lund University, Lund, Sweden, (2002).
- [14] C. Lucas, D. Shahmirzadi, N. Sheikholeslami, "Introducing BELBIC: Brain Emotional Learning Based Intelligent Controller", *International Journal of Intelligent Automation and Soft Computing*, Vol. 10, NO.1, (2004), pp. 11-22.
- [15] M. Fatourehchi, C. Lucas and A. Khaki Sedigh, "Reducing Control Effort by means of Emotional Learning", *Proc. of 9<sup>th</sup> Iranian Conf. on Electrical Engineering, ICEE'01*, Tehran, Iran, (2001), Vol. 41, pp. 1-8.
- [16] L.I. Perlovsky, "Emotions, Learning and control", *Proc. Of IEEE Int. symp. On Intelligent control/Intelligent systems and semiotics*, Cambridge, MA, (1999), 132-137.
- [17] R. Ventura, and C. Pinto Ferreira, "Emotion based control systems", *Proc. of IEEE Int. symp. On Intelligent control/Intelligent systems and semiotics*, Cambridge, MA, (1999), pp. 64-66.

- [18] K. Inoue, K. Kawabata and H. Kobayashi, "On a Decision Making System with Emotion", *Proc. 5<sup>th</sup> IEEE International Workshop on Robot and Human Communication*, (1996), pp. 461- 465.
- [19] A. Jazbi and C. Lucas, "Intelligent control with emotional Learning", *7<sup>th</sup> Iranian Conference on Electrical Engineering, ICEE'99*, Tehran, Iran, (1999), pp. 207-212.
- [20] R. W. Picard, E. Vyzas and J. Healey, "Toward machine emotional intelligence: Analysis of affective physiological state", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 10, ( 2001), pp. 1175-1191.
- [21] R. Mohammadi, C. Lucas and B. N. Araabi, "A novel controller for a power system based BELBIC", *Proceedings of World Automation Congress*, Vol. 18, (2004), pp. 409-420.
- [22] M. J. Kharaajoo, "Application of brain emotional learning based intelligent controller (BELBIC) to active queue management", *International Conference on Computational Science, Lecture Notes in Computer Science*, Vol. 3037, (2004), pp. 662-665.
- [23] C. Lucas, R. Mohammadi and B. N. Araabi, "Intelligent modeling and control of washing machine using LLNF modeling and modified BELBIC", *Asian Journal of Control*, Vol. 8, No. 4, (2006), pp. 393-400
- [24] A. R. Mehrabian, C. Lucas, J. Roshanian, "Aerospace launch vehicle control: An intelligent adaptive approach", *Aerospace Science and Technology*, Vol. 10, NO. 2, (2006), pp. 149-155.
- [25] R. Mohammdi, C. Lucas, B.N. Arraabi, T. S. Radwan, M. A. Rahman, "Implementation of emotional controller for interior permanent magnet synchronous motor drive", *Industry Applications Conference*, Vol. 4, (2006), pp. 1767-1774.
- [26] H. Rouhani, M. Jalili, B. N. Araabi, W. Eppler and C. Lucas, "Brain emotional learning based intelligent controller applied to neuro-fuzzy model of micro-heat exchanger", *Expert Systems with Applications*, Vol. 32, (2007), pp. 911-924.
- [27] Z. Ziyang, W. Daobo and W. Zhisheng, "Flight simulation servo system based on learning based intelligent controller", *Proceedings of the Fourth International Conference on Impulse and Hybrid Dynamic Systems*, (2007), pp. 1372-1375.
- [28] A. Torabi, M. Boroushaki, G. Vosoughi, "Design a brain emotional learning based intelligent controller (BELBIC) in delayed systems", *14th-International conference of Iranian Society of Mechanical Engineering (ISME2006)*, (2006), Isfahan, Iran.
- [29] A. R. Mehrabian, C. Lucas, "Emotional Learning Based Intelligent Robust Adaptive Controller for Stable Uncertain Nonlinear Systems", *International Journal of Intelligent Technology (IJIT)*, Vol. ACKNOWLEDGMENT 1, No. 1, (2005), pp. 34-40.



- [30] S. Jafarzadeh, R. Mirheidari, M. R. J. Motlagh and M. Barkhordari, "Intelligent Autopilot Control Design for a 2-DOF Helicopter Model", *International Journal of Computers, Communications & Control*, Vol. 3, (2008), pp. 337-342.
- [31] E. Daryabeigi, G. Arabmarkadeh and C. Lucas, "Simultaneously, speed and flux control of an induction motor, with brain emotional learning based intelligent controller (BELBIC)", *IEEE International Conference on Electric Machines and Drives*, (2009), pp. 894 – 901.
- [32] D. Purves, G. J. Augustine, D. Fitzpatrick, L. C. Katz, A. LaMantia, J. O. McNamara, S. M. Williams, *Neuroscience*, Sinauer Associates, (2001).
- [33] J. E. LeDoux, *In Search of an Emotional System in the Brain: Leaping from Fear to Emotion and Consciousness*. Cambridge, MA: MIT Press, (1995).
- [34] E. T. Rolls, *A Theory of Emotion and Consciousness, and Its Application to Understanding the Neural Basis of Emotion*. Cambridge, MA: MIT Press. (1995).
- [35] J. M. Fuster, *The Prefrontal Cortex: Anatomy, Physiology, and Neuropsychology of the Frontal Lobe*, Philadelphia, PA: Lippincott-Raven, (1997).
- [36] J. P. Kelly, *The Neural Basis of Perception and Movement, Principles of Neural Science*, London. UK: Prentice Hall, (1991).
- [37] A. Ohman and S. Mineka, "Fears, Phobias, and Preparedness: Toward and Evolved Module of Fear and Fear Learning", *Journal of Psychological Review*, Vol. 108, No. 3, (2001), pp. 483-522.
- [38] D. G. Amaral, J. L. Price, A. Pitkanen and S. T. Carmichael, *Anatomical Organization of the Primate Amygdaloid Complex, The Amygdala: Neurobiological Aspects of Emotion, Memory, and Mental Dysfunction*, New York: Wiley, (1992).
- [39] S. Schachter, "Some Extraordinary Facts About Obese Humans and Rats", *American Psychologist*, Vol. 26, (1970). pp. 129-144.
- [40] E. C. Tolman and C. H. Honzik, *Introduction and Removal of Reward and Maze Performance in Rats*, California: University of California Publications in Psychology, (1930).
- [41] J. O'Keefe and L. Nadel, *The Hippocampus as a Cognitive Map*, Oxford, UK, Clarendon Press, (1978).
- [42] C. Lucas, D. Shahmirzadi and H. Ghafoorifard, "Eliminating Stator Oscillations through Fin Placement", *J. Eng. Simul.*, Vol. 3, No. 1, (2002), pp. 3-7.
- [43] X. Xu, H. G. He and D. Hu, "Efficient Reinforcement Learning Using Recursive Least-Square Methods", *Journal of Artificial Intelligence Research*, Vol. 22, (2002), pp. 259-292.
- [44] M. Samadi, A. Afzali-Kusha and C. Lucas, "Power Management by Brain Emotional Learning Algorithm", *Proceedings of 7th International Conference on ASIC*, (2007), pp. 78 – 81.

- [45] M. A. Rahman, R. M. Milasi, C. Lucas, B. Nadjar Araadi and T. S. Rawan, "Implementation of Emotional Controller for Interior Permanent-Magnet Synchronous Motor Drives", *IEEE Transactions on Industry Applications*, Vol. 44, No. 5, (2008), pp. 1466-1476.
- [46] S. S. Khorramabadi, M. Boroushaki and C. Lucas, "Emotional learning based intelligent controller for a PWR nuclear reactor core during load following operation", *Annals of Nuclear Energy*, Vol. 35, (2008), pp. 2051–2058.
- [47] A. Gholipour, C. Lucas, D. Shahmirzadi, "Predicting Geomagnetic Activity Index by Brain Emotional Learning", *WSEAS Transactions on Systems*, Vol. 3, No.1, (2004), pp. 296-299.
- [48] S. Jafarzadeh, R. Mirheidari, M. Jahed Motlagh and M. Barkhordari, "Designing PID and BELBIC Controllers in Path Tracking Problem", *International Journal of Computers, Communications and Control*, Vol. 3, (2008), pp. 343-348.
- [49] C. Lucas and S. Moghimi, "Applying BELBIC (Brain Emotion Learning Based Intelligent Controller) to an Auto landing System", *Proceedings of Conference on WSEAS AIKED'03*, (2003).
- [50] M. Ghalia and A. Alouani, "Robust Control of an Autolanding System", Tennessee Technological University.