COMPUTATIONAL MODELING OF THE BRAIN LIMBIC SYSTEM AND ITS APPLICATION IN CONTROL ENGINEERING

A thesis report

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Submitted by

Arpit Jain

Roll No: 80751006

Under Esteemed Guidance of

Dr. Yaduvir Singh

Associate Professor

Electrical and Instrumentation Engineering Department

THAPAR UNIVERSITY

PATIALA (PUNJAB) -147004

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CERTIFICATE

This is to certify that my work presented in this thesis entitled "**Computational Modeling of the Brain Limbic System and its Application** in **Control Engineering**" in partial fulfillment of the requirement for the award of the degree of **Master of Engineering at Thapar University Patiala,** is an original record under supervision and guidance of **Dr. Yaduvir Singh.** The matter embodied in this report has not been submitted anywhere for the award of any other degree of this or any other University.

Date: 06/07/09

Arpit
Arpit Jain
80751006

It is certified that the above statement made by the student is correct to the best of my knowledge.

06/07/09
Dr. Yaduvir Singh
Associate Professor, EIED
Supervisor
Thapar University, Patiala

S. Ghosh
07/07/2009
Dr. Smarajit Ghosh
Professor & Head, EIED
Thapar University, Patiala

RK Sharma
Dr. R K Sharma 21/7/09
Dean of Academic Affairs
Thapar University, Patiala

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Arpit

Place: Thapar University, Patiala
Date: 06/07/09

Arpit Jain
Roll no: 80751006

Abstract

This study mainly deals with the various aspects of modeling the learning processes within the brain limbic system and studying the various aspects of using it for different applications in control engineering.

The current study is a multi-aspect research effort which not only requires a background of control engineering, but also a basic knowledge of some biomorphic systems.

The main focus of this study is on biological systems which are involved in emotional processes. In mammalians, a part of the brain called the *limbic* system is mainly responsible for emotional processes. Therefore, general brain emotional processes and specific aspects of the limbic system are reviewed in the early parts of this study.

Next, we describe developing a computational model of the limbic system based on these concepts. Since the focus of this study is on the application of the model in engineering systems and not on the biological concepts, the model established is not a very complicated model and does not include all the components of the limbic system. In fact, we are trying to develop a model which captures the minimal and basic properties of the limbic system which are mainly known as the Amygdala-Orbitofrontal Cortex system.

Next, we took a SISO submarine model than designed a control system for this application. The results of the performance of the control system in presence of disturbance are compared with results without the presence of controller (making the gain of controller 0). This comparison clearly shows that BEL based control systems have an amazing performance. Even this performance can also be improved if this field is properly developed and some unknown details of this model like Emotional Signal is properly understood.

Organization of Thesis

1. The first chapter gives the introduction about the motivation and objective of this work, followed by background which describes previous work done on this subject in a very brief manner.
2. The second chapter is the review of literature i.e. a summary about the developments in the subject so far.
3. The third chapter covers the biological aspects of the brain limbic system – the anatomy and architecture in detail. It covers description and function of each part which comes under our problem domain.
4. The fourth chapter describes the computational mode of the limbic system. This is the chapter where the main essence of thesis starts. It describes the mathematical aspects regarding the limbic system. Then we have discussed how to apply this system to a linear control system.
5. The fifth chapter discusses the programming tool needed for designing a control system.
6. The most important chapter, here we took a control system problem (*MIMO Submarine model*) and applied the *BEL* controller to this system and simulated results based on various disturbances and various set point.
7. The seventh chapter concludes the thesis and discusses the future prospects of *BEL* controller.

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Abbreviations

Abbreviation	**Meaning**
BELBIC	Brain emotional learning based intelligent controller
BEL	Brain emotional learning
Amyg	Amygdala
OFC	Orbitofrontal cortex
t	Time
α	Amygdala learning rate
β	OFC learning rate
y	Plant output
OC, OC_i	OFC output
A, A_i	Amygdala nodal output
ES	Emotional signal
e	Control reference error
SI	Sensory input
PID	Proportional Integral Derivative controller
e.g.	Example
RTEA	Real time emotional architecture
LOLIMOT	Locally Linear Neuro Fuzzy net with Model Tree learning
UAV	Unmanned aerial vehicle

A-O	Amygdala-Orbitofrontal
G_A	Amygdala gain
G_{OFC}	OFC gain
LTI	Linear time invariant
GUI	Graphical user interface
Mux	Multiplexer
Hz	Hertz

Chapter 1
Introduction

1.1 Overview

A fundamental property, which distinguishes an intelligent system from a traditional one, is the capability of learning. The learning process can occur at different levels of complexity, but a common characteristic is the adaptation of the system parameters to better cope with the changing environment.

Moreover, any learning algorithm requires an evaluation mechanism to assess the operating condition of the system. One type of evaluation is based on the so called emotional cues, which assess 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.

The learning strategy which is based on emotional evaluations is appropriately called emotional learning. In mammalian brains this process occurs in the part of the brain called the limbic system, which constitutes one of the core elements of the brain [1].

The proposed study initially aims at developing a computational model of those parts of the mammalian limbic system which are more directly involved in emotional processing. The model can then be utilized as a versatile learning module in a system to associate the external conditions with certain internal criteria to refine the behavior of the system.

The focus of this study is to adapt this learning model for control systems.

Increased scientific attention is being drawn towards understanding the decision architecture of the Human Brain. Interest has been showed by neurophysiologists, cognitive scientists, artificial intelligence researchers, and control engineers. Till late, emotions were considered a negative trait by neurophysiologists and cognitive scientists and were considered a weakness of the human individual. Rational thought is considered to be objective and repetitive [1]. Repetition suggests the existence of a well defined mapping between input and outputs that shall be followed by the system and multiple instances would allow the decision system to reveal this hidden relation.

On the other hand, Emotional thought is considered to be involuntary and there exists little conscious control over such thought. Nonetheless, these involuntary emotions can easily and frequently change conscious thought [1]. Thus under certain conditions, inner symptoms and cues are given more relevance than external stimuli. LeDoux [2] presented several examples where the emotional capability of a human subject was lost due to some accident/surgery; however cognition and other capabilities were unaffected. This indicates that the two systems, the emotional system and the cognitive system, are separate and also that the connection from the emotional to the cognitive system is far stronger than the reverse relation.

However it has been understood lately that emotions actually help in learning. As an example [3]: one single occurrence of an emotionally charged-up situation remains in one’s memory for years to come, whereas the memory of some task that one performs daily would not be equally vivid and easily recalled. This actually questions the common perception that repetition ‘memorizes’ information into our brain. Through this example, one can also comment that sustained cognitive inputs were not able to develop the effect that one single internal cue can generate.

Learning is a process by which a decision scheme's outputs are made more appropriate based upon experience. An appropriate decision is one which makes the attainment of the desired goal more probable [4]. Hence research in artificial intelligence is also aiming to understand the value judgments that emotions bring in. Situations such as an unmanned vehicle in a battle scenario need an artificial driver which would be able to emulate a human's decision mechanism and take the right decision in "real-time" and also incorporate information from previous exposures to similar scenarios. In fact, Samad mentions that the only intelligent systems that exist are biological and hence biomimicry is the first logical step to develop artificial intelligence and autonomous systems, unless one can think about and develop an autonomous system which is not inspired by a biological system [5]. Even the development of a non-biologically inspired autonomous system would involve the study of biological intelligence and search for its shortcomings.

The emotional system has also been attributed the task of what engineers would call multi-objective optimization. Without emotions, a human being would not be able to develop complicated ideas and thoughts. Without the emotional system, a human brain would only process and evaluate different stimuli for different objectives: the inter-related evaluation and associations, which we call as context, are also provided by the emotional system. For example: compromises and strategies would not be possible without the relative emotional prioritization of various goals [1]. In fact this very prioritization demarcates species of higher intelligence from those of lower intelligence. Young reptiles have to fend for their own food and can be eaten by their own mothers, while primates are able to make compromises and provide nutrition to their young ones.

The evaluation or prioritization that each individual allocates to the same set of stimuli, introduces individual traits. A particular individual may allocate more importance to a particular feature or emotion so that its decision would be strikingly different from another individual's. Again the outcomes of such previous situations would ensure the evaluations that the particular individual would make in the current situation. Note that such emotional prioritization in individuals is at a level higher than the varying ability of emotional prioritization in different species as shown in the example above. Albus [4] terms such individual prioritization as derived from the higher levels of the so-called Behavior Generating Hierarchy.

1.2 Objectives

This study mainly deals with the various aspects of modeling the learning processes within the brain limbic system and the challenges in using it for different engineering applications. The major objectives of this thesis can be listed as follow:

- Understanding the biological mechanisms of brain limbic system in emotional processing.
- Establishing a computational model capturing the minimum characteristics of the limbic system.
- Developing a system for control engineering perspective and comparing the results so as to completely evaluate the system’s performance.

1.3 Background

From a control engineering perspective, the task of learning and making decisions more appropriate is the purview of adaptive control. By bio-inspired adaptive control, one's attention is readily drawn towards Artificial Neural Networks. However, artificial neural networks model the synaptic connections and the Hebbian learning phenomena at the level of individual neurons, which allow incorporating complex information into the decision scheme where no conventional or mathematical input-output relations are available. One may also consider emotions to be intangible and un-modeled; and eventually, inside the human brain, they are represented in networks of neurons. We will explore, in a later paragraph that Artificial Neural Networks are relevant and are being used for some studies, but the habituation or sensitization of neurons is at a much lower level than the emotional mechanism. The brain emotional mechanism is a macro-level setup which would incorporate a very large number of neurons clustered into various components of the emotional system network. By looking at the emotional system, one is looking at and emulating the system level architecture that a biological intelligence scheme would have. One need not choose an artificial network of neurons to implement this system level design.

Albus and Samad, as referred earlier, have individually proposed that the most logical and probable strategy towards understanding and implementing artificial intelligence is to understand and mimic the biological decision architecture present in the central nervous system of humans and other higher mammals. This higher mammalian central nervous system has been perfected over millions of years of evolution and is very much the standard and *de facto* decision scheme against which our entire understanding of basic concepts of intelligence, learning and autonomy is defined and verified.

Interestingly there exists a reverse inclination amongst a school of neurophysiologists who believe that the easiest way to understand the complicated functionalities of the brain and the central nervous system is to model them as adaptive control models, or as their artificial neural network equivalents [6], [7].

The main interest that neurophysiologists had was to identify how the brain was able to handle tasks such as involuntary bodily processes, reflex action as well as voluntary motor coordination, cognition, etc. And why different parts of the brain were utilized for such purposes, as was experimentally discovered through innumerable electroencephalogram experiments on normal and special individuals. The main agenda was to identify modes in which the central nervous system's components behaved. For example [7]: classifying the task as of adaptive signal processing or adaptive filtering. In fact, a more structural approach also exists which classifies the components acting as a scaling device, (which will be called a gain in control engineering terminology) vis-à-vis a time-delay device (a differentiator/integrator).

Due to the complexity of the mammalian nervous system, this study is not limited to theorizing models [6] but intricate experiments [7] have also been used to validate these models. And this, in a way, lends force to the earlier proposition that a clear understanding of natural intelligence is a logical step towards modeling intelligence and autonomy into artifacts.

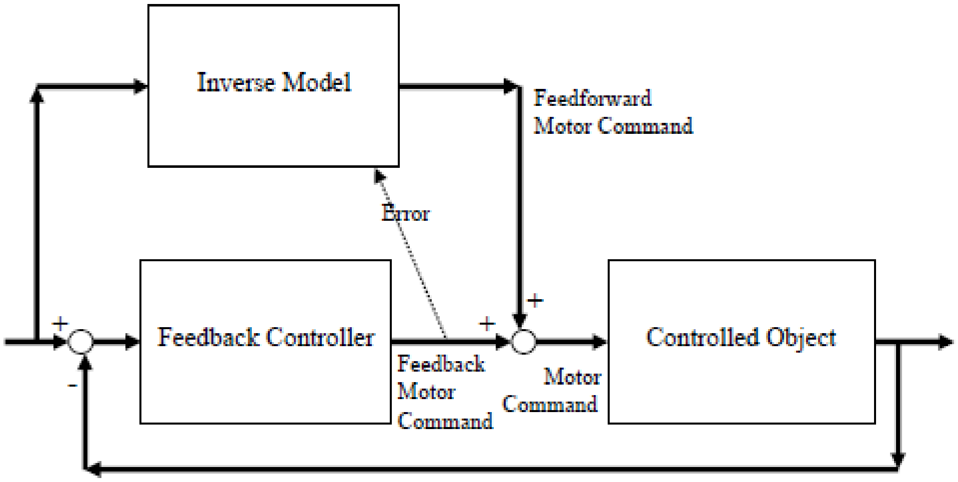


Fig 1.1 Feedback error learning scheme to acquire inverse model of the controlled object (as referenced in [7])

Barlow [7] presents a number of control models, developed by several researchers of this school of thought, to explain the architecture of the human brain, specifically the human cerebellum. Barlow summarizes the various attempts by several researchers over decades, and shows that the tendency is towards an adaptive control representation, due to the several features that Adaptive Control Theory offers, e.g. time-development of parameters, even under situations where limited prior knowledge of the system is available. Earlier non-adaptive models were proposed, but they suffered from several shortcomings which only adaptive systems could provide. Figure 1 [7] presents a schematic flow diagram of motor behavior acquisition in vertebrates. Any control engineer would clearly identify this diagram as the closed loop diagram of an adaptive process. Barlow also presents a number of Artificial Neural Network models of the cerebellum and other parts of the brain involved in complete circuits of some bodily task. It is also pointed that the use of Artificial Neural Networks is also due to its ability to manipulate weights of the various signal paths according to the error between the desired state and the current state.

However the models presented therein are mainly explanations of how the human cerebellum acts like an adaptive controller while regulating bodily processes like posture and locomotion. A control mechanism based on the emotional setup in the brain is still not available.

Apart from the role that emotions play, the human brain is known to be having several redundant connections in its setup. In fact calling them redundancies is not very appropriate as these alternate pathways provide robustness and also validate and support each other's outputs. Also all connections are not identical, some of them are fast connections, and often inferior in the quality of judgment they result in. The Limbic System, which, due to experimental work by neurophysiologists, is considered to be the emotional processing mechanism in the mammalian nervous system, is made of two loops. The Orbitofrontal Cortex acts as an outer loop and receives information from the Amygdala, as well, which only receives sensory input. It is interesting to note that emotional responses can occur without the sensor information going into the higher brain, where more complicated processing is undertaken [2]. Hence this loop structure provides for a mechanism where a quick decision from the inner loop can be actually modified by the outer loop.

Hence an emotion-based control mechanism has still not been researched primarily due to two reasons: the role of emotions in the human brain was not understood and also due to the unavailability of a mathematical/computational model of the emotional learning mechanisms in the brain.

However it should be clear from the outset that by an emotion based control mechanism, one does not mean an artificial emotion processing setup or an artificial agent that can generate emotions. Neither are we attempting an Artificial Intelligence problem. Artificial Intelligence and control systems have different goals. In fact, by itself, emotional learning and intelligence are not equivalent: emotional learning is only a small but crucial component of the entire concept of intelligence. Besides emotions, an intelligent being ought to display perception, reasoning, planning, self-consciousness besides other high level abstract features which have little to do with control engineering [3], [4].

Chapter 2
Literature Review

Christian Balkenius and Jan Morén in 1998 abstract: He described work in progress with the aim of constructing a computational model of emotional learning and processing inspired by neurophysiological findings. The main areas modeled were the amygdala and the orbitofrontal cortex and the interaction between them. They showed that (a) there exists enough physiological data to suggest the overall architecture of a computational model, (b) emotion plays a clear role in learning and behavior.

Christian Balkenius and Jan Morén in 2000 abstract: The amygdala has repeatedly been implicated in emotional reactions and in learning of new emotionally significant stimuli. The system forms an important part of motor learning as well as attention. Their paper presents a neurologically inspired computational model of the amygdala and the orbitofrontal cortex that aims to partially reproduce the same characteristics as the biological system. The model has been tested in simulations, the results of which are presented.

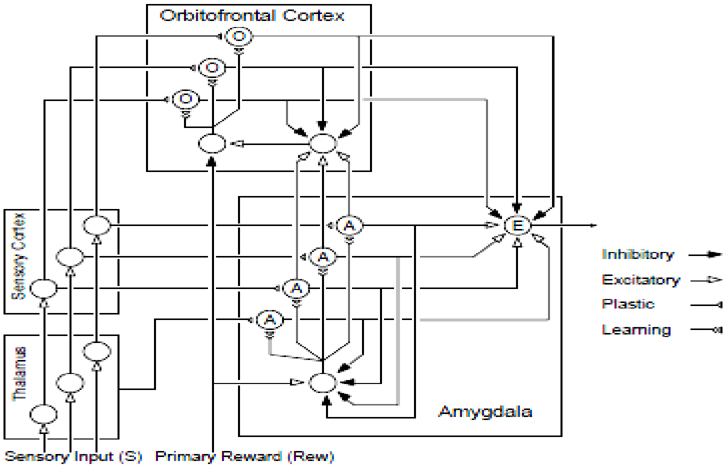


Fig 2.1 A graphical depiction of the model.

At the top is the rudimentary orbitofrontal part (here without an external context), at the bottom right is the amygdaloid part and at left are the thalamic and sensorycortical modules. The thalamic and sensory-cortical parts are just place-holders in this version of the model. 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 *Rew* enters both the amygdaloid and orbitofrontal parts.

Jean-Marc Fellous, Jorge L. Armony and Joseph E. LeDoux in 2002 abstract: Emotion is clearly an important aspect of the mind; yet it has been largely ignored by the "brain and mind (cognitive) sciences" in modern times. However, there are signs that this is beginning to change. In this article, we survey some issues about the nature of emotion, describe what is known about the neural basis of emotion, and consider some efforts that have been made to develop computer-based models of different aspects of emotion.

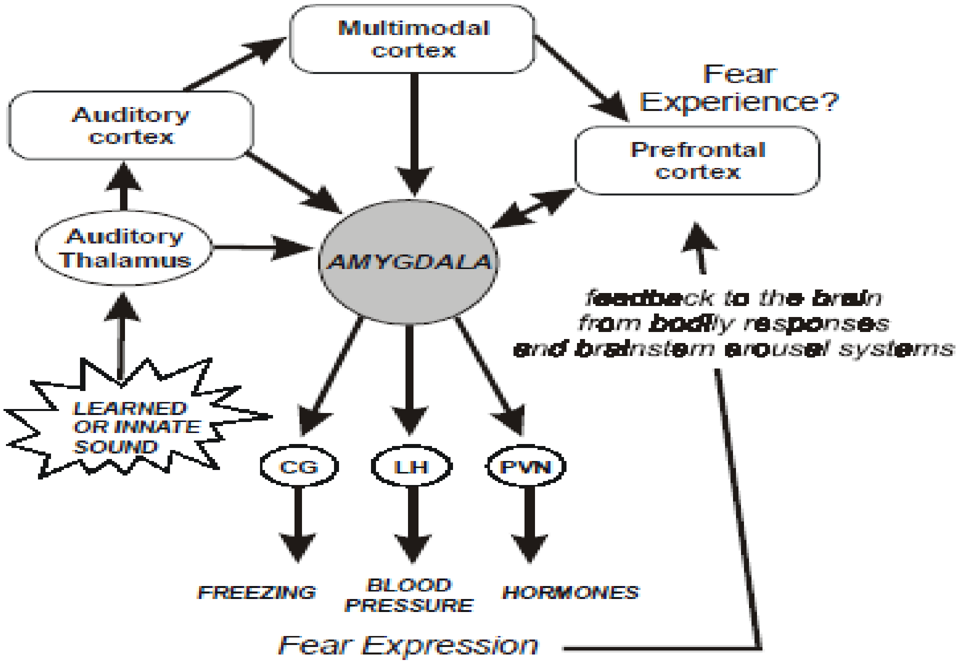


Fig 2.2 Emotional expression and emotional experience of auditory fear

Suzanne C. Lewis and Darryl N. Davis in 2002 abstract: CRIBB Children's Reasoning about Intentions, Beliefs and Behaviour) is a computational model of belief-desire reasoning. Their paper presents an analysis of CRIBB and the initial design for an extension that involves the implementation of a model of emotions. The impetus for this research is evidence that emotion plays a fundamental role in a variety of cognitive functions such as decision-making, learning and perception. We consider theories of emotion, perception and reasoning and also the affect that emotion has on these cognitive processes. This research was closely related to BELBIC

CARO LUCAS, DANIAL SHAHMIRZADI& NIMA HEIKHOLESLAMI in 2004 abstract: Modeling emotions has attracted much attention in recent years, both in cognitive psychology and design of artificial systems. Far from being a negative factor in decision making, emotions have shown to be a strong faculty for making fast satisficing decisions. In this paper, they have adapted a computational model based on the limbic system in the mammalian brain for control engineering applications. They applied the proposed controller (termed BELBIC) for some SISO, MIMO and nonlinear systems. Their results demonstrate excellent control action, disturbance handling and system parameter robustness for BELBIC.

Ali Reza Mehrabian, Caro Lucas and Jafar Roshanian in 2006 abstract: Theoretical analysis of on-line autonomous intelligent adaptive tracking controller based on emotional learning model in mammalians brain (BELBIC) for aerospace launch vehicle is presented. The control algorithm is provided with some sensory inputs and reward signal, subsequently it autonomously seeks the proper control signal to be executed by actuators, thus eliminating tracking error without pre-knowledge of the plant dynamics.

Manik Chandra and Reza Langari in 2006 abstract: **T**heir paper presents a control algorithm developed from the mammalian emotional processing network. A discrete event model was modified for application to a continuous time plant. It resulted in a system with a connected equilibrium set. To understand the dynamics, first integrals are identified and a proof of stability is given.

Ali Reza Mehrabian, and Caro Lucas in 2006 abstract: In this paper a new control strategy based on Brain Emotional Learning (BEL) model has been introduced. A modified BEL model has been proposed to increase the degree of freedom, controlling capability, reliability and robustness, which can be implemented in real engineering systems. The performance of the proposed BEL controller has been illustrated by applying it on different nonlinear uncertain systems, showing very good adaptability and robustness, while maintaining stability.

Carlos Dominguez, Houcine Hassan and Alfons Crespo in 2006 abstract: Recent research in emotional systems has identified the important role of emotions in the control and the organisation of the behaviour of robotic systems. RTEA is a real-time emotional architecture for robotic agents. Emotions in RTEA modulate the thoughts' motivation that affect the final agent's behaviour. An emotional state is reached from the appraisal of a situation of the environment. The way this appraisal contributes to the emotional state and how this state affects the behaviour depends on the emotional sensibility.

Maziar A. Sharbafi and Caro Lucas in 2006 abstract: The Combination of path planning and path following is the main purpose of this paper. This paper describes the developed practical approach to motion control of the *MRL* small size robots. An intelligent controller is applied to control omni-directional robots motion in simulation and real environment respectively. The Brain Emotional Learning Based Intelligent Controller (*BELBIC*), based on *LQR* control is adopted for the omni-directional robots.

D. Shahmirzadi, R. Langari, L.J. Ricalde and E.N. Sanchez in 2006 abstract: In this paper, a new algorithm BELBIC is used to control a model of a tractor-semitrailer. The model is previously derived, validated and a sliding mode control is also tested which demonstrates reasonable performance. The oscillatory motions of the vehicle motivate using an alternative control algorithm to improve passenger comfort and safety. The main improvements are the smoother roll and yaw performances, limited excursions of the roll angle, and cheaper control actions. The sliding mode control offers better performance in certain limited respects, e.g. better yaw-rate tracking in braking and lower roll angles in acceleration. The control performances are compared for three simulations of braking, acceleration and cornering.

Hossein Rouhani, Mahdi Jalili, Babak N. Araabi, Wolfgang Eppler and Caro Lucas in 2007 abstract: In this paper, an intelligent controller is applied to govern the dynamics of electrically heated micro-heat exchanger plant. The brain emotional learning based intelligent controller (BELBIC) based on PID control is adopted for the micro-heat exchanger plant. The contribution of BELBIC in improving the control system performance is shown by comparison with results obtained from classic PID controller without BELBIC. The results demonstrate excellent improvements of control action, without any considerable increase in control effort for PID + BELBIC.

Hossein Rouhani, Arash Sadeghzadeh, Caro Lucas and Babak Nadjar Araabi in 2007 abstract: In this paper, rotor speed and position of a Switched Reluctance Motor (SRM) are controlled using an intelligent control algorithm. The controller is working based on a PID signal while its gain is permanently tuned by means of an Emotional Learning Algorithm to achieve a better control performance. Here, nonlinear characteristic of SRM is identified using an efficient training algorithm (LoLiMoT) for Locally Linear Neurofuzzy Model as an unspecified nonlinear plant model. Then, the Brain Emotional Learning Based Intelligent Controller (BELBIC) is applied to the obtained model. While the intelligent controller works based on a computational model of a limbic system in the mammalian brain, its contribution is to improve the performance of a classic controller like PID without much more control effort. The results demonstrate excellent improvements of control action in different working situations.

Caro Lucas in 2007 abstract: A new paradigm has come to replace the symbol- system representational approach that had been dominant during the past five decades of the formal history of artificial intelligence. The new designs are not only biologically inspired, but also sociologicaslly, behaviorally, and cognitively motivated as well. Two techniques that can be utilized in such smart environments: BELBIC, the "Brain Emotional Learning Based Intelligent Controller", and LOLIMOT, the "Locally Linear Neuro Fuzzy net with MOdel Tree learning", are described as design patterns for providing good solutions to problems that appear again and again in these systems, but never in the same form.

Guoyong Huang, Ziyang Zhen and Daobo Wang in 2008 abstract: A novel intelligent control strategy based on brain emotional learning (BEL) model is investigated in the application of the attitude control of the unmanned aerial vehicle (UAV) in the paper. The UAV is in the flat flight under the disturbance of the wind. The BEL based intelligent controller (BELBIC), which is based on emotional learning process in amygdala-orbitofrontal (A-O) system of the mammalians brain, is proposed to develop the stability control performance of the UAV attitude loop. A control scheme of the UAV with nonlinear dynamic properties based on BELBIC is built up. The simulation results illustrate that the BELBIC has characteristics of good adaptability, strong robustness, and small computational cost, so that the BELBIC will be attractive in the control applications of real-time nonlinear systems.

Saeed Jafarzadeh, Rooholah Mirheidari, Mohammad Reza Jahed Motlagh and Mojtaba Barkhordari in 2008 abstract: Their paper proposes a new intelligent control approach for path tracking of a vehicle used in automated highway systems. Brain emotional learning based intelligent controller (BELBIC) is an intelligent controller based on the model of emotional part of brain. A modified BELBIC controller has 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 is considered.

Saeed Jafarzadeh, Rooholah Mirheidari, Mohammad Reza Jahed Motlagh and Mojtaba Barkhordari in 2008 abstract: In this paper, they introduced a new intelligent control approach called Brain Emotional Learning Based Intelligent Controller (BELBIC). BELBIC is a controller based on emotional model of human brain which has been introduced not for so long. This controller has been applied to a nonlinear model of a helicopter. Feedback linearization method has also been applied to the system, and the performance of two controllers has been compared as an intelligent and a classical control method. An Input to State linearization method with some changes has been used to control the system. The performance of the controllers has been justified by the simulation.

M. Masoudinejad, R. Khorsandi, A. Fatehi, C. Lucas, S. Fakhimi Derakhshan and M. R. Jamali in 2008 abstract: Brain emotional learning based intelligent controller (BELBIC) is based on computational model of limbic system in the mammalian brain. In recent years, this model was applied in many linear and nonlinear control applications. Previous studies show that this controller has fast response, simple implementation and robustness with respect to disturbances. It is also possible to define emotional signal based on control application objectives. But in the previous studies, internal instability of this controller was not considered and control task were done in limited time period. In this article mathematical description of BELBIC is investigated and improved to avoid internal instability. Simulation and implementation of improved model was done on level plant. The obtained results showed that instability of model has been solved in the new model without loss of performance by using Integral Anti Windup (IAW).

A.R. Mehrabian and C. Lucas in 2009 abstract: This paper presents a new intelligent approach for adaptive con- trol of non-linear dynamic systems. Based on past researches on emotionally intelligent-control systems, the introduced method is a modified version of Brain Emotional

Learning Based Intelligent Controller (BELBIC), a physiologically motivated system previously developed and successfully used in control applications. The pro- posed approach is able to quickly respond to change in environmen- tal and dynamic system and realizes online direct-adaptive-control scheme. Showing very good robustness, BELBIC is very simple in implementation and imposes very low computation load on the con- trol system. This modified algorithm has been successfully applied to real-time longitudinal control of an agile air-to-air missile which has ever-changing non-linear dynamics.

The various algorithms that were stated by different researchers in this field are depicted in figures below:

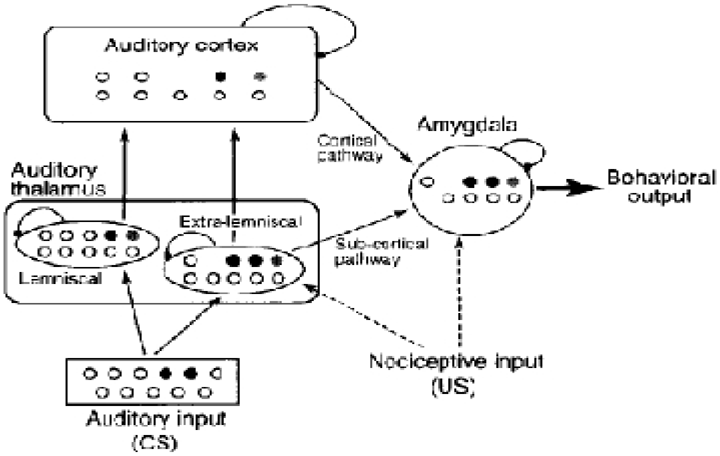


Fig 2.3 Armony 1997

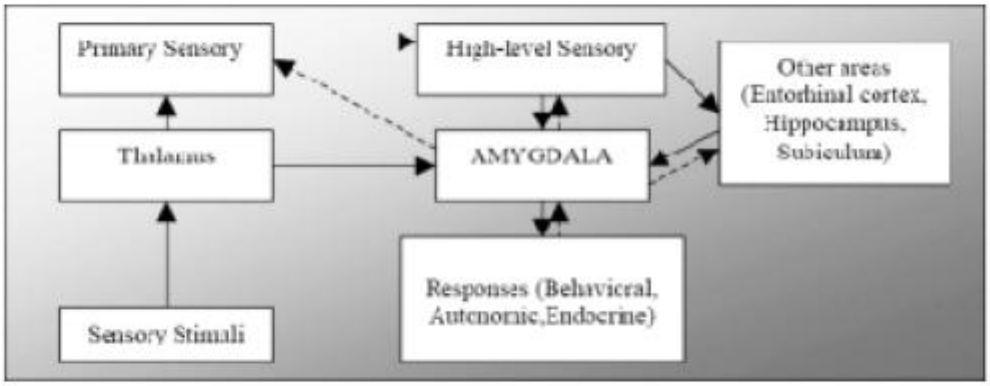


Fig 2.4 Manzotti, Metta, Sandini 1999

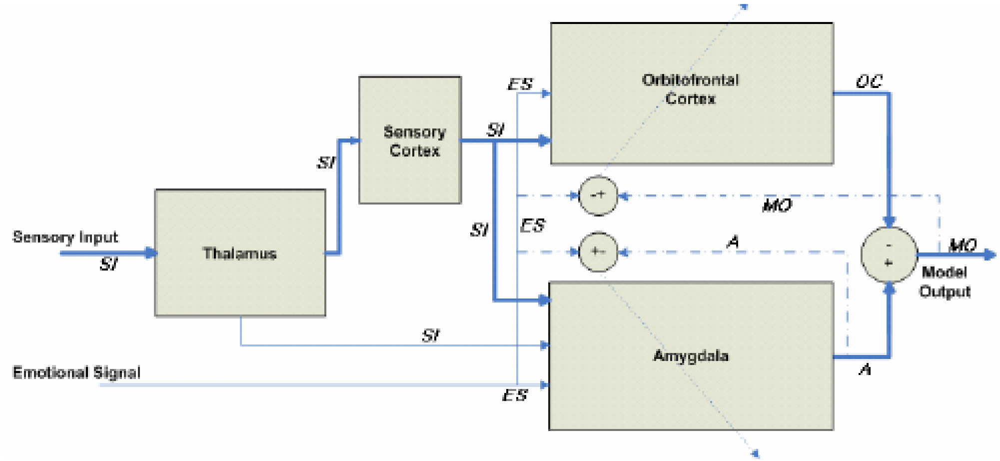


Fig 2.5 Balkenius, Moren 2000

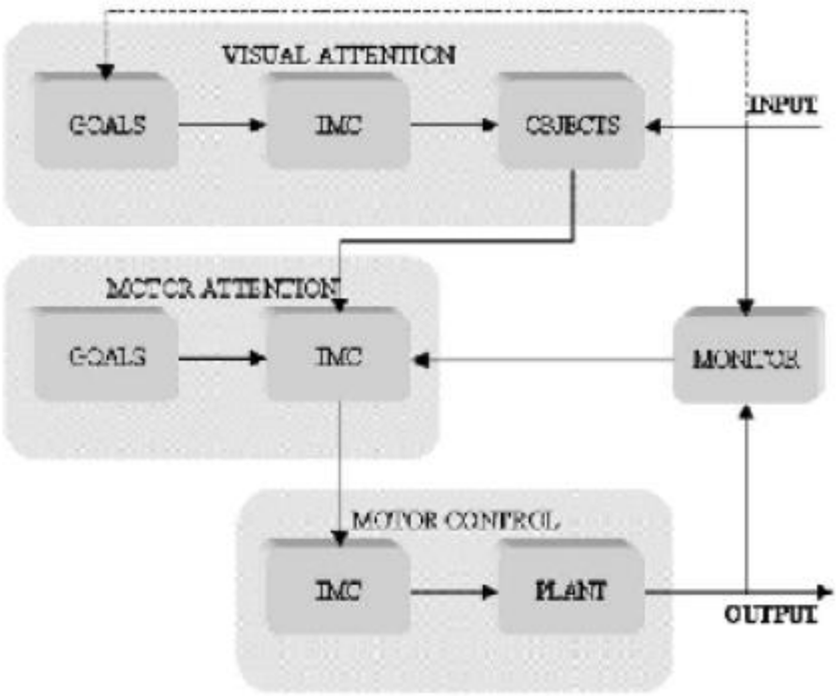


Fig 2.6 Fragopanagos, Taylor 2006

These were the algorithms that were recently developed as a computational model of emotional learning system of human brain.

Chapter 3
Biological Background

3.1 Introduction

The current study is a multi-aspect research effort which not only requires a background of control engineering, but also needs a basic knowledge of some biomorphic systems. Therefore, this section tries to make the reader familiar with some basic materials of those biomorphic systems which are used in this study.

In fact, the main concern is studying those biological systems which are involved in emotional processes. As it is mentioned before, a part of the mammalian brain called *limbic* system is mainly known responsible for this purpose. Therefore, the brain emotional processes in general and the limbic system in particular are studied in the next two sections.

The limbic system

The emotional processing setup inside the mammalian brain is called the limbic system. The limbic system is closely associated with the functions of memory and learning, besides emotional processing and emotional learning. The limbic system evolved further into what is called the neocortex configuration [1]. The neocortex configuration was the system that allowed *Homo sapiens* to have an emotional life, including complicated combinations of elementary and even contradictory emotions. The size of the neocortex is considered proportional to the complexity and the breadth of the spectrum of the emotions the individual feels (or more correctly ‘emotes’). This occurs due to the existence of more neuron connections within the limbic system or the neocortex, which allow the processing of multiple and more comprehensive responses to the same set of stimuli. It is the occurrence of these varied responses in higher animals that marks them as intelligent and ‘higher’ than other animals whose central nervous systems lacks the limbic setup and hence can only process the inputs to fewer and often single responses. E.g. when threatened a lower animal will flee, whereas higher animals might behave along different plans.

The name limbic system was suggested by MacLean in 1952 [2] to a regrouping of a part called limbic cortex with other parts. The term ‘limbic’ in the limbic cortex had a structural implication, whereas MacLean’s sense was more function-oriented when he clubbed other related sub cortical regions to form the system. When this theory was put forth, the experimental sciences were not as well developed, so MacLean suggested that the primitive architecture of this setup leads to the irrationality, multiplicity and confusion about emotional behavior. However later on it emerged that the existence of several well-defined loops or processing paths actually provide this setup a sophisticated computational power which accounts for complicated emotional behavior.

It should be clarified here that the current understanding of the limbic system and the neocortex was never static and has been disputed often and changes suggested periodically. LeDoux [2] in his book gives a good discussion about it. MacLean’s theory about the limbic system has not been able to generate sufficient experimental evidence; however some parts of this theory have not been discarded outright and have been accepted as being true though poorly organized. Hence usually a consensus is agreed upon which says that some limbic areas of the brain are related with certain emotional processes and such relations are generalized to say that the entire limbic system is related to emotional thought and processing. LeDoux goes further to even say that the classical limbic areas have been experimentally shown to not being dedicated to emotions, but the theory still persists, as an elementary proposition that links evolution and emotions. However, our emphasis here is engineering and for our engineering goals, such a theory is good enough to pick up and try a few ideas that might not have been studied as yet and can lend important insight into engineering as well as the original biological context.

Emotional process

Learning is arguably the most vital factor through which the complex organisms are able to survive [23]. To be sure, all organisms have capabilities that enable them to operate within their environment, but complex organisms are generally endowed with the additional ability to learn from and adapt to their environment. Indeed, we differentiate between adaptation across generations through evolutionary processes versus learning within one generation and in response to specific environmental stimuli. This fact can be noticed specifically from two standpoints:

- How much an organism would be smart to intelligently interact with its environment at a specific time, it still requires some learning abilities. The reason is that the environment itself is changing constantly. So in order to keep the same level of performance within the ever changing environment, the organism should possess adaptation mechanisms.
- Another reason is some adaptations should be learned by the animal within a much shorter time scope rather than generations.

On the other hand, the learning system should be able to evaluate the current environmental condition. This helps the system to check the direction of learning and if it helps reaching the objectives of the system.

To this end, the organism must evaluate its performance relative to some, internally or externally supplied, criteria and modify its actions accordingly [24, 25, 26]. These continuing experiences help the organism make associations between the environmental conditions, the actions it takes and the resulted impact in satisfying the criteria. The sequence of the growing associations and dissociations builds a learning capability, through which the organism refines its performance and, in principle, leads to a more adaptive behavior over time.

In this connection, internal cues originating within the organism often play a stronger role than external ones. This is generally due to the inherent autonomy of complex organisms. From this perspective, the internal state of the organism – both emotional and cognitive - play key roles in learning. Emotional factor has historically been considered a negative factor hindering the rational decision making process. However, the importance of emotions in human cognitive activities is progressively being documented by psychologists [27, 28]. Indeed, it has become clear that far from being a negative trait, emotions are positive forces crucial for intelligent behavior in natural systems [18, 29].

One of the primary functions of emotion is evaluating the stimuli. When an environmental stimulus occurs in association with an emotionally charged stimulus, the emotional system will associate this new stimulus with the same or a similar emotional content. The second function of emotional systems is to focus the attention of the system on the signals which contribute the most to reach the objectives of the system. Instead of spending the resources on all the many sensory stimuli, the emotional evaluation can help focusing on relevant stimuli which are more decisive in generating the appropriate actions.

In the fields of cognitive science researches, the emotions and emotionally charged signals are distinguished as positive versus negative signals. The positive emotions indicate a likely reward for the system, e.g. hope, whereas the latter ones forecast that there would be a punishment, e.g. fear [30, 31]. In the course of this study, we are not distinguishing between the emotional signals in that sense. This is because we are developing a computational model and any positive or negative emotional signal will be automatically reflected in the output of the system through the model.

3.2 Architecture of the Limbic System

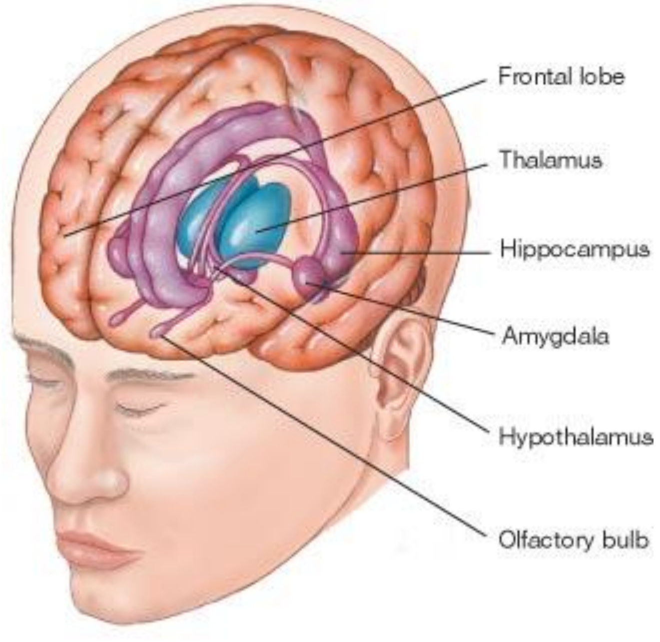
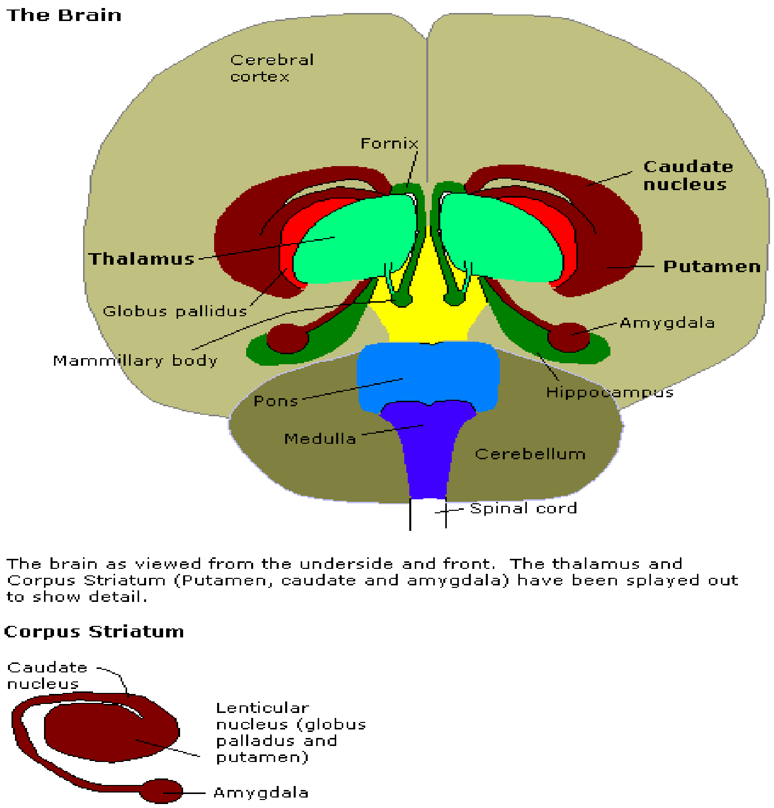


Fig 3.1 A generic view of the important components of the human limbic system. Other higher mammals also possess similar structure.

The primary components of the human limbic system are shown above in figure. The main components of the limbic system involved in emotional processes are Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Cortex, Hypothalamus, Hippocampus and some other areas. In this section, we are trying to briefly describe these components and their tasks.



The brain as viewed from the underside and front. The thalamus and Corpus Striatum (Putamen, caudate and amygdala) have been splayed out to show detail.

Fig 3.2 figure showing physical structures of some parts of Limbic system.

The primary affective conditioning of the system occurs in the Amygdala. The Amygdala is a small almond-shaped subcortical area as shown in figure 3.2 which placed in a way to communicate with all other sensory cortices and areas within the limbic system [9]. Figure 3.3 shows the connections of the Amygdala to/from other componenets. It is indeed believed that the association between a stimulus and its emotional consequences takes place in the Amygdala [32, 33]. 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. The role of the Amygdala is in fact to assign emotional value to each stimulus that is paired with a primary reinforcement signal. It has been experimentally verified that this lobe undergoes classical conditioning over the various stimuli presented to it. The output of this lobe is further transmitted to hypothalamus and other structures. The hypothalamus is responsible for generating the emotional reactions. The amygdala receives three kinds of input signals: first, the sensory information from the sense organs; second, the internal significance of the stimuli, and third, the mode of operation for the being itself. [8] As can be seen these signals mix external and internal cues to deliver complete information and context to the individual.

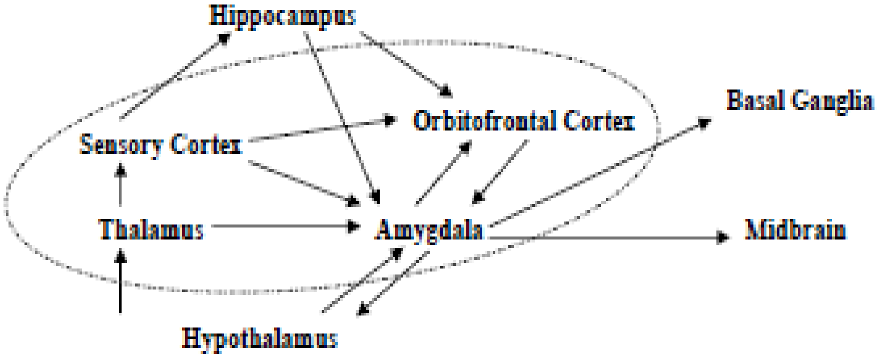


Fig 3.3 Connections of the Amygdala with other components of the Limbic System

The Orbitofrontal Cortex as shown in figure 3.4 is another component that interacts with the Amygdala reciprocally. In general, it performs three interrelated functions which are *Working Memory*, *Preparatory Set* and *Inhibitory Control* [34]. The concept of working memory is captured by representing the current events and actions, as well as such events in the recent past. 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 reacts to omit the expected reward or punishment and control the extinction of the learning in the Amygdala [35]. The orbitofrontal cortex tries to reduce the strength of earlier established connections which are no longer appropriate as the goal or the context has changed. Hence one can say that the orbitofrontal cortex is responsible for the working memory of the individual which comprises of similar events in the past and a representation of the events and actions of the present situation. Hence the orbitofrontal cortex regulates the mapping of the stimuli to the emotional response occurring through the amygdala. This can be called habituation of the senses to some stimulus which though present repeatedly has little relevance to the main mode of operation or has delivered its information content to the brain and has therefore lost its importance status, and the focus has shifted after assimilating this information content. The Hippocampus is believed to provide the orbitofrontal cortex with information about the current context. The orbitofrontal cortex receives the same set of data as the amygdala, but it forms a sort of outer loop as it also receives the amygdala states.

Hence the orbitofrontal cortex tracks the difference between the system predictions and the actual reinforcer from the amygdala and learns to inhibit the system output proportionate to the mismatch. Different regions of the orbitofrontal cortex are functionally related to the different sensory stimuli and provide different levels of regulatory action to different stimuli.

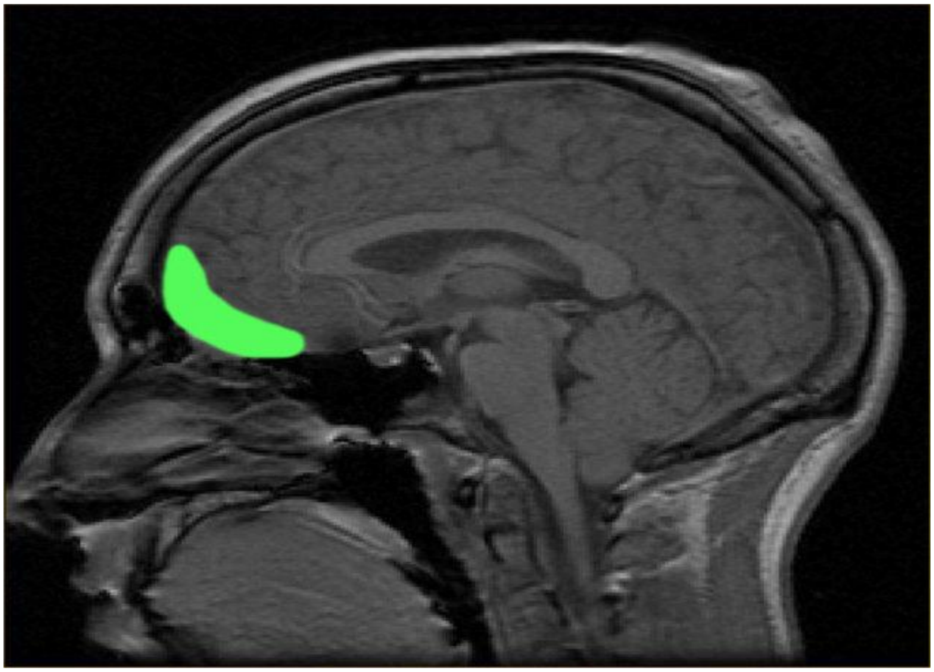


Fig 3.4 Orbitofrontal Cortex shown in green colour

The Thalamus as shown in figure 3.5 is a non-homogenous subcortical structure that lies next to the basal ganglia. Its major role is being a way-station between subcortical and cortical structures. Most sensory information is relayed from the peripheral sensory systems to the sensory cortices through various parts of the Thalamus [36]. In particular, 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 signal from Thalamus to Amygdala skips the processes involved in Sensory Cortex and other following components. So the Thalamus provides a non-optimal but fast stimulus to the Amygdala where this signal is often a characteristic signal among the input stimuli [36]. However this mechanism is not very clearly understood as yet [8]. For instance the olfactory stimuli do not pass through the thalamus.

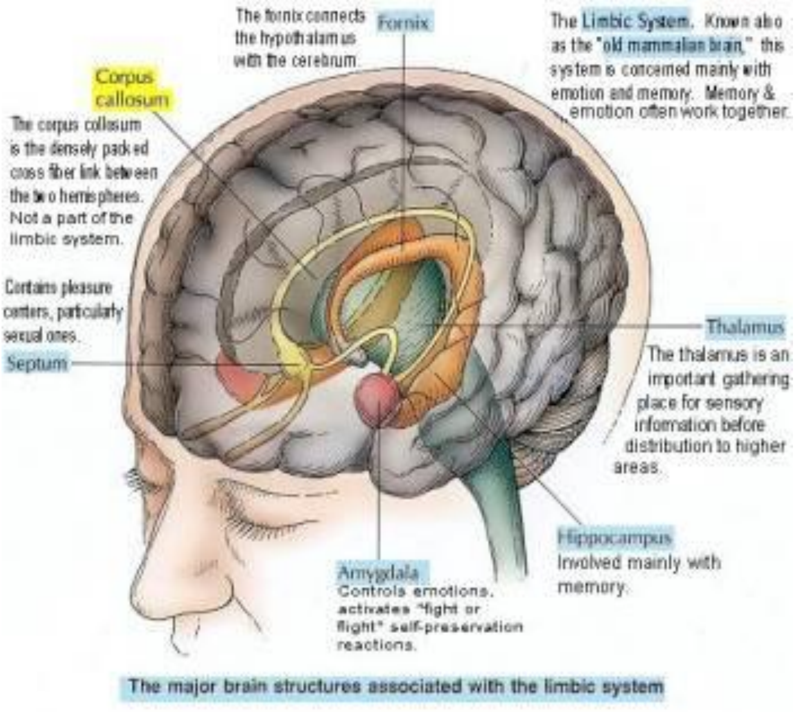


Fig 3.5 Thalamus and Hippocampus

The Hypothalamus lies below the Thalamus and it is believed in connection with various functions that regulate the endocrine system, the pituitary gland, the autonomous nervous system and primary behavioral surviving states [39]. There are connections from different regions of the Amygdala to the lateral regions of Hypothalamus, and the other way around, which are thought to be involved in motivational control of the structures within the Hypothalamus [40]. The pituitary gland is the all important center of the endocrine system where hormonal secretion is controlled which enacts through the different body organs, all the emotional processing undertaken by the limbic system.

The Sensory Cortex is the component next to the Thalamus and receives its inputs through this component. In fact, the information from the sensory areas is extensively processed within the Sensory Cortex. The Amygdala and Orbitofrontal Cortex receive highly analyzed input from the sensory cortex [32, 35, 38]. In general, these areas are mainly responsible for higher perceptual processing in mammalians, though their exact functions are still an open subject of research.

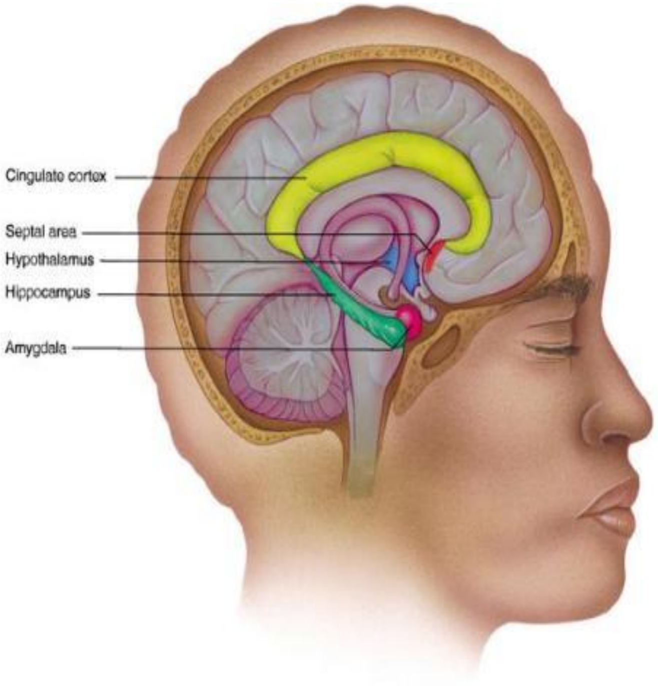


Fig 3.6 Position of Hypothalamus in brain.

The Hippocampus as shown in figure 3.5 is a complex twisting structure which lies within the same subcortical region as the Amygdala does. It is believed that Hippocampus is responsible for mapping the environment mainly based on environmental cues. The Hippocampus has roles in different functions including spatial navigation, laying down of the long-term memory and formation of the contextual representations [41].

As was pointed earlier, the understanding of the limbic system is not accurate and equally convincing in all regards. Hence neurophysiologists are still actively engaged in refining and suggesting newer explanations of the emotional processing system. A keen reader with a background in neuroanatomy can find several other published resources similar to [2], [8], [9], [10].

3.3 Summary

This chapter provided a baseline for the studies of this research and answered why in general we need *Autonomous* systems. In this chapter, we introduced the theory of *Learning* and the importance of having this capability in the mechanisms for them to be able to survive in a changing environment. Then it is described that any learning system requires an *Evaluation* mechanism to assess the conditions of the system which is implemented through defining performance criteria. In fact, the system uses the evaluation mechanism to establish associations between different sets of condition-action pairs.

Then, in the same vein, we introduced the Emotional evaluation and learning which is the base for emotional decision making in mammalians. In mammalians, the system which is responsible for emotional processing is the part of the brain called limbic system. The limbic system and its mechanisms in emotional processing are further described.

Finally, the main components of the limbic system are enumerated and the task of each of them is briefly explained.

Chapter 4
Computational model of the Limbic System

4.1 Introduction

From an engineering viewpoint we need a computational model of the emotional processing network that can represent the system relationships of the individual elements. What the previous chapter discussed was a descriptive model of the emotional processing network. It was a qualitative discussion about the various parts of the brain and more stress was given to make the functioning of the system easy to understand. Such a model presents the salient features only and serves well for an introduction. However little stress was laid upon how this understanding was attained or developed and one can easily be mislead with a model that appears to explain the underlying phenomena, but is flawed or may not be verified as exhaustively as it should be.

By a computational model, one implies a model which can be worked with. It is not a description of the phenomena, but is rather an attempt to show it running. A computational model through this definition appears to be a model that can be represented as a set of equations that quantitatively define the phenomenon. From an engineering viewpoint, a computational model is the outcome of a system identification process: not only is the functional form identified but also the parameter values are also learnt. For the current aim of picking up the limbic system and using it for control engineering purposes, there is no need to identify the parameter values. The parameters would be set by the control engineering problem that one would like to study using this emotional processing model.

4.2 Computational model

In figure 3.1, we saw the main components of the limbic system which interact with Amygdala in emotional processes. 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. These elements and their interactions with other components of the limbic system are illustrated in figure 3.1 with a dotted oval. Furthermore, from the aforementioned components, the first two play a key role in the processing of emotions while the rest 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 [9, 36, 42]. 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 [38], where in this study it is modeled as a computational delay [9]. The fundamental idea behind decision-making based on emotional learning, following [9, 43], is to generate the action (output), which minimizes an emotional stress (or maximizes an emotional reward), while the 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.

Morén and Balkenius [11], and Morén's Ph.D. thesis [8] offer us a computational model of the limbic system. This model is certainly not complete and neither does it intend to equally capture all dimensions of the human limbic architecture. However it has been verified by the authors above to provide simulation results which match with experimental data and also agree with the descriptive understanding developed in the field of brain modeling. Hence such a model agrees with our definition of the computational model, that we just elucidated in section 4.1.

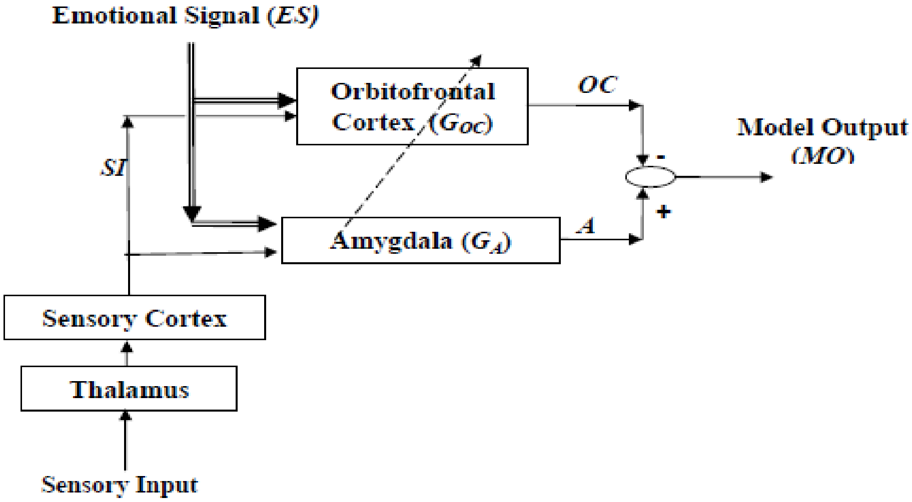


Fig 4.1 A general block diagram showing computational model of BELBIC

Figure 4.1 above represents the Morén-Balkenius model in a simple, yet effective manner and which is good enough for our engineering aims. Primarily it can be seen that there are two input signals: namely the sensory input coming from the stimulus being registered in the sense organs.

The other signal called the Primary Reward is an internal signal. In fact, the understanding of this Primary Reward signal (also referred to as Emotional Signal *ES*, for reasons to be mentioned later) is inconclusive as yet: the exact source of this Emotional Signal *ES* is unclear, as of now it is considered to be a generic signal from the thalamus , hypothalamus and the basal ganglia regions of the brain. The understanding of the main parts of the emotional processing network has not been mastered, as yet; hence our understanding of these regions is all the more primitive. In fact this lack of previous information is a good sign for innovation, and the generation of the reward signal will become important for our study within the next few pages.

The functional relationships between the various signals are now defined. The signal entering the orbitofrontal cortex (OFC) and the amygdala blocks are called the SI_i for Sensory Input, as processed (or filtered) through the sensory cortex and the thalamus. Note that here all quantities have a subscript, as inside the natural emotional processing network, there are several such loops, and all of the outputs from individual loops are summed up in the end to give the Model Output *MO*. The amygdala and the OFC blocks are basically gains, G_A and G_{OC} acting over the Sensory Input *SI* and these gains are updated by ΔG_A and ΔG_{OC} depending on the emotional signal and other signals. The output signal from the amygdala is A_i and that from the orbitofrontal cortex is the OC_i. The following lists the signal representations and the update rules that actually define the mathematics inside the emotional processing network, as given in [8]:

$$
\begin{aligned}
A_i &= G_{A_i}.SI_i \\
OC_i &= G_{OC_i}.SI_i \\
\Delta G_{A_i} &= \alpha.SI_i.\max(0, ES - \sum_i A_i) \\
\Delta G_{OC_i} &= \beta.SI_i.R_o \\
\text{where } R_0 &= \begin{Bmatrix} \max(0, \sum_i A_i - ES) - \sum_i OC_i & \forall ES \neq 0 \\ \max(0, \sum_i A_i - \sum_i OC_i) & \forall ES = 0 \end{Bmatrix}
\end{aligned}
$$

$$MO = \sum_i A_i - \sum_i OC_i$$

Here α, β are constants and represent rates of learning for the individual components. It should be noted that α and β remain the same over the various loops. A higher value of α, β means that the system values are updated faster, as in each iterative pass, the update is larger. R_o is called the internal reinforcer for the orbitofrontal cortex (OFC).

Also note that the manner in which these equations are constructed, the updates or the learning in the amygdala gain G_{Ai} are monotonic: the amygdala gain G_{Ai} can only increase. However the OFC gain update rules are not monotonic. In the presence of a reward, the internal reinforcer represents the discrepancy between the reward and the amygdala outputs A_i minus the OFC output OC_i. However if there is no reward, then the OFC behaves differently: the internal reinforcer is only the surplus of the amygdala outputs over the OFC outputs (OC_i). That means that without a reward, the OFC gain G_{OCi} is updated upwards if the amygdala responds more sharply than the OFC. Hence this leads to a setup in which OFC regulates the amygdala response. An interpretation can be worked out that the amygdala attempts to match the reward/emotional signal and whenever it is unable to do so the orbitofrontal cortex (OFC) tries to fine-tune the system. Hence it can be said that the amygdala tries to learn the associations between the sensory and the emotional inputs. And the updates of amygdala are monitored by the OFC gains, which inhibit the amygdala if the response is more acute than necessary. Note that as the amygdala gain updates are monotonic, the amygdala gains are not inhibited, but the amygdala response is inhibited by increasing the OFC gain.

The set of rules as defined by these equations is independent of time as of now. Morén [8] comments that the absence of time related effects is the shortcoming of this model, and all stimuli are considered to be pulses, lasting one clock period.

One also needs to identify the Emotional Signal *ES* or the Primary Reward. Morén [8] outlines several theories for the Reward or the Reinforcing Signal. The Emotional Signal is of importance to the entire model. It is understood that this signal is generated internally & combines external sensory inputs with internally generated cues to develop a complete understanding of the situation: internal as well as external. The internal cues represent the goals of the individual against which it is comparing its performance as measured by the sensory inputs. Hence this signal is called the Emotional Signal. In fact if we pay attention to LeDoux's definition [2] quoted below then it is more appropriate to call this signal as emotional signal, which is what we will follow in this thesis.

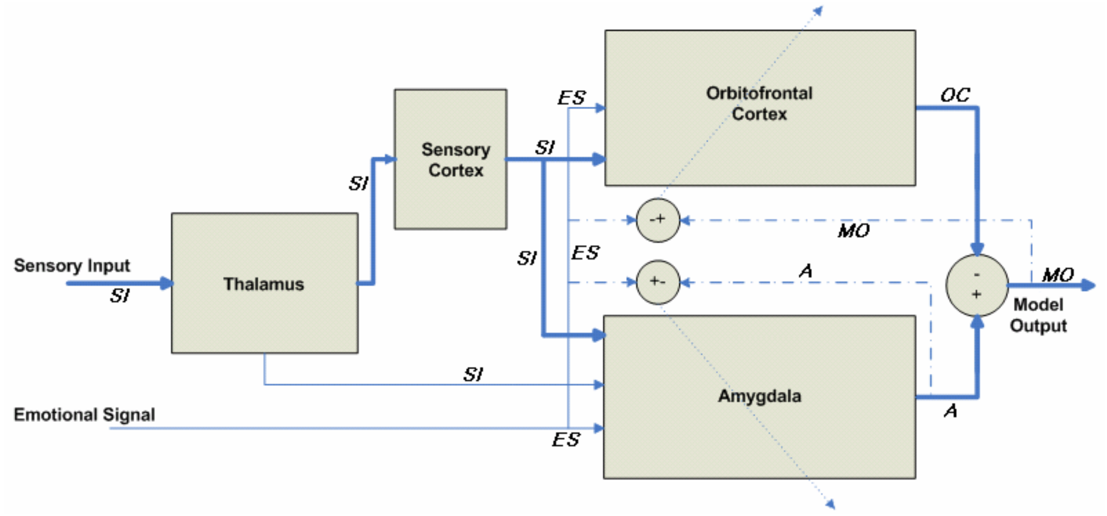


Fig 4.2 Block Diagram of the Simplified Limbic Model (BEL)

“When information from the external world is integrated with sensations arising from within the body, we have feelings.”

4.3 Previous work

A number of attempts have been reported [12], [13] which utilize the above model for varied control engineering applications: e.g. control of MIMO and nonlinear systems. These articles used the Morén-Balkenius model as a feedback law to generate control input to the plants. However no reasoning into the probable causes for the applicability of this model for such tasks was presented. One should not implement any function as a feedback law: firstly, an underlying rationale for doing so should be available and secondly a method should be available in order to generalize the concepts introduced so that a controller can be designed for other problems as well.

Also the examples presented were not in continuous time mode: these were Simulink® based simulations of continuous time descriptions of plants being fed back with a control scheme which was in discrete time mode. The gain development rules were written as difference equations, very close to what Morén presented.

However these results present an initial interest in the area of using ideas from the emotional processing network for control engineering purpose. Interest in understanding biological systems and modifying salient features for application to artificial systems is the most prominent thrust in engineering research as of now. They have presented that the emotional processing network is a suitable candidate for feedback law and more work is needed to understand it.

Application to a Linear System

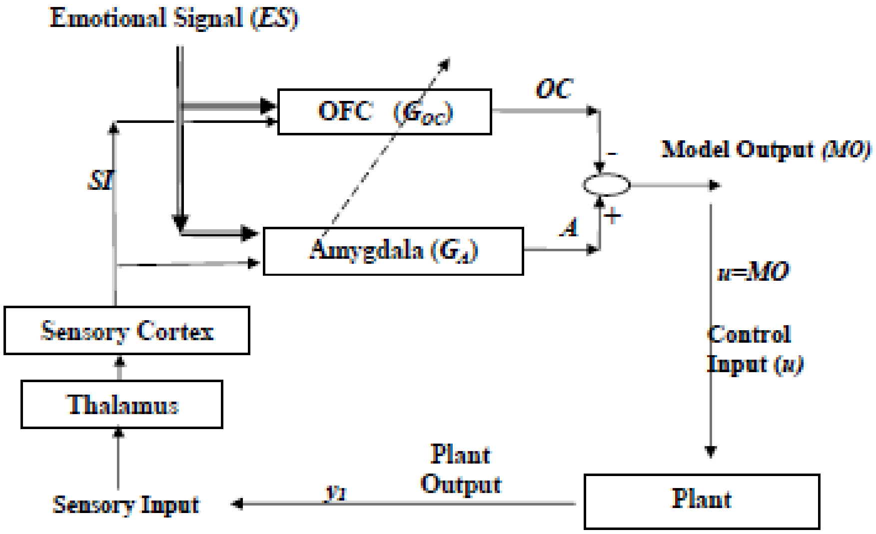


Fig 4.3 The plant in a closed loop with the controller.

The Morén-Balkenius model is now adapted to be used as the feedback law for the regulation of a first order linear time invariant system given by:

$$\dot{y}_1 = -ay_1 + bu$$

where y_1 is the state, *u* is the control input and $a>0$. Figure 4.3 outlines this feedback law. Using the limbic system model, we propose the following linear feedback rule which uses the model output *MO* for a single set of amygdala and OFC (i.e. $i=1$ only).

$$MO = A_1 - OC_1 = (G_A - G_{OC}).SI$$

as the control input *u* for the system. As the amygdala and the OFC gains are dynamic in nature, we define two more state variables, y_2 and y_3 representing G_A and G_{OC} respectively. We also define the Sensory Input *SI* to be the plant output or state y_1. Note that we are allowed flexibility in deciding the *SI* and it can involve derivatives of the plant output as well, but for analytical simplicity we have chosen *SI* to be y_1. Hence we can write the following:

$$u = (y_2 - y_3)y_1$$

Now we define the Reward or the Emotional Signal *ES* as a combination of the external signal x_1 (external to the controller) and the internal signal u.

$$ES = w_1.y_1 + w_2.u$$

The weights w_1 and w_2 help in defining the relative importance that has to be given to either signal. Actually the external signal should be the error, but as this is a regulation problem, the error is identical to the output. From a biological perspective, by mixing these two signals we are attempting to incorporate the separate information of what needs to be done and what can be done at the present situation.

The update rules are rewritten to relate the time derivatives of the gains with the same functional form as in the emotional processing network. This is valid as it can be understood that the discrete updates are occurring at a high frequency and the sampling time can be absorbed into the constants. Also we remove the max operator as well, for analytical simplicity. Further work shall show that for continuous time development the maximum operator is not required as such.

Hence (1) is simplified to yield the following set of equations:

$$\begin{aligned} A &= G_A.SI \\ OC &= G_{OC}.SI \\ \frac{dG_A}{dt} &= \alpha.SI.(ES - A) \\ \frac{dG_{OC}}{dt} &= \beta.SI.(A - OC - ES) \\ MO &= A - OC \end{aligned}$$

Chapter 5
Programming tool used for Modeling and Simulation

Introduction

Now as we have the controller architecture, the next challenge was the designing and implementation of the system using suitable programming tool, so that we can extract complete information from the behavior of the system and at the same time we have complete flexibility to change the parameters of the model. Hence the model should be an interactive type (or GUI) which aids to the flexibility. The obvious choice was Matlab™ Simulink® which gives us enough flexibility and tolls for making a control system (i.e. tolls like LTI system, Pole-Zero representation of the transfer function, various signal routing tools and many more).Now two questions arises here (a) what is Simulink? (b)How is it applicable for our current problem?

5.1 What is Simulink

Simulink is a software package for modeling, simulating, and analyzing dynamic systems. It supports linear and nonlinear systems, modeled in continuous time, sampled time, or a hybrid of the two. Systems can also be multirate, i.e., have different parts that are sampled or updated at different rates.

Simulink encourages you to try things out. You can easily build models from scratch, or take an existing model and add to it. You have instant access to all the analysis tools in MATLAB®, so you can take the results and analyze and visualize them. A goal of Simulink is to give you a sense of the fun of modeling and simulation, through an environment that encourages you to pose a question, model it, and see what happens. Simulink is also practical. With thousands of engineers around the world using it to model and solve real problems, knowledge of this tool will serve you well throughout your professional career.

For modeling, Simulink provides a graphical user interface (GUI) for building models as block diagrams, using click-and-drag mouse operations. With this interface, you can draw the models just as you would with pencil and paper (or as most textbooks depict them). This is a far cry from previous simulation packages that require you to formulate differential equations and difference equations in a language or program. Simulink includes a comprehensive block library of sinks, sources, linear and nonlinear components, and connectors. You can also customize and create your own blocks.

After you define a model, you can simulate it, using a choice of integration methods, either from the Simulink menus or by entering commands in the MATLAB Command Window. The menus are particularly convenient for interactive work, while the command-line approach is very useful for running a batch of simulations (for example, if you are doing Monte Carlo simulations or want to sweep a parameter across a range of values). Using scopes and other display blocks, you can see the simulation results while the simulation is running. In addition, you can change many parameters and see what happens for "what if" exploration. The simulation results can be put in the MATLAB workspace for postprocessing and visualization.

The next question which arises is how does Simulink looks like and how to build a model in Simulink.

5.2 How to build a model in Simulink

To create the model, first enter Simulink in the MATLAB Command Window. On Microsoft Windows, the Simulink Library Browser appears as shown in figure 5.1.

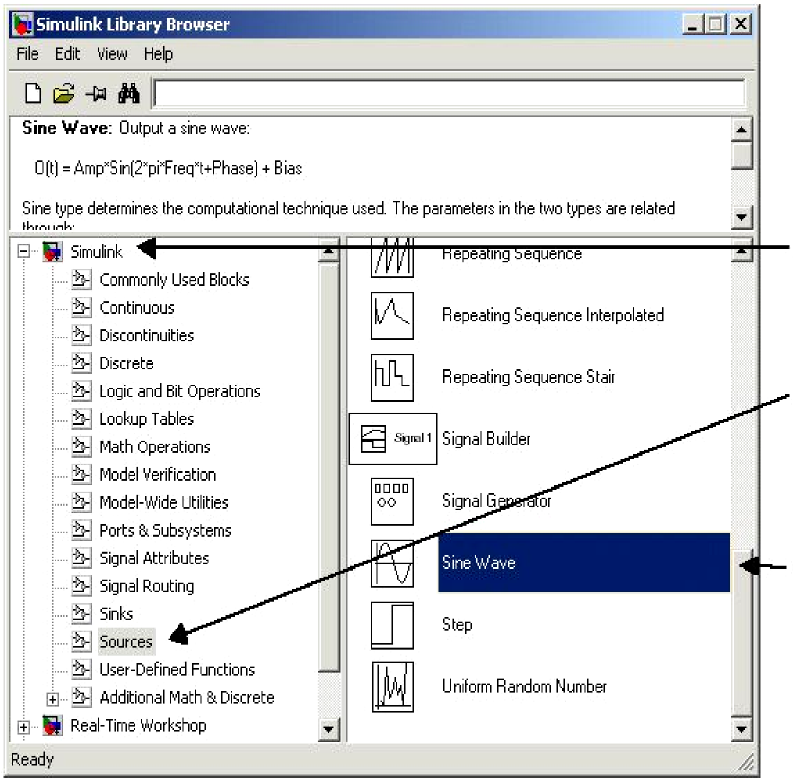
To create a new model on Windows, click the New Model button on the Library Browser's toolbar.

To create any model, you need to copy some blocks into the model from the Simulink block libraries (for example take an arbitrary model which needs following blocks):

- Sources library (the Sine Wave block)
- Sinks library (the Scope block)
- Continuous library (the Integrator block)
- Signal Routing library (the Mux block)

To copy the Sine Wave block from the Library Browser, first expand the Library Browser tree to display the blocks in the Sources library. Do this by clicking the Sources node to display the

Sources library blocks. Finally, click the Sine Wave node to select the Sine Wave block. Now drag a copy of the Sine Wave block from the browser and drop it in the model window.



Sine Wave: Output a sine wave:

O(t) = Amp*Sin(2*pi*Freq*t+Phase) + Bias

Sine type determines the computational technique used. The parameters in the two types are related through:

Simulink library

Sources library

Sine Wave block

Fig 5.1 Library Browser

Copy the rest of the blocks in a similar manner from their respective libraries into the model window. You can move a block from one place in the model window to another by dragging the block. You can move a block a short distance by selecting the block, then pressing the arrow keys. With all the blocks copied into the model window, the model should look something like as shown in figure 5.2. Notice that one or both sides of the blocks have angle brackets. The > symbol pointing out of a block is an output port; if the symbol points to a block, it is an input port.

Now it's time to connect the blocks. Connect the Sine Wave block to the top input port of the Mux block. Position the pointer over the output port on the right side of the Sine Wave block. Notice that the cursor shape changes to crosshairs. Hold down the mouse button and move the cursor to the top input port of the Mux block. Notice that the line is dashed while the mouse button is down and that the cursor shape changes to double-lined crosshairs as it approaches the Mux block.

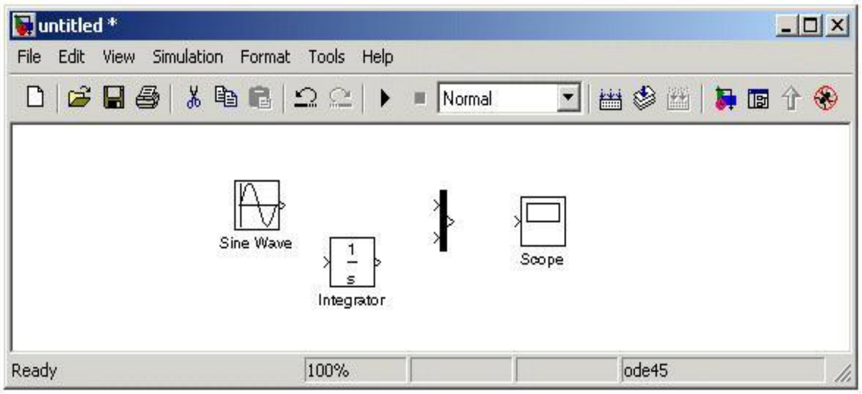


Fig 5.2 An example model

Now release the mouse button. The blocks are connected. You can also connect the line to the block by releasing the mouse button while the pointer is over the block. If you do, the line is connected to the input port closest to the cursor's position. If you look again at the model at the beginning of this section, you'll notice that most of the lines connect output ports of blocks to input ports of other blocks. However, one line connects a line to the input port of another block. This line, called a branch line, connects the Sine Wave output to the Integrator block, and carries the same signal that passes from the Sine Wave block to the Mux block. Drawing a branch line is slightly different from drawing the line you just drew. To weld a connection to an existing line, follow these steps:

- First, position the pointer on the line between the Sine Wave and the Mux block.
- Press and hold down the Ctrl key (or click the right mouse button). Press the mouse button, then drag the pointer to the Integrator block's input port or over the Integrator block itself.
- Release the mouse button. Simulink draws a line between the starting point and the Integrator block's input port.

Finish making block connections. When you're done, your model should look something like as shown in figure 5.3

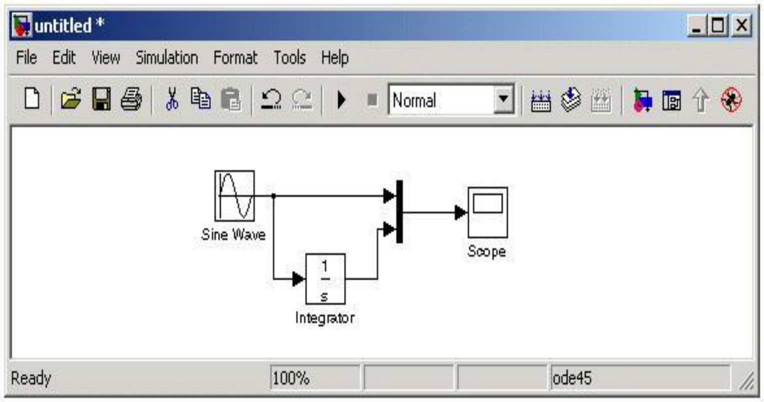


Fig 5.3 Block diagram after al the connections are complete

The Now set up Simulink to run the simulation for 10 seconds. First, open the Configuration Parameters dialog box by choosing Configuration Parameters from the Simulation menu. On the dialog box that appears, notice that the Stop time is set to 10.0 (its default value). Or set a value for which you want to evaluate the system.

Now double-click the Scope block to open its display window as shown in figure 5.4. Finally, choose Start from the Simulation menu and watch the simulation output on the Scope. The simulation stops when it reaches the stop time specified in the Configuration Parameters dialog box or when you choose Stop from the Simulation menu or click the Stop button on the model window's toolbar To save this model, choose Save from the File menu and enter a filename and location. That file contains the description of the model.

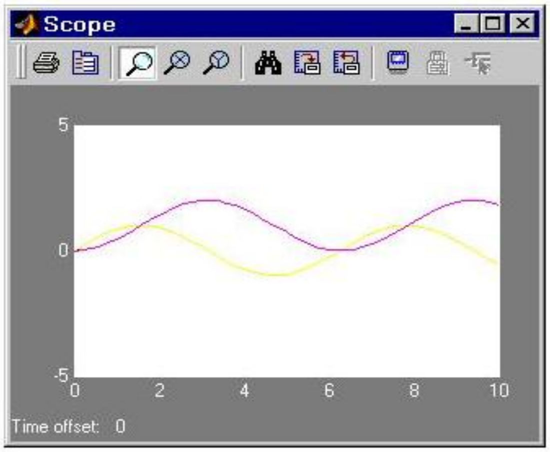


Fig 5.4 Example scope window.

Chapter 6
Applications and Results

6.1 Introduction

In this chapter we are describing the utilization of the developed model in MIMO control system. In fact, the main effort is focused on applying the model to control system where the model acts as the controller block.

The reason for using emotional learning in control engineering has been previously discussed [22, 48]. In this connection, the first issue in using the model for a control system configuration is how to embed it within the overall architecture of the system. Of course, there is no unique way of doing this, because the fundamental characteristic of the model is its flexibility in achieving multiple objectives based on receiving different sensory inputs and emotional signals. Figure 4.3 demonstrates a reasonable candidate for embedding the BEL (Brain Emotional Learning) model within a typical feedback control block diagram.

In our problem the entire architecture looks like as shown in figure 6.1. The upper half of this block diagram is of BEL controller and the rest part is the plant and model part. To plant we are giving (a) Control signal (b) Set point (c) Disturbance. To model we are giving the set point, and now we are comparing the model's output and the plant's output employing a Mux. Various scopes used are for monitoring: (a) Disturbance (b) Plant and model output's comparison (c) Set point. The plant and model blocks are simple Pole-Zero transfer function blocks. Various parameters such as gains are set depending on the control problems. The Sensory input and Emotional signal are:

$$SI = Ke \qquad \& \qquad ES = K(e + \int e\, dt)$$

Although there are many confusions about the origin of Emotional signal i.e. how it is generated and what is its function and is an open topic for research now a days. But right now control engineers are taking such kind of emotional signal until and unless some important discoveries regarding it does not takes place.

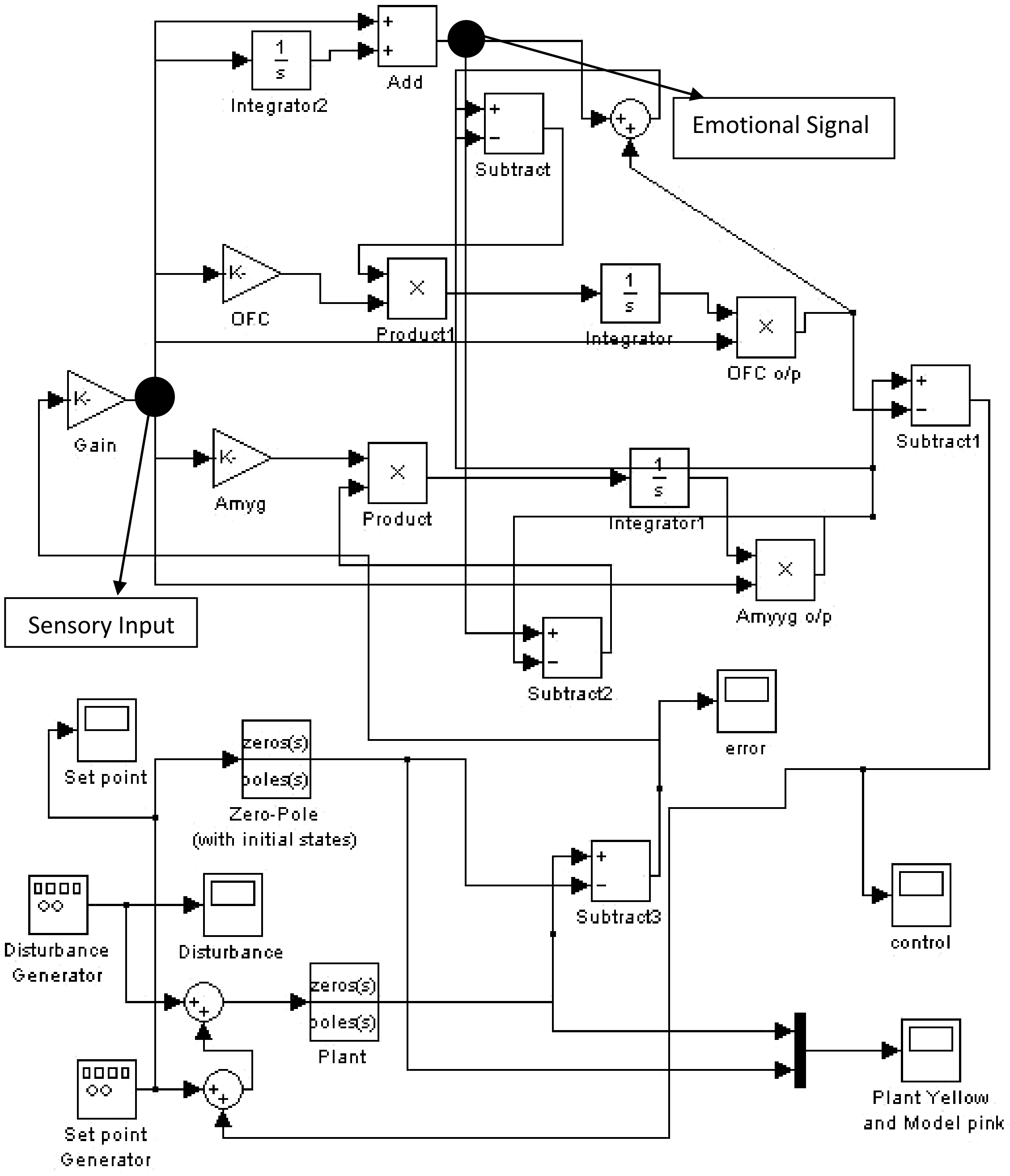


Fig 6.1 Model of the control architecture which will be discussed now onwards.

In this thesis we have taken a MIMO submarine model and have compared the performance of the control system with uncontrolled models response (in presence of disturbance).

6.2 Submarine model

We start the simulations with a linear Single Input-Single Output (SISO) model of a submarine system. The system is designed as a set point tracking control problem. The transfer function of the system is:

$$\frac{.1(S+1)^2}{S(S^2+0.09)}$$

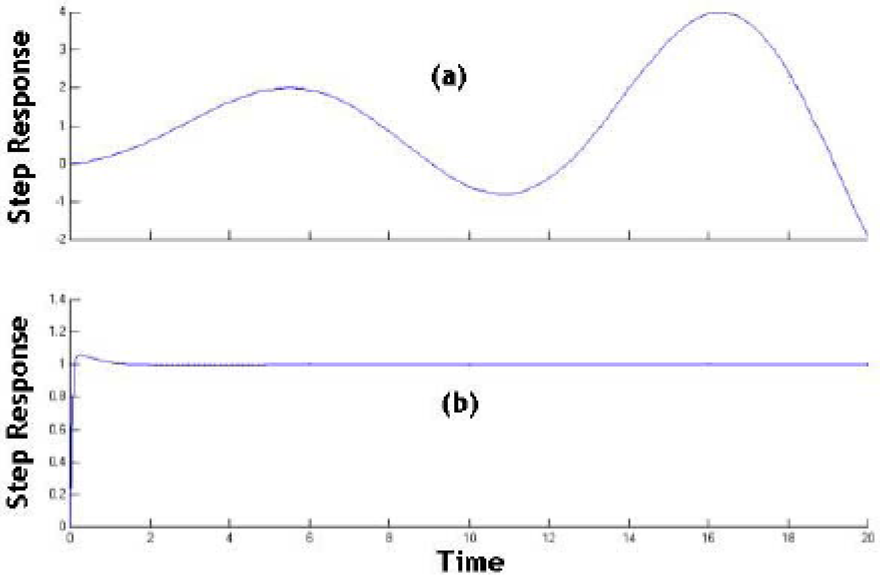


Fig 6.2 Closed loop response of the submarine model (a)without controller (b)with BEL controller

As figure 6.2 (a) shows, the closed loop system, by itself, is unstable. Then we used the BEL controller for the system, figure 6.2 (b), it can be seen that the system response reaches the reference value of one with an acceptable performance indices.

Now two questions arise. (a) What are the systems parameters? (b) How is the systems performance if various disturbances along with changing set points is applied to the system?

The parameters are as follows:

- Gain K for SI = 100

- Learning rate of Amygdala = 100
- Learning rate of OFC = 100

Twenty different cases of random disturbance patterns, changing set points have been made. For each set of system parameters the comparison of plant and model output’s with and without controller is illustrated. For each disturbance pattern we will discuss output of the following scopes: (a) Disturbance (b) Plant and Model comparison (plants output being in green colour and models output being in blue colour), (i) without controller (ii) with controller (c) Set point.

For patterns 1 to 12 the set point is set to a square wave of amplitude 1 unit and frequency of .1 Hz as shown in figure 6.3(a) and for patterns 13 to 20 the set point is changed to a sawtooth wave having amplitude = 1 unit and frequency = .1 Hz as shown inf figure 6.3 (b).

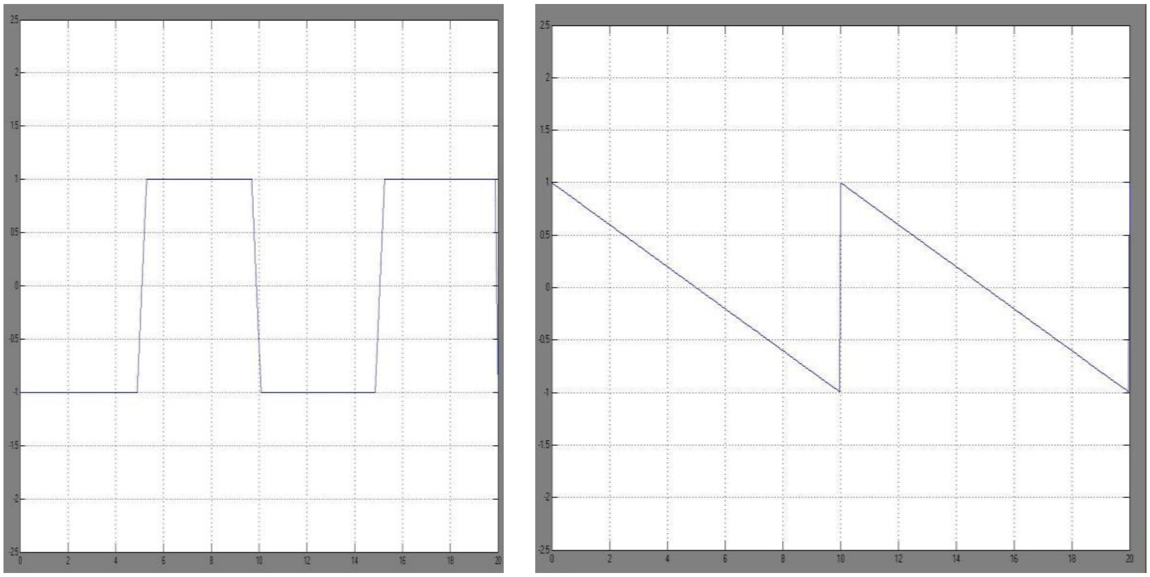


Fig 6.3(a) Set point for patterns 1 to 12 (b) set point for patterns 13 to 20.

6.3 Results

Pattern 1:

Disturbance: – *sine* wave of amplitude = 1 and frequency = .5 Hz. Figure 6.4 illustrates the pattern, with Plant output being the blue curve and model output being green curve.

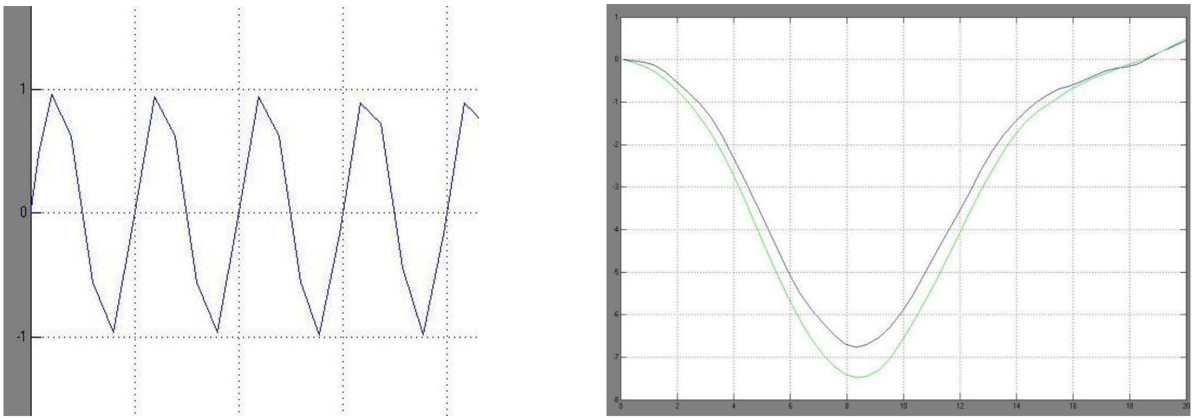


Fig 6.4 (a) disturbance (b) plant and model output without controller

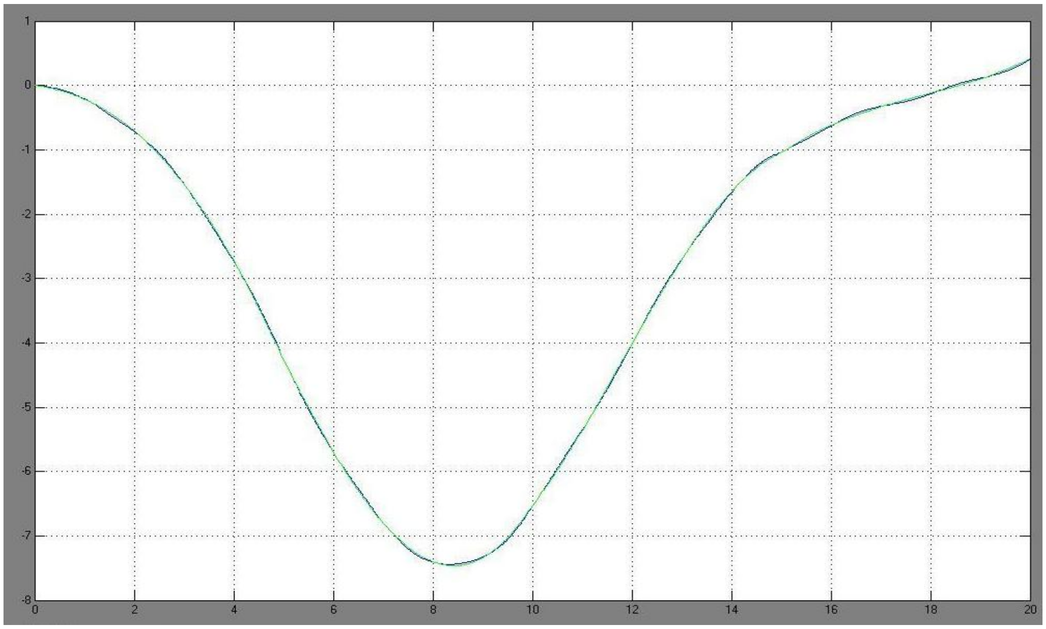


Fig 6.4 (c) plant and model output with controller.

Pattern 2:

Disturbance: – *square* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.5 illustrates the pattern, with Plant output being the blue curve and model output being green curve.

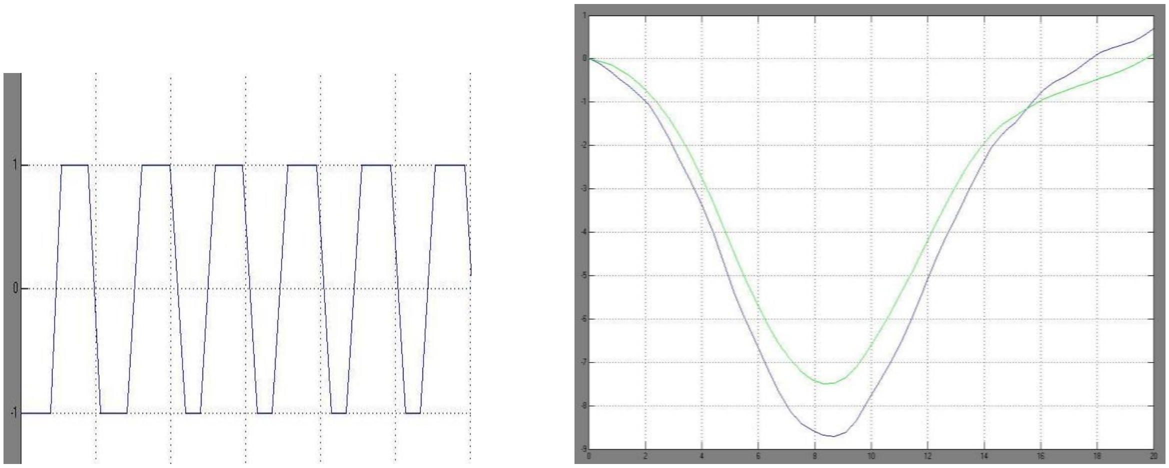


Fig 6.5 (a) disturbance (b) plant and model output without controller

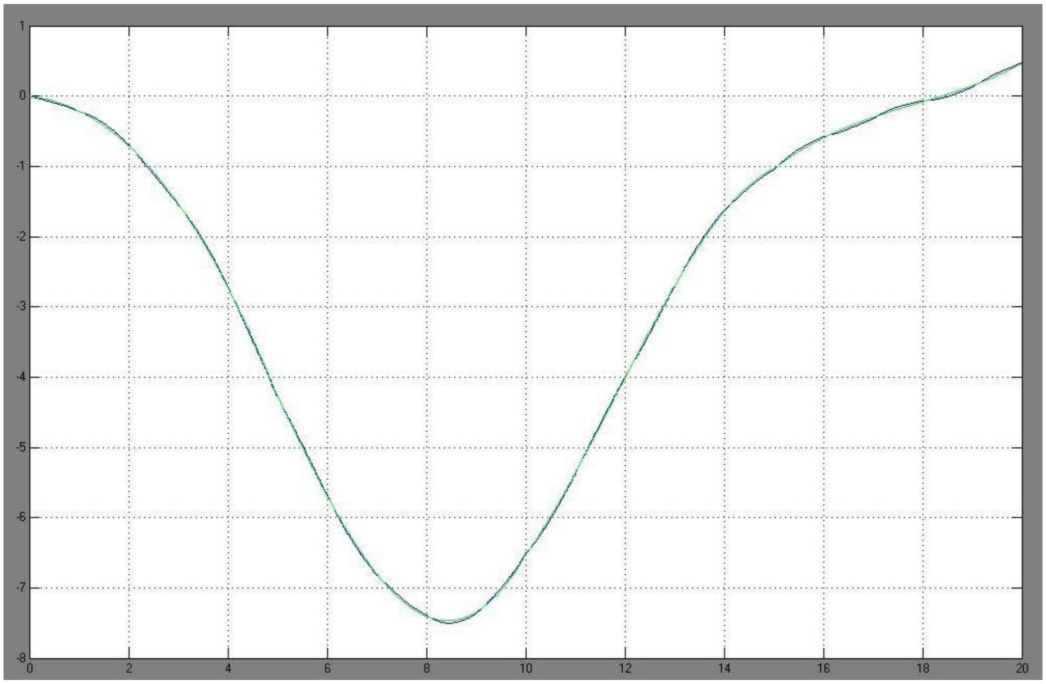


Fig 6.5 (c) plant and model output with controller.

Pattern 3:

Disturbance: – *sawtooth* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.6 illustrates the pattern, with plant output being the blue curve and model output being green curve.

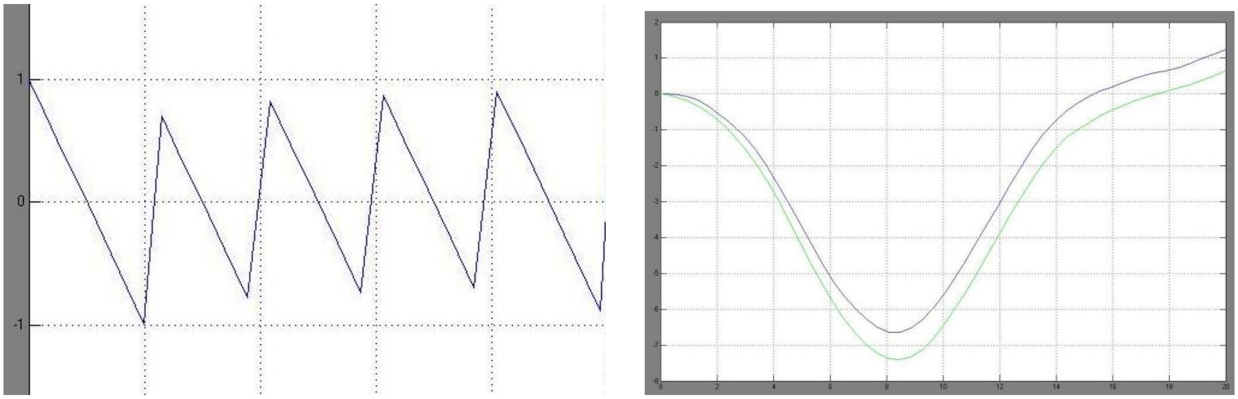


Fig 6.6 (a) disturbance (b) plant and model output without controller

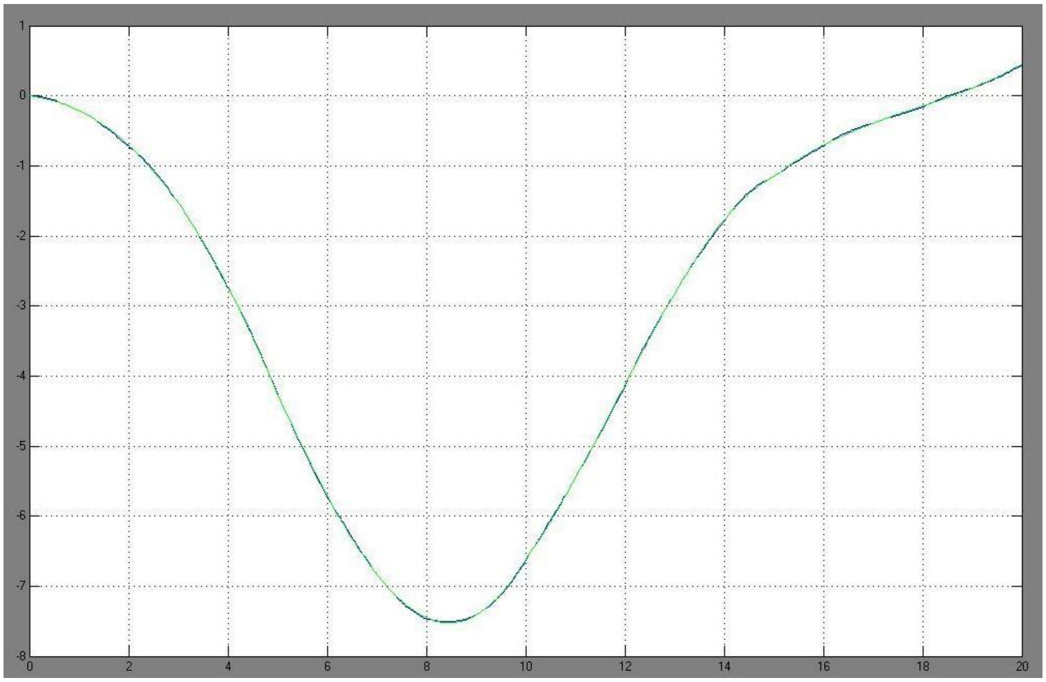
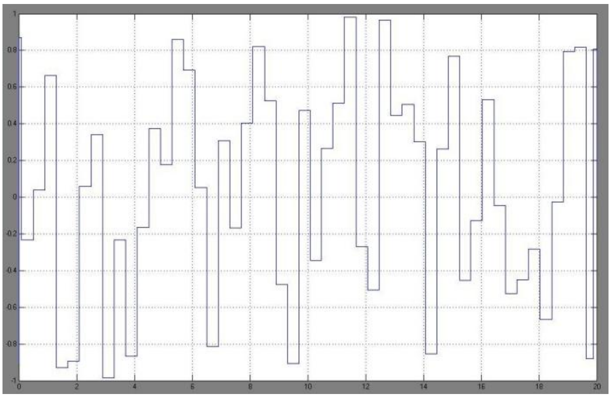


Fig 6.6 (c) plant and model output with controller.

Pattern 4:

Disturbance: – *random* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.7 illustrates the pattern, with plant output being the blue curve and model output being green curve.



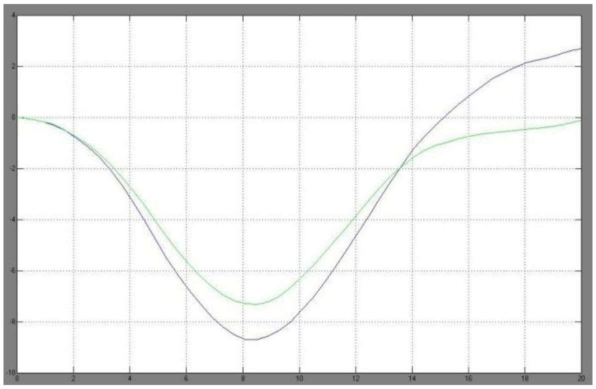


Fig 6.7 (a) disturbance (b) plant and model output without controller

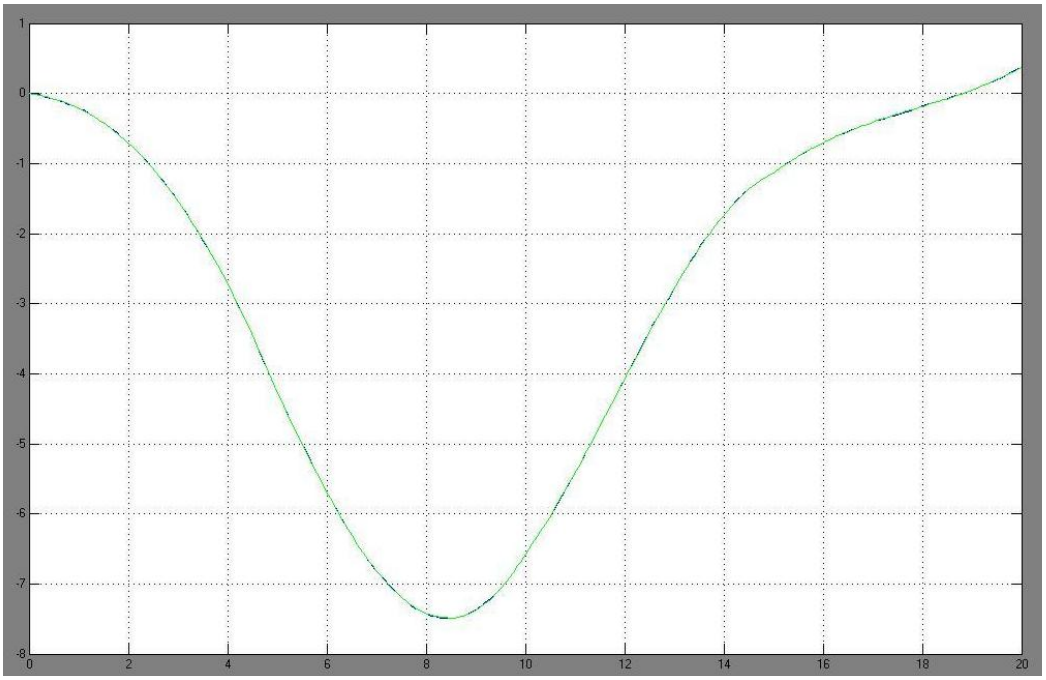


Fig 6.7 (c) plant and model output with controller.

note- for patterns 5 to 8 the amplitude of the disturbance is increased.

Pattern 5:

Disturbance: – *sine* wave of amplitude = 2 unit and frequency = .5 Hz. Figure 6.8 illustrates the pattern, with plant output being the light gray curve and model output being the blue curve and model output being green curve.

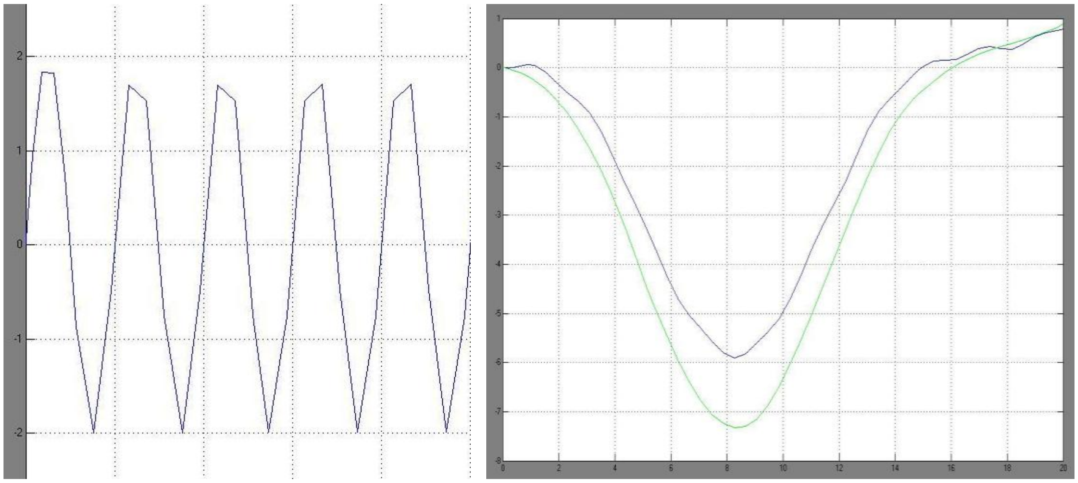


Fig 6.8 (a) disturbance (b) plant and model output without controller

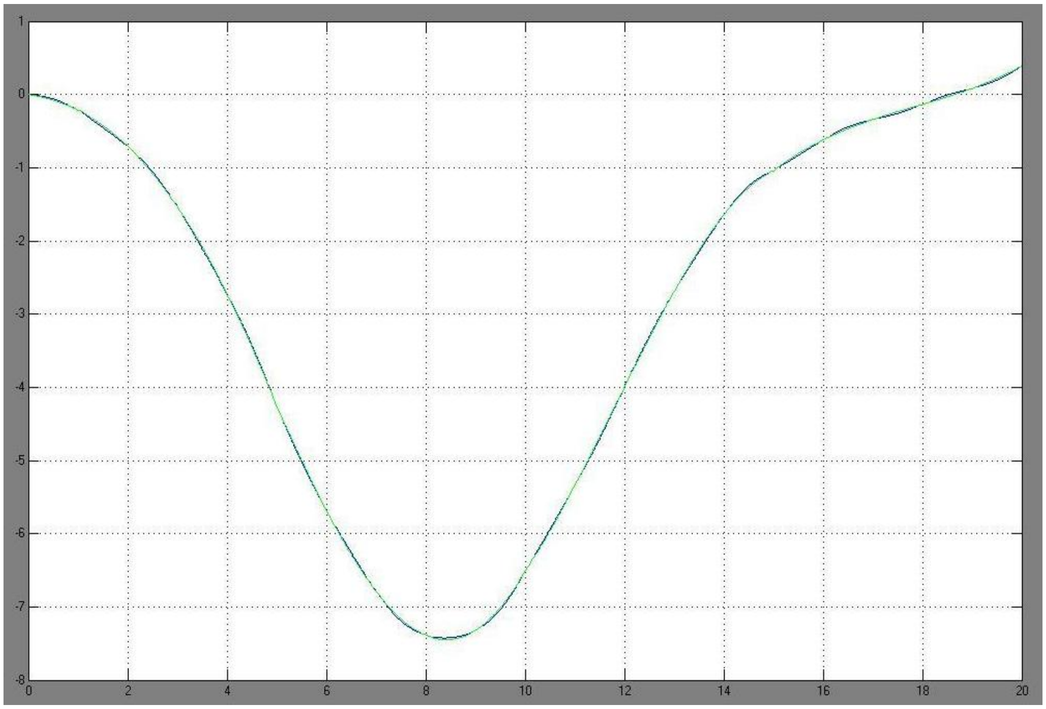


Fig 6.8 (c) plant and model output with controller.

Pattern 6:

Disturbance: – *square* wave of amplitude = 2 unit and frequency = .5 Hz. Figure 6.9 illustrates the pattern, with plant output being the blue curve and model output being green curve.

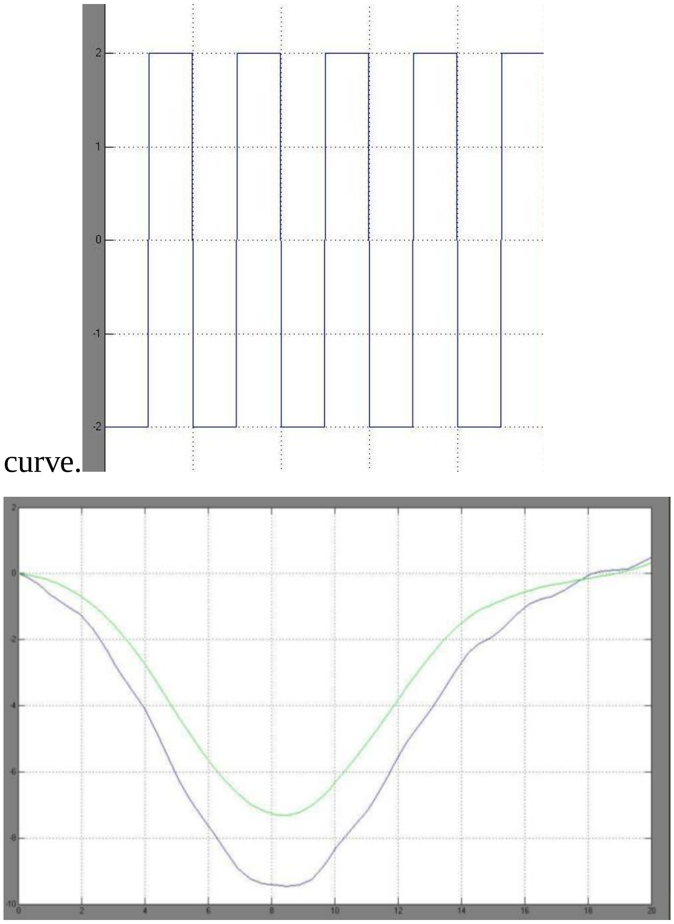


Fig 6.9 (a) disturbance (b) plant and model output without controller

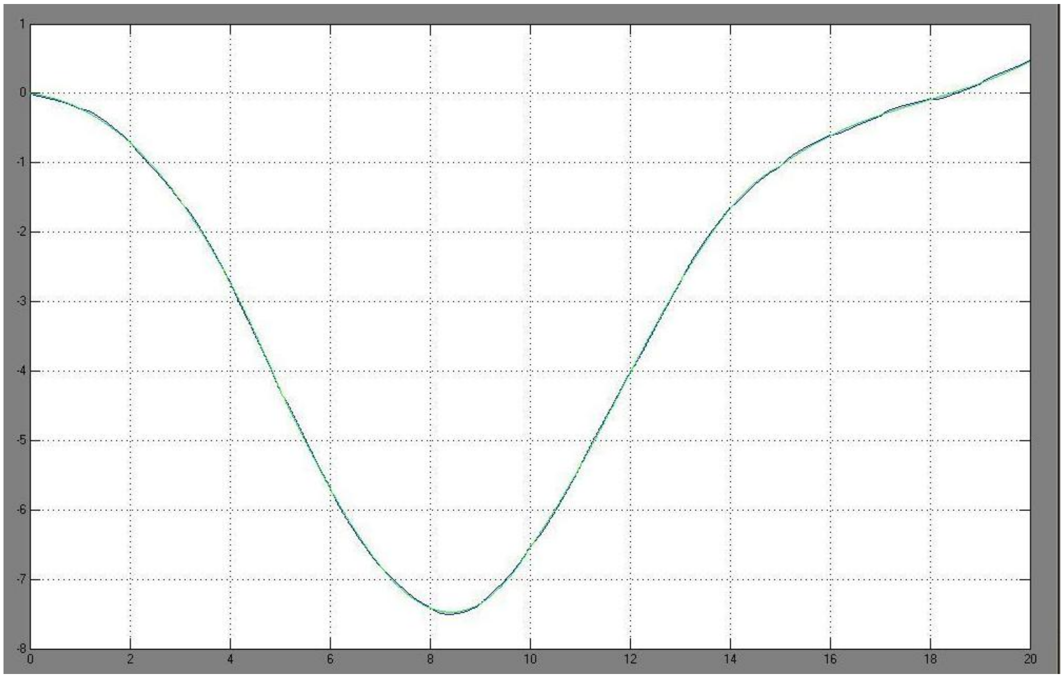


Fig 6.9 (c) plant and model output with controller.

Pattern 7:

Disturbance: – *sawtooth* wave of amplitude = 2 unit and frequency = .5 Hz. Figure 6.10 illustrates the pattern, with plant output being the blue curve and model output being green curve.

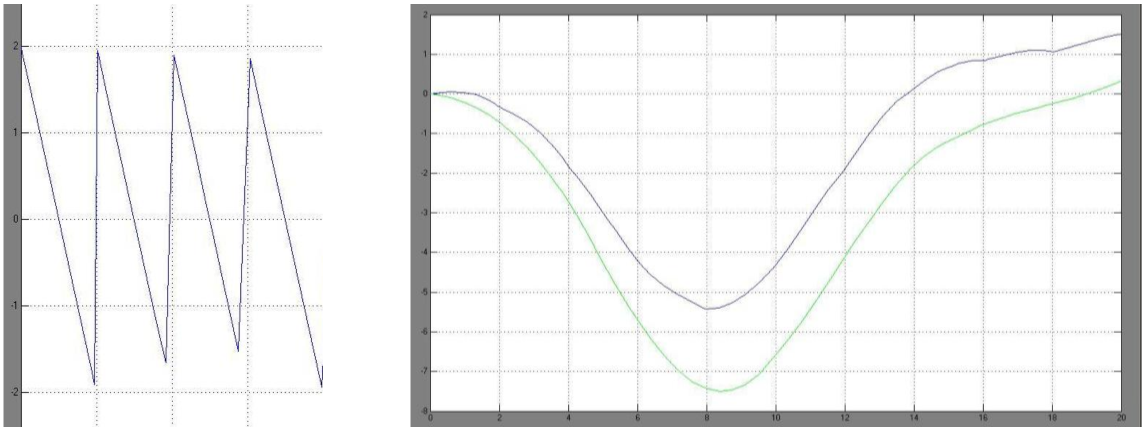


Fig 6.10 (a) disturbance (b) plant and model output without controller

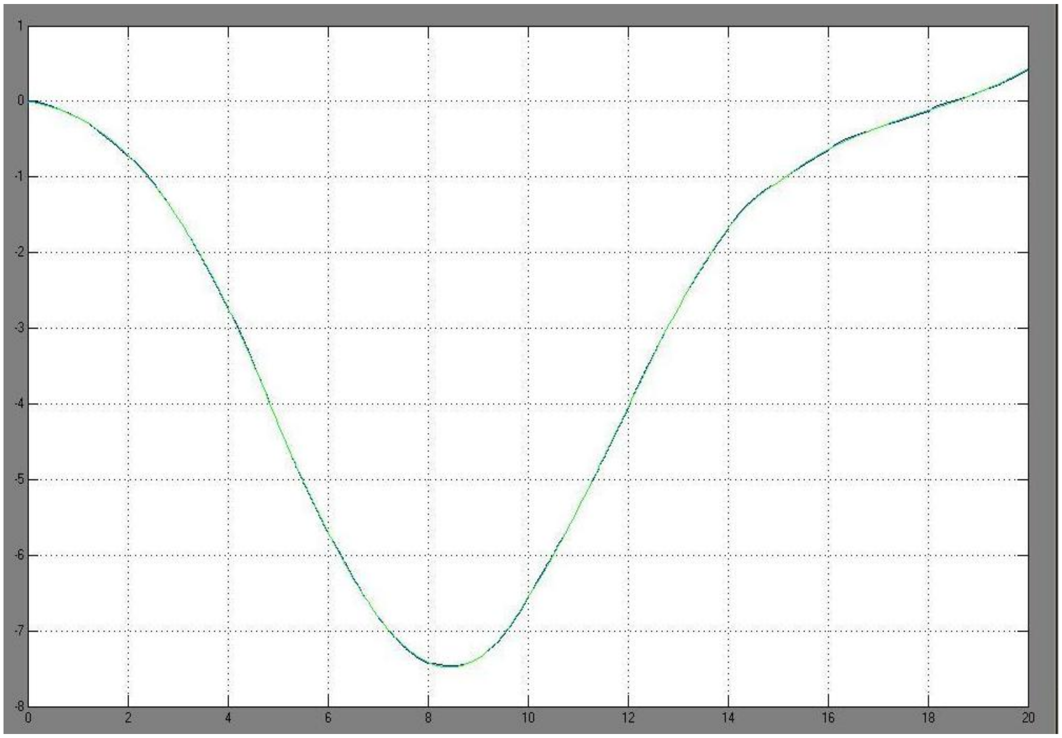


Fig 6.10 (c) plant and model output with controller.

Pattern 8:

Disturbance: – *random* wave of amplitude = 2 unit and frequency = .5 Hz. Figure 6.11 illustrates the pattern, with plant output being the blue curve and model output being green curve.

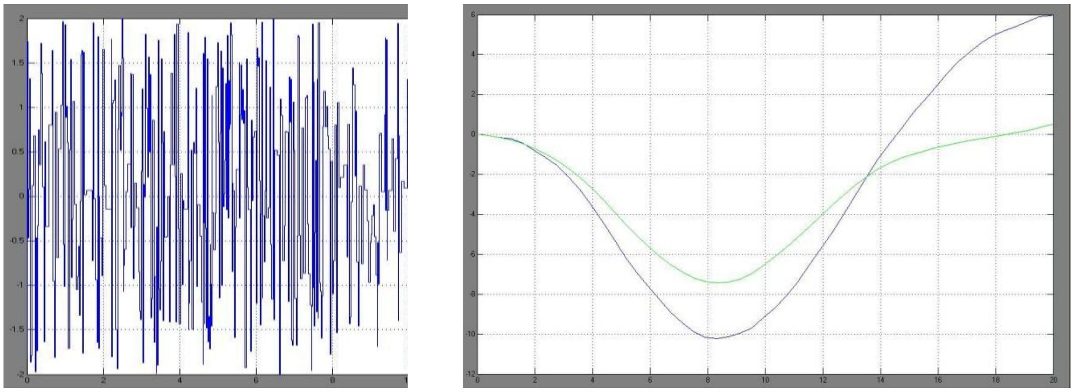


Fig 6.11 (a) disturbance (b) plant and model output without controller

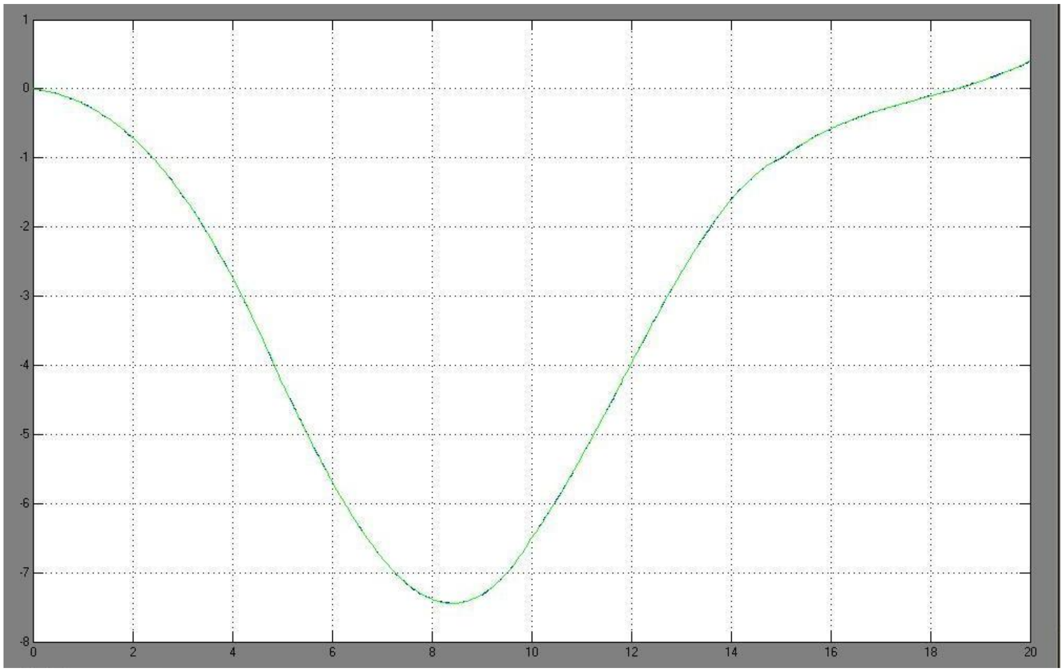


Fig 6.11 (c) plant and model output with controller.

note – for patterns 9 to 12 the amplitude is decreased but the frequency is also decreased which implies that the disturbance will affect the system for long time as there is slow change in disturbance hence will effect more

Pattern 9:

Disturbance: – *Sine* wave of amplitude = 1 unit and frequency = .1 Hz. Figure 6.12 illustrates the pattern, with plant output being the blue curve and model output being green curve.

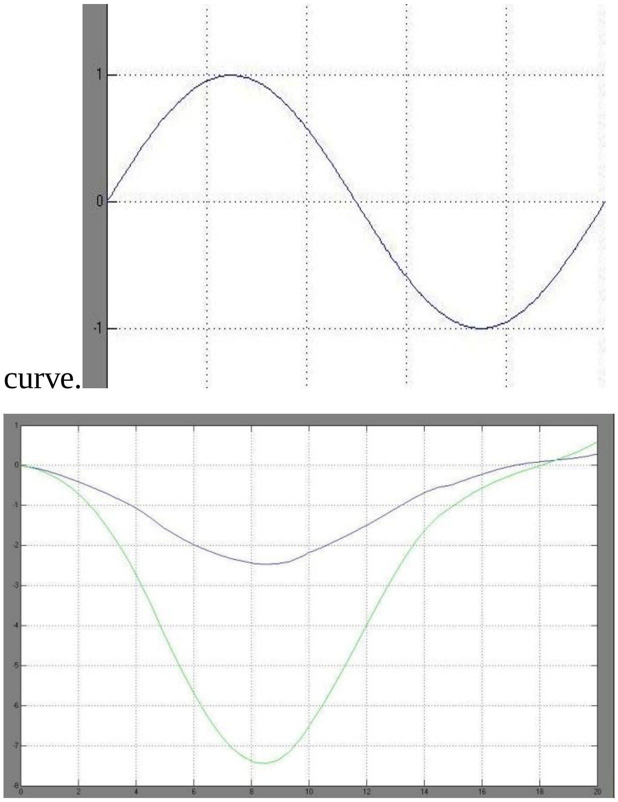


Fig 6.12 (a) disturbance (b) plant and model output without controller

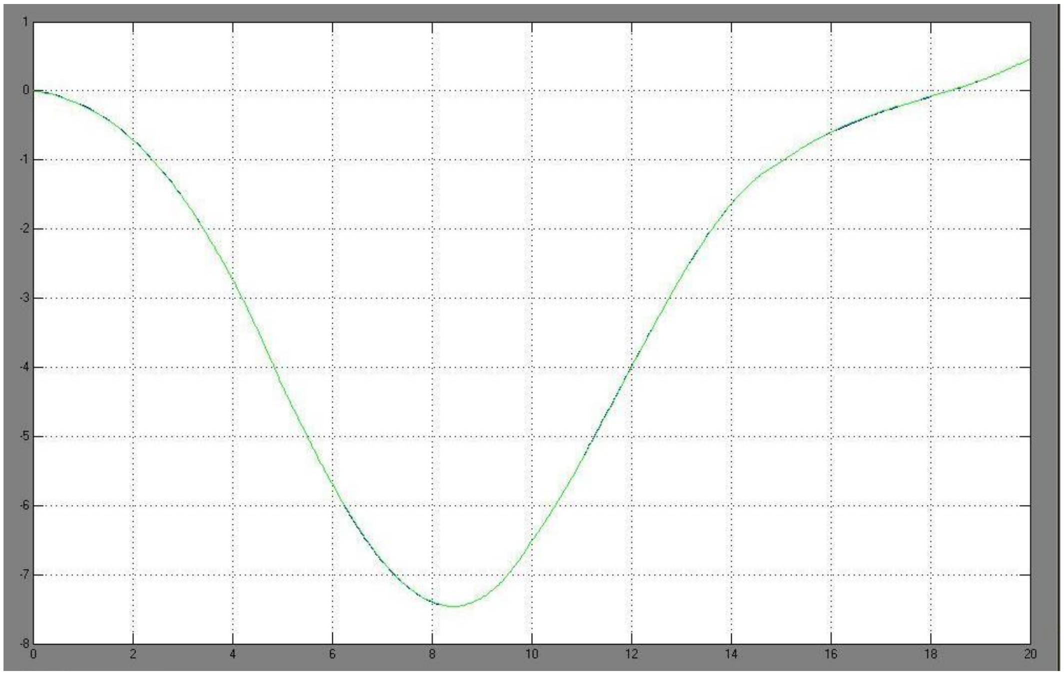


Fig 6.12 (c) plant and model output with controller.

Pattern 10:

Disturbance: – *Square* wave of amplitude = 1 unit and frequency = .1 Hz. Figure 6.13 illustrates the pattern, with plant output being the blue curve and model output being green curve.

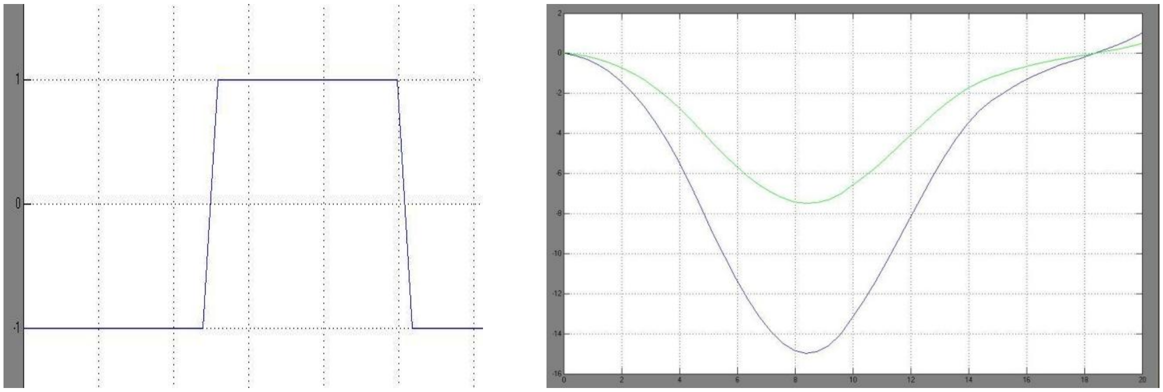


Fig 6.13 (a) disturbance (b) plant and model output without controller

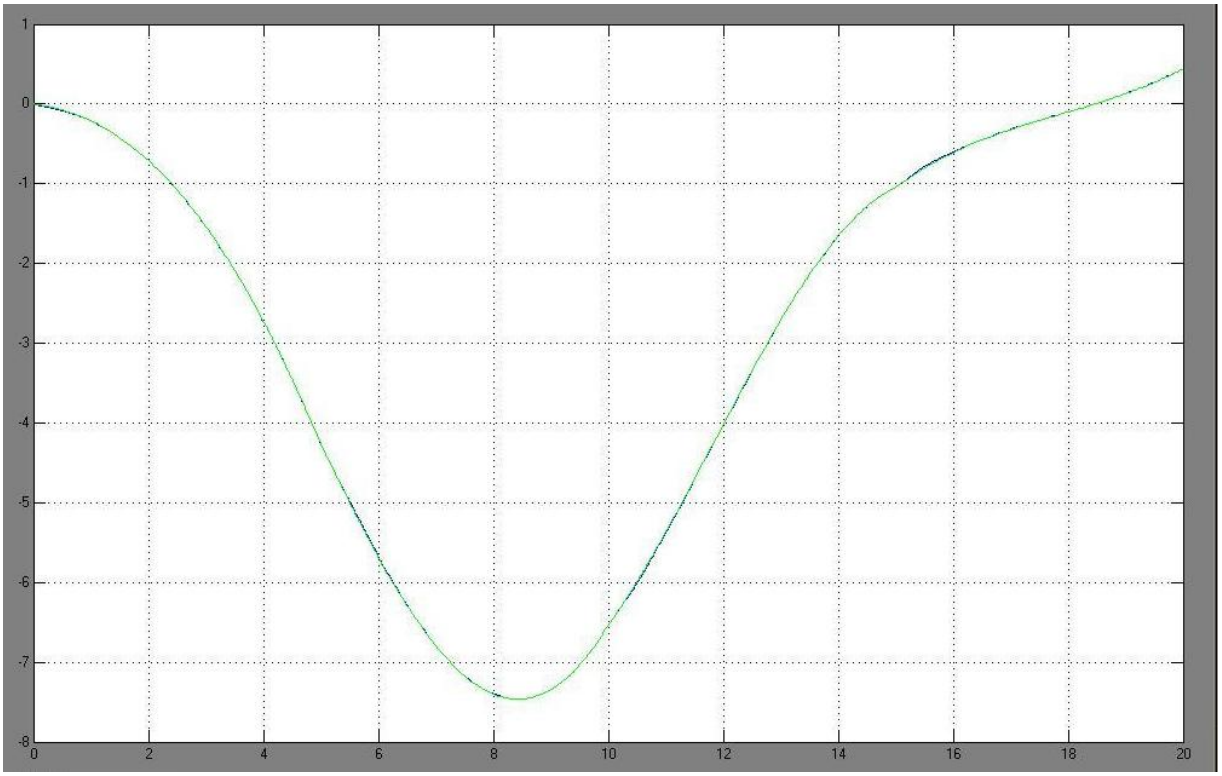
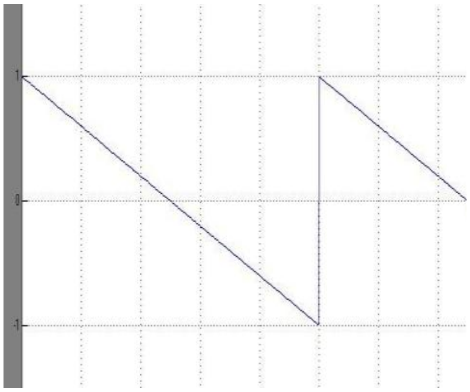


Fig 6.13 (c) plant and model output with controller.

Pattern 11:

Disturbance: – *Sawtooth* wave of amplitude = 1 unit and frequency = .1 Hz. Figure 6.14 illustrates the pattern, with plant output being the blue curve and model output being green curve.



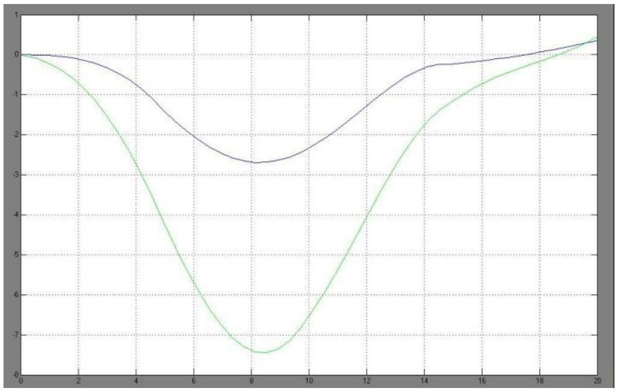


Fig 6.14 (a) disturbance (b) plant and model output without controller

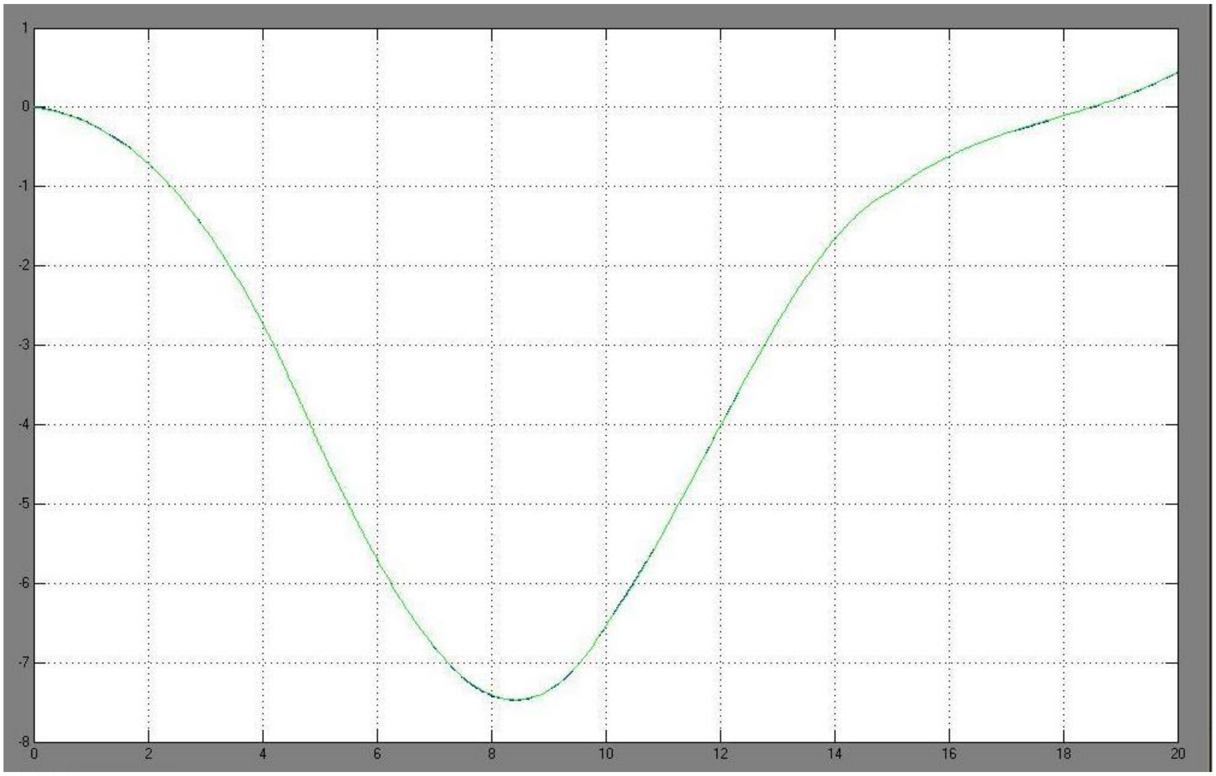


Fig 6.14 (c) plant and model output with controller.

Pattern 12:

Disturbance: – *random* wave of amplitude = 1 unit and frequency = .1 Hz. Figure 6.15 illustrates the pattern, with plant output being the blue curve and model output being green curve.

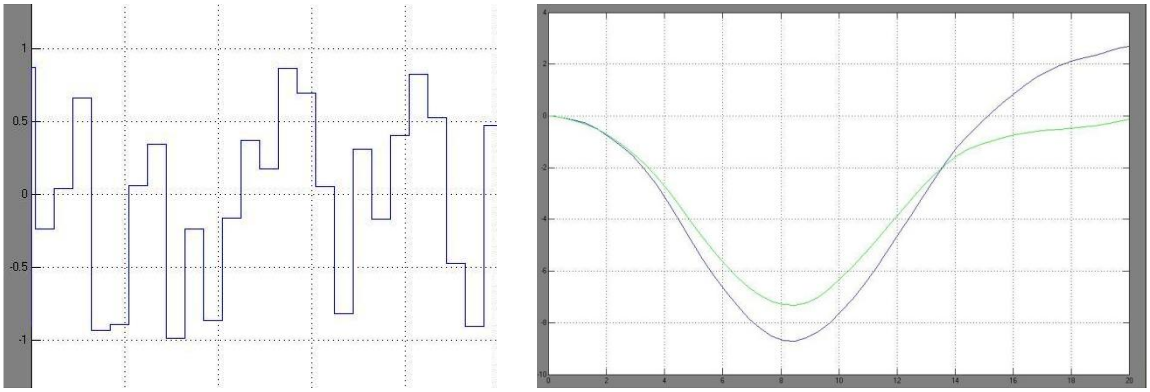


Fig 6.15 (a) disturbance (b) plant and model output without controller

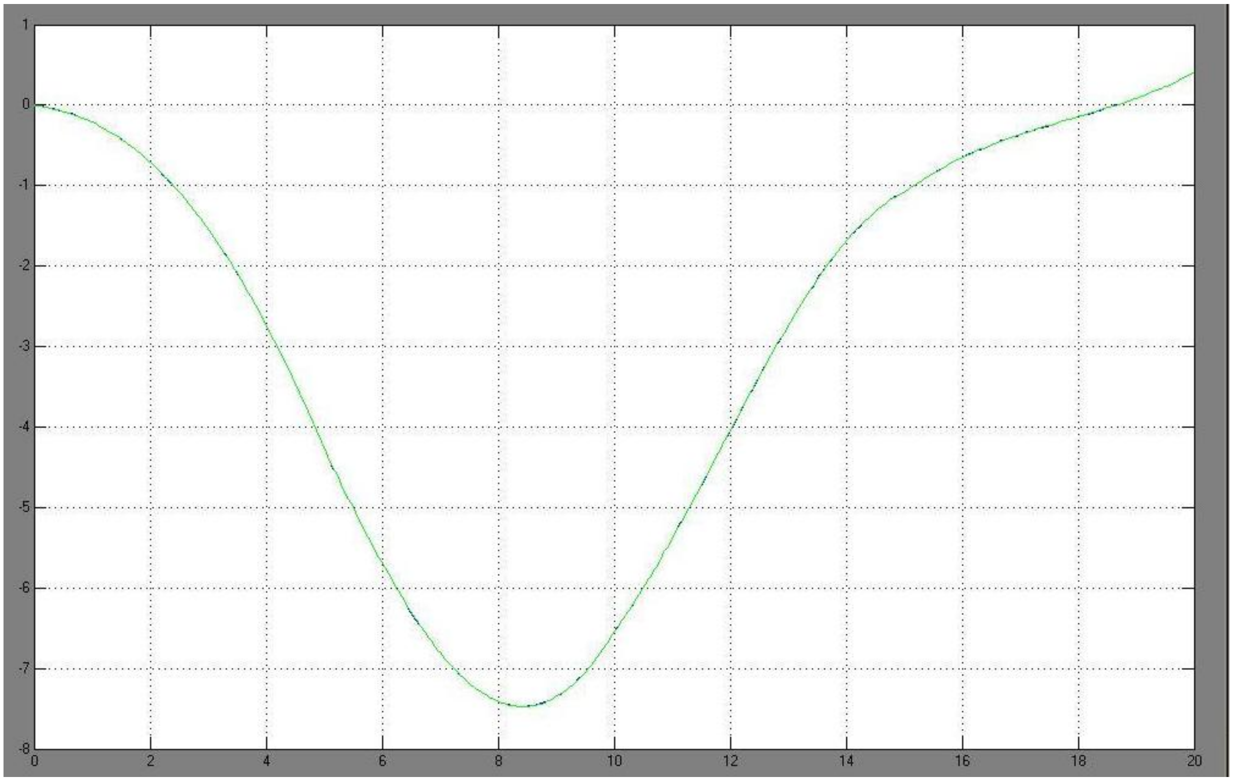


Fig 6.15 (c) plant and model output with controller.

Pattern 13:

Disturbance: – *sine* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.16 illustrates the pattern, with plant output being the blue curve and model output being green curve.

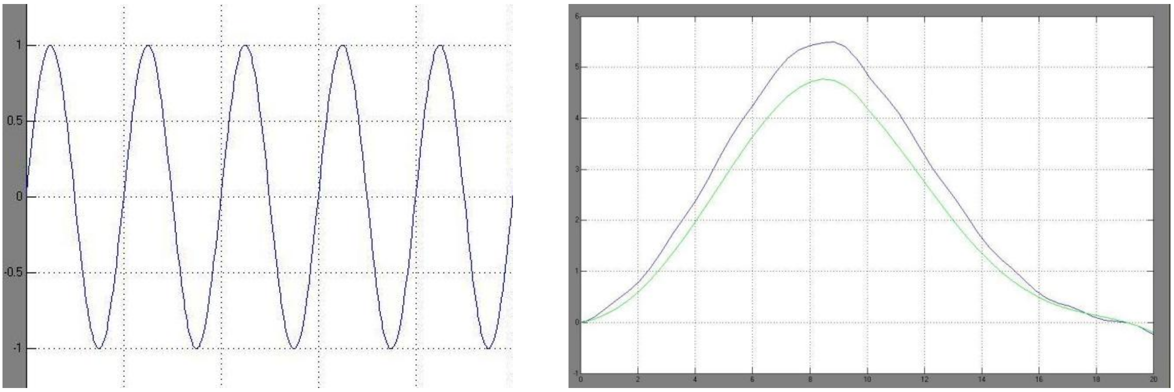


Fig 6.16 (a) disturbance (b) plant and model output without controller

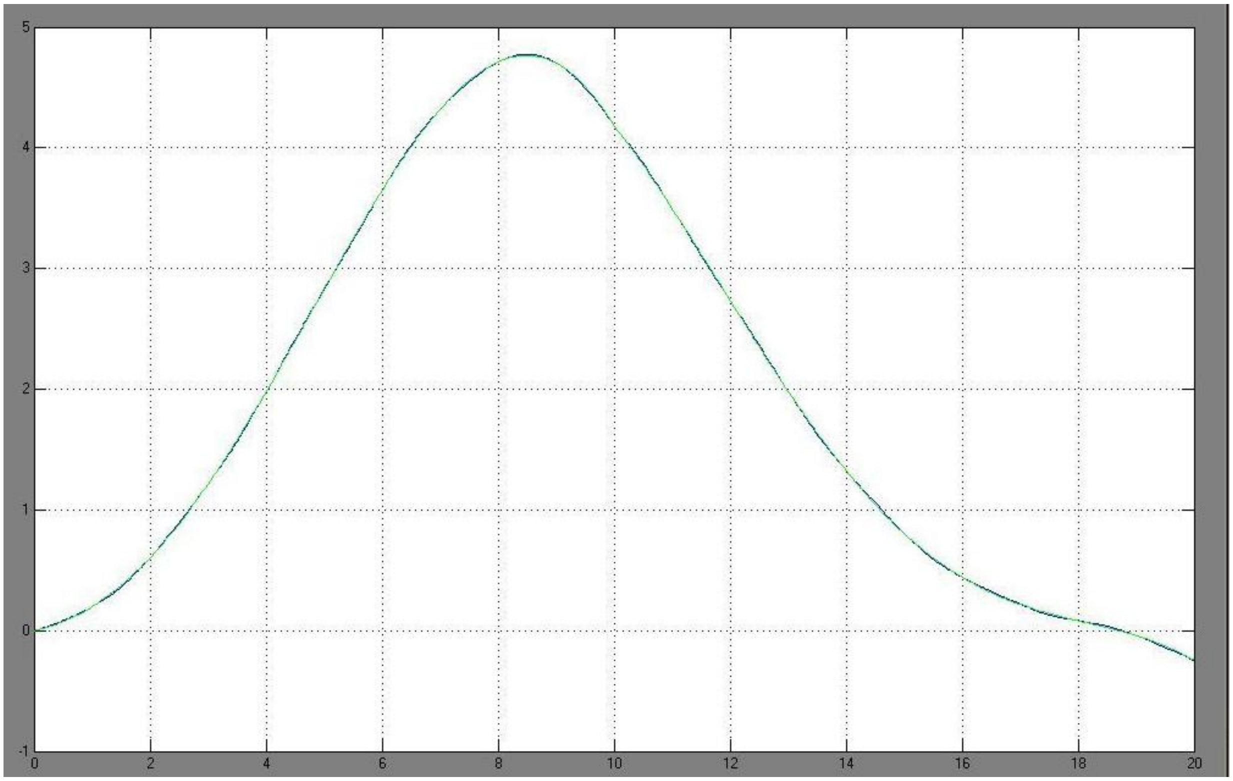


Fig 6.16 (c) plant and model output with controller.

Pattern 14:

Disturbance: – *square* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.17 illustrates the pattern, with plant output being the blue curve and model output being green curve.

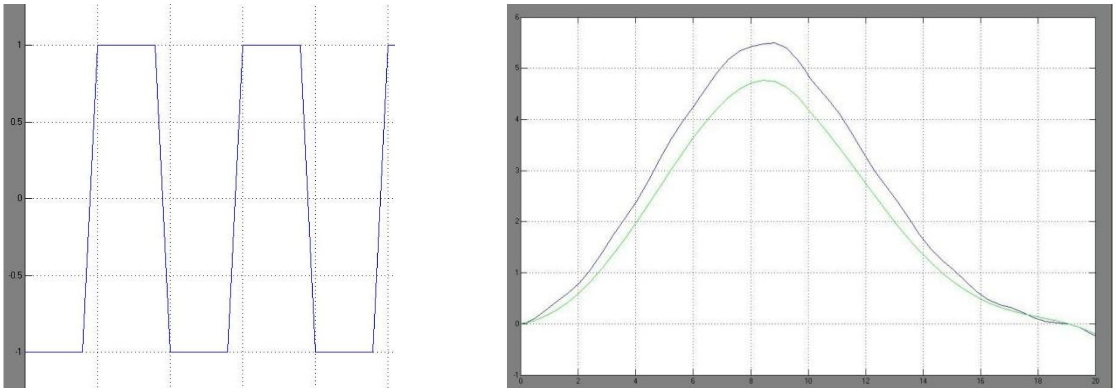


Fig 6.17 (a) disturbance (b) plant and model output without controller

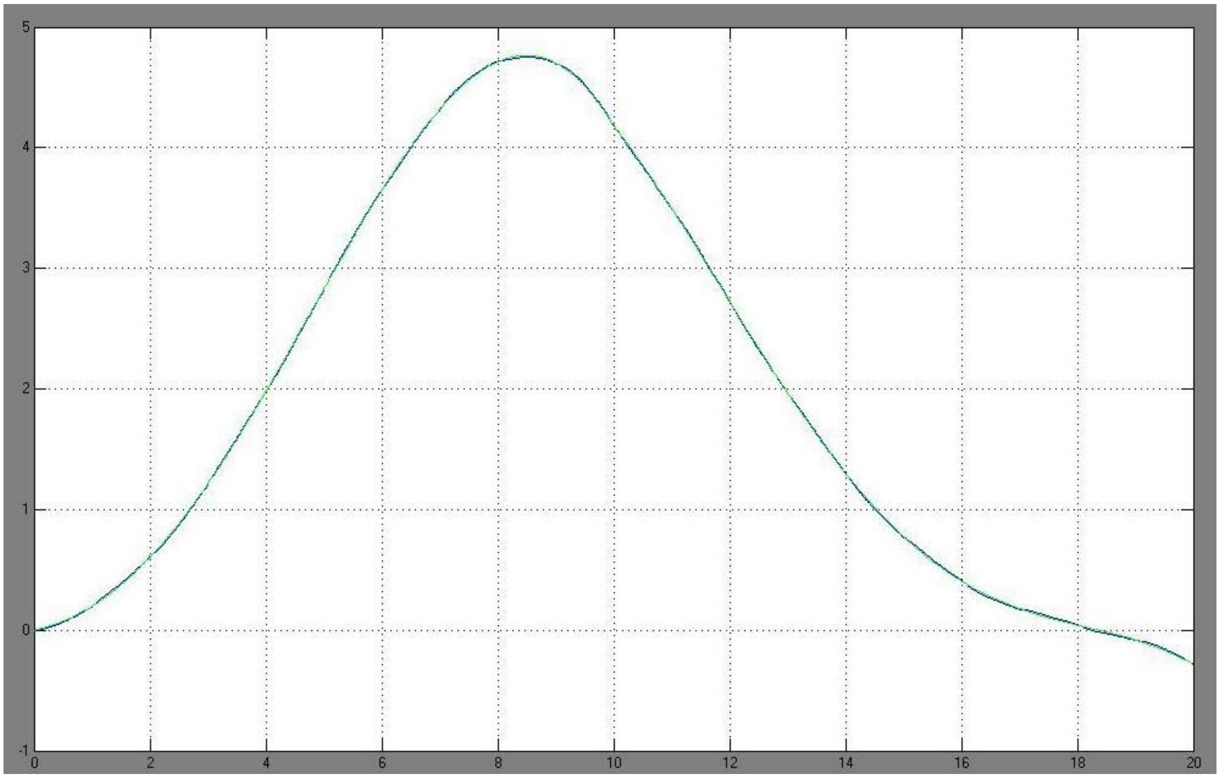
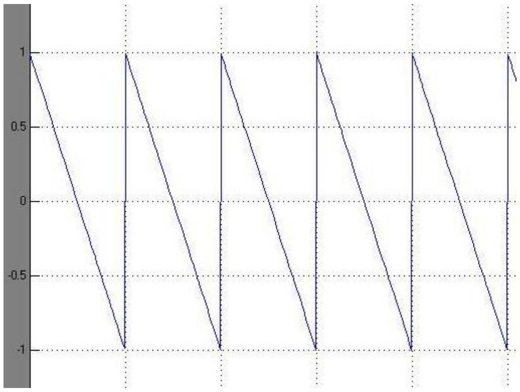


Fig 6.17 (c) plant and model output with controller.

Pattern 15:

Disturbance: – *sawtooth* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.18 illustrates the pattern, with plant output being the blue curve and model output being green curve.



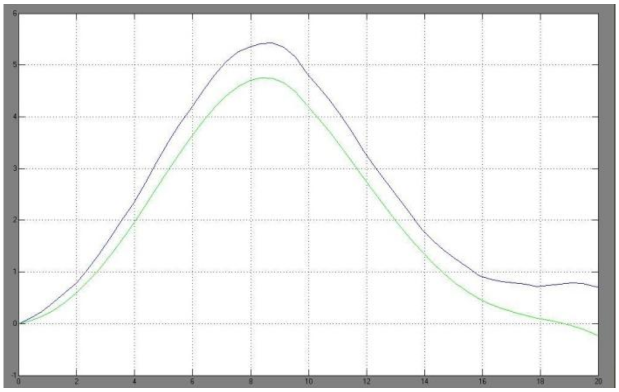


Fig 6.18 (a) disturbance (b) plant and model output without controller

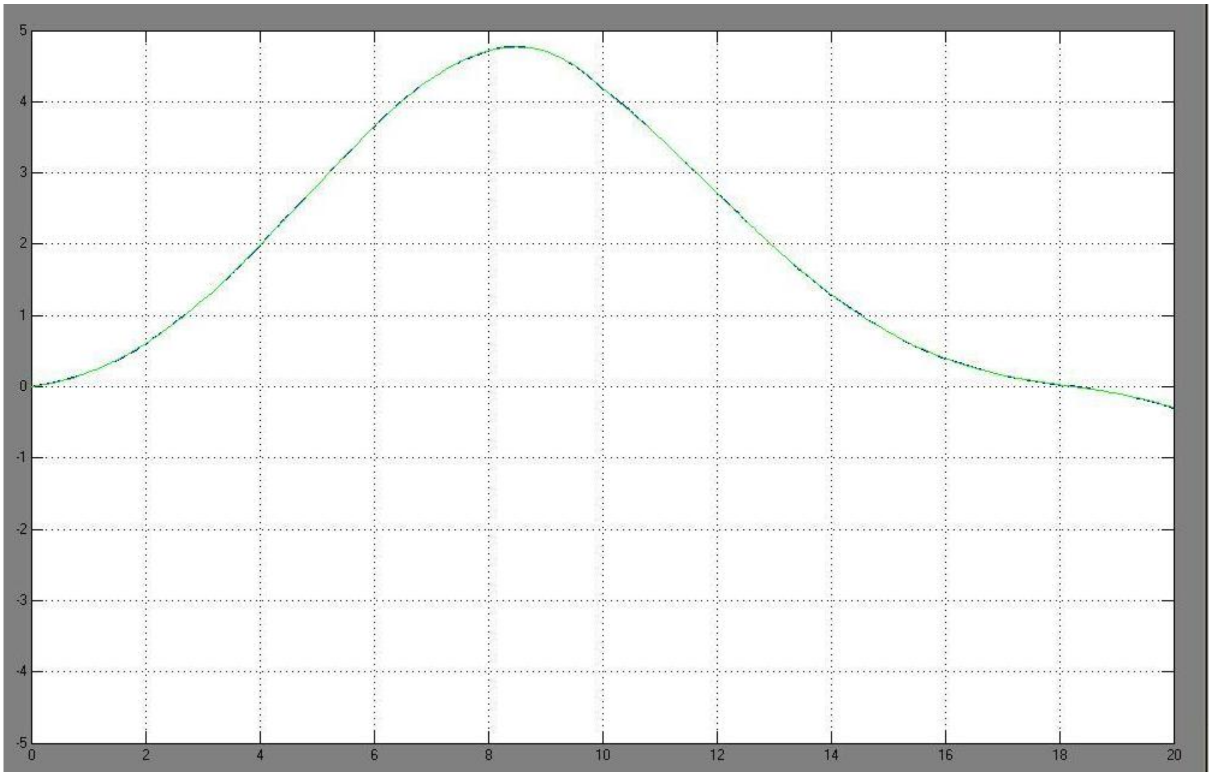


Fig 6.18 (c) plant and model output with controller.

Pattern 16:

Disturbance: – *random* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.19 illustrates the pattern, with plant output being the blue curve and model output being green curve.

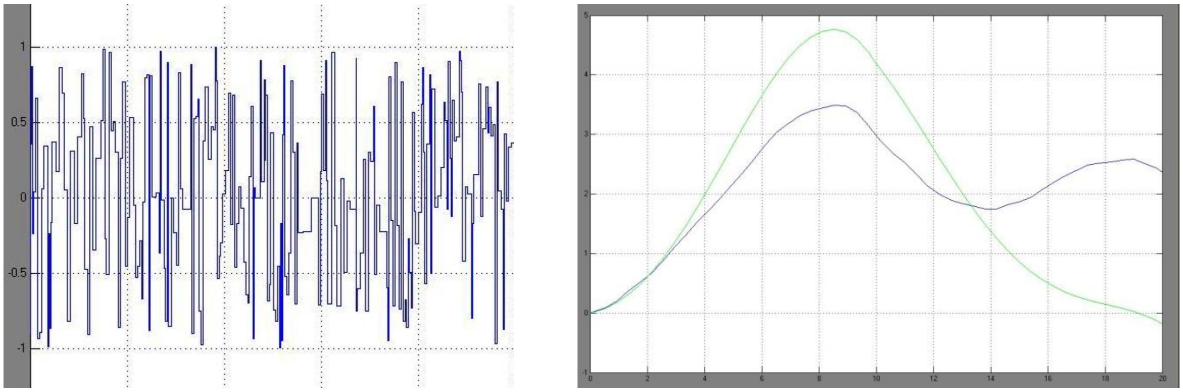


Fig 6.19 (a) disturbance (b) plant and model output without controller

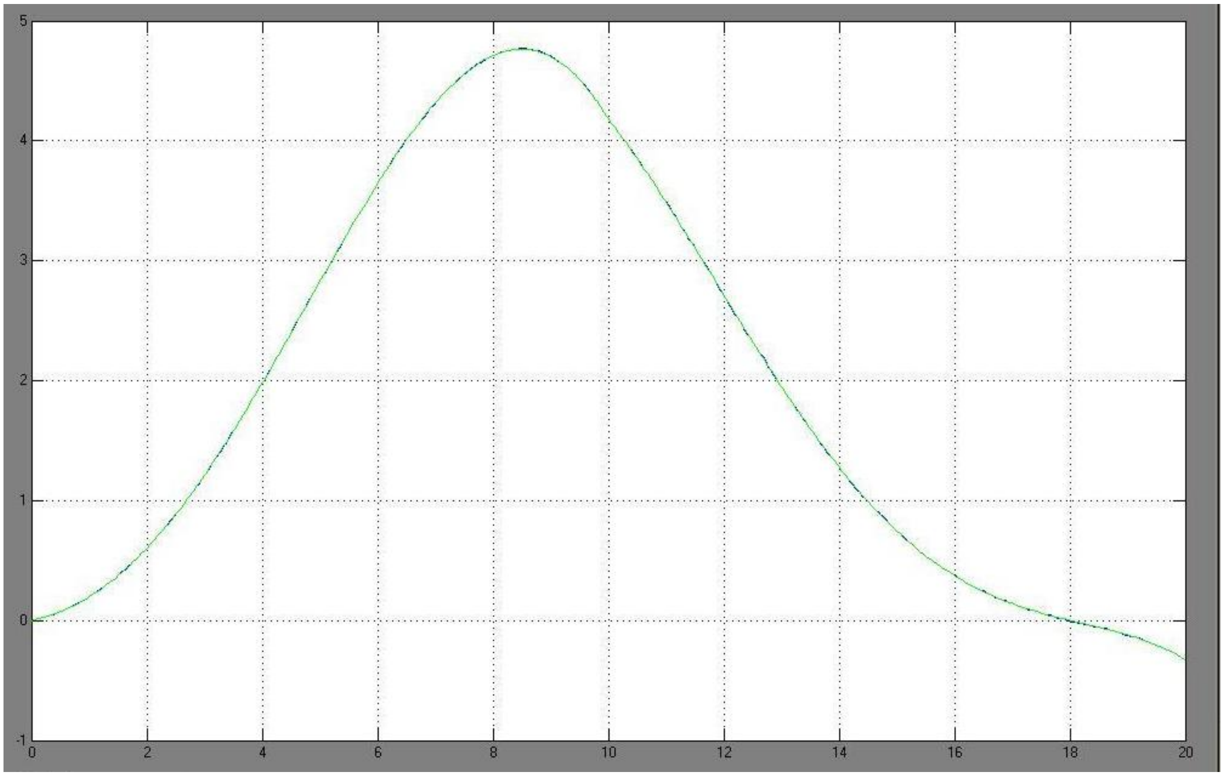


Fig 6.19 (c) plant and model output with controller.

note – for patterns 17 to 20 the amplitude is decreased but the frequency is also decreased which implies that the disturbance will affect the system for long time as there is slow change in disturbance hence will effect more

Pattern 17:

Disturbance: – *sine* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.20 illustrates the pattern, with plant output being blue curve and model output being green curve.

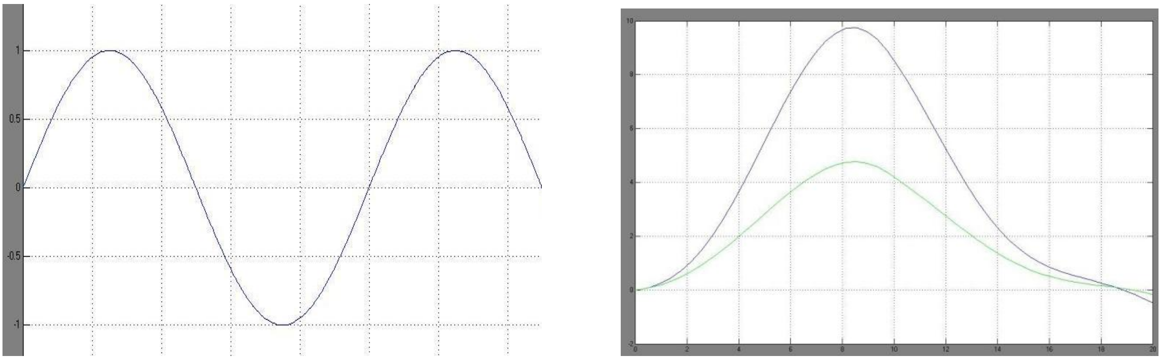


Fig 6.20 (a) disturbance (b) plant and model output without controller

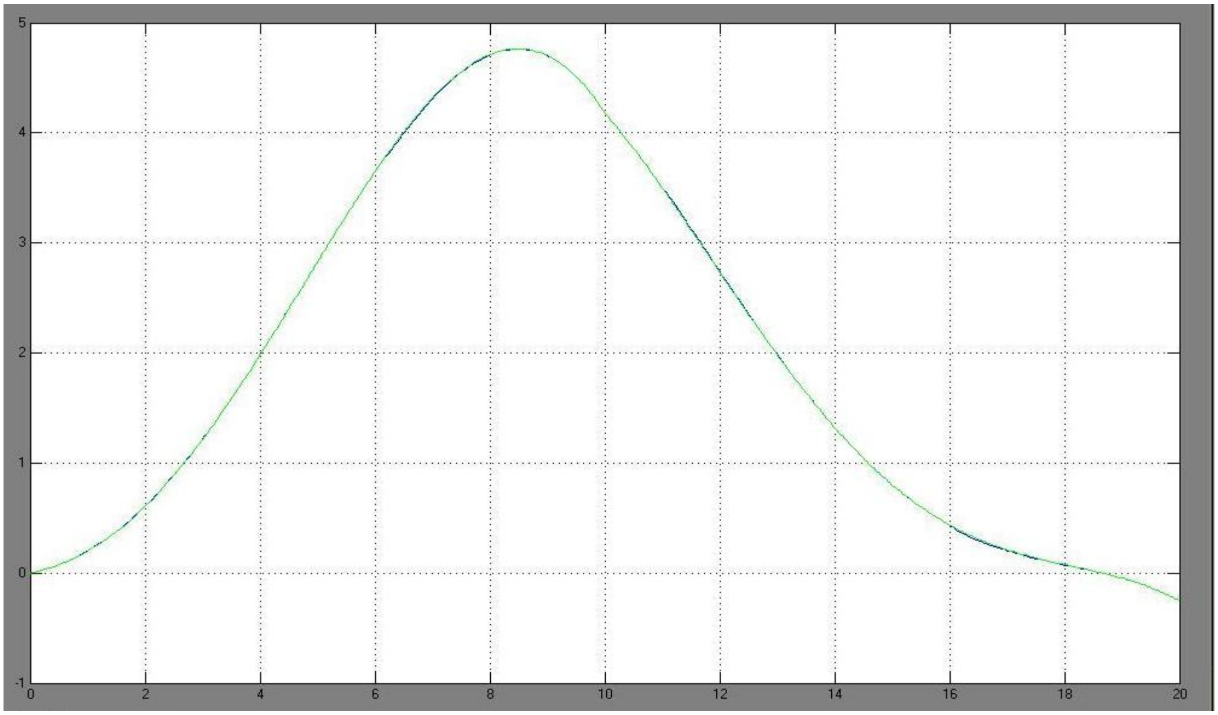


Fig 6.20 (c) plant and model output with controller.

Pattern 18:

Disturbance: – *square* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.21 illustrates the pattern, with plant output being the blue curve and model output being green curve.

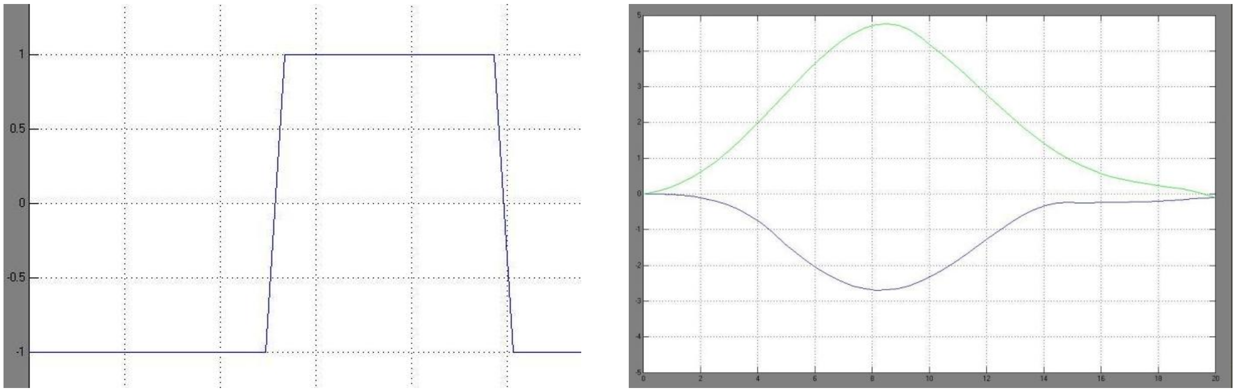


Fig 6.21 (a) disturbance (b) plant and model output without controller

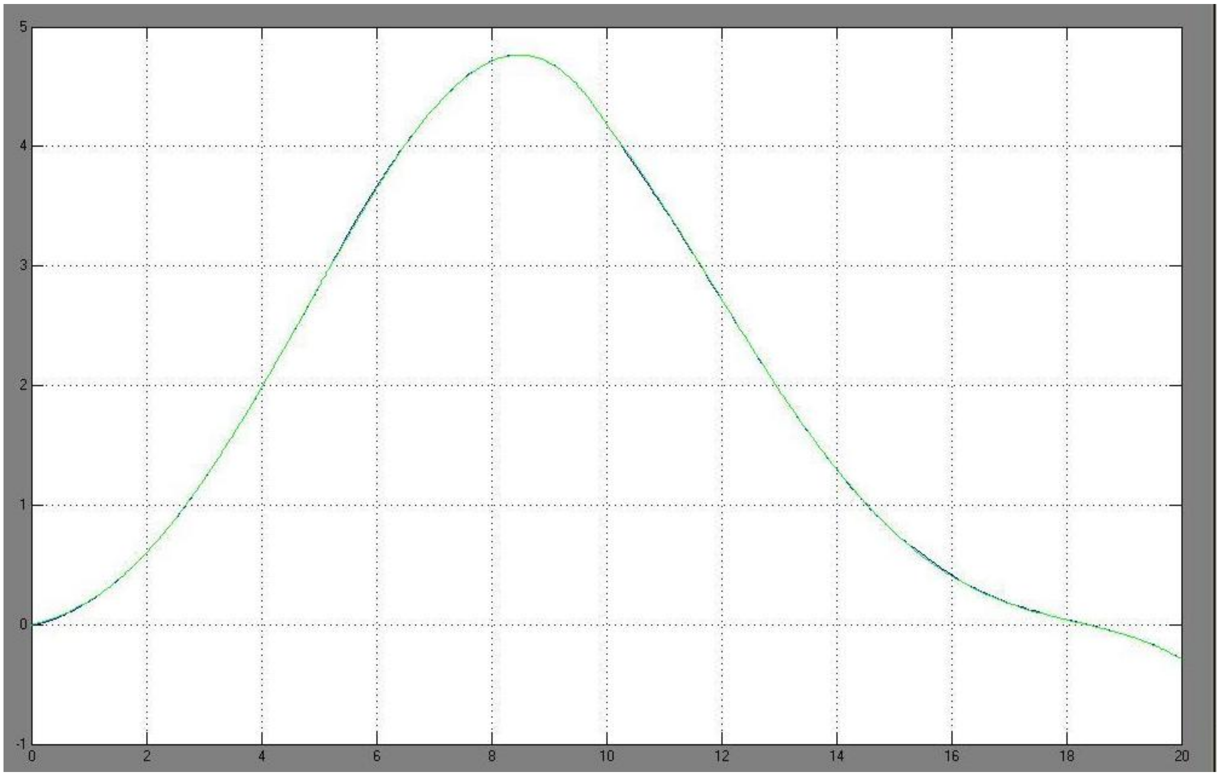
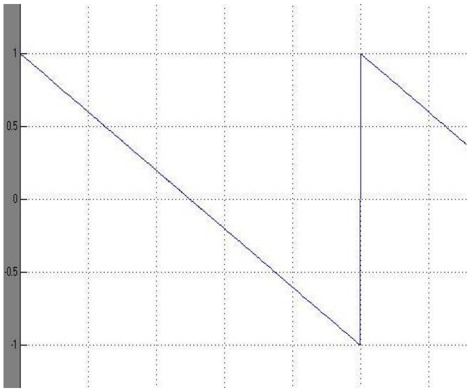


Fig 6.21 (c) plant and model output with controller.

Pattern 19:

Disturbance: – *sawtooth* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.22 illustrates the pattern, with plant output being the blue curve and model output being green curve.



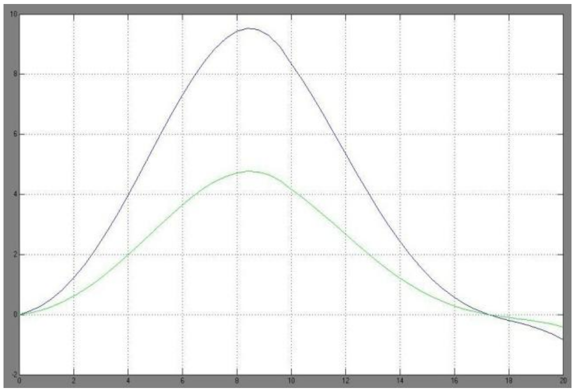


Fig 6.22 (a) disturbance (b) plant and model output without controller

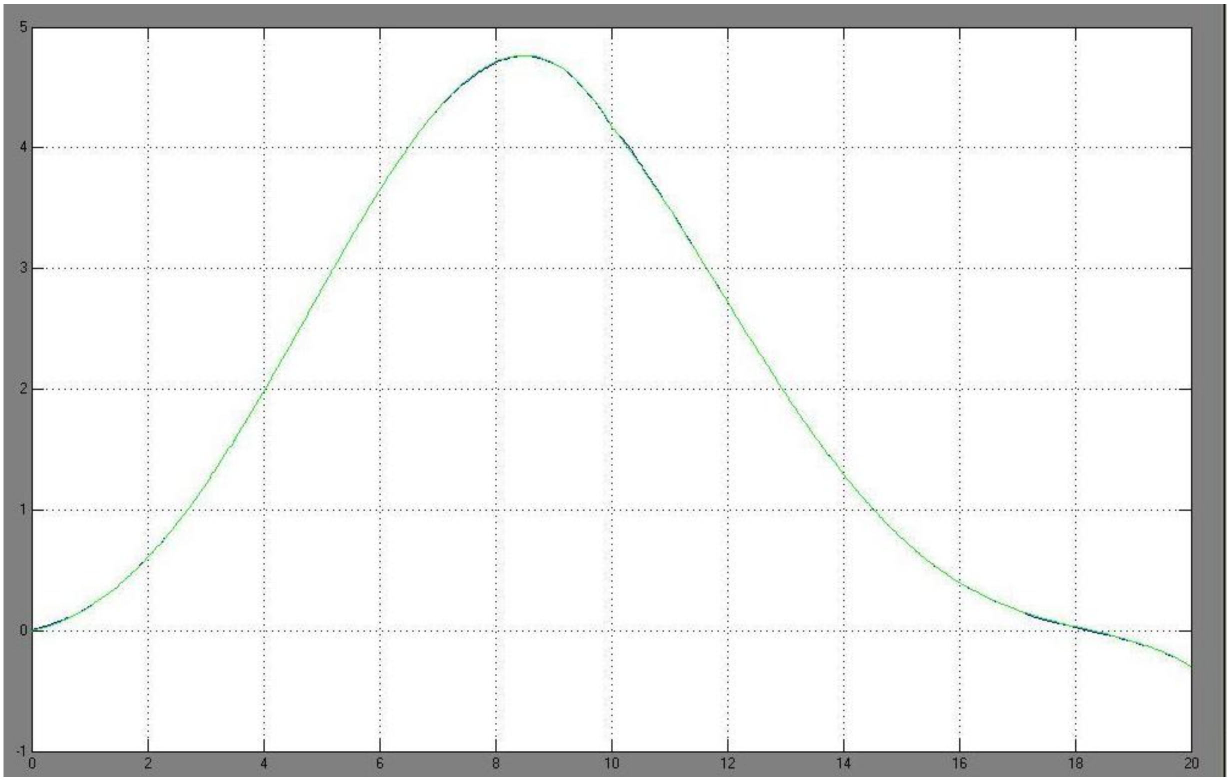


Fig 6.22 (c) plant and model output with controller.

Pattern 20:

Disturbance: – *random* wave of amplitude = 1 unit and frequency = .5 Hz. Figure 6.23 illustrates the pattern, with plant output being the blue curve and model output being green curve.

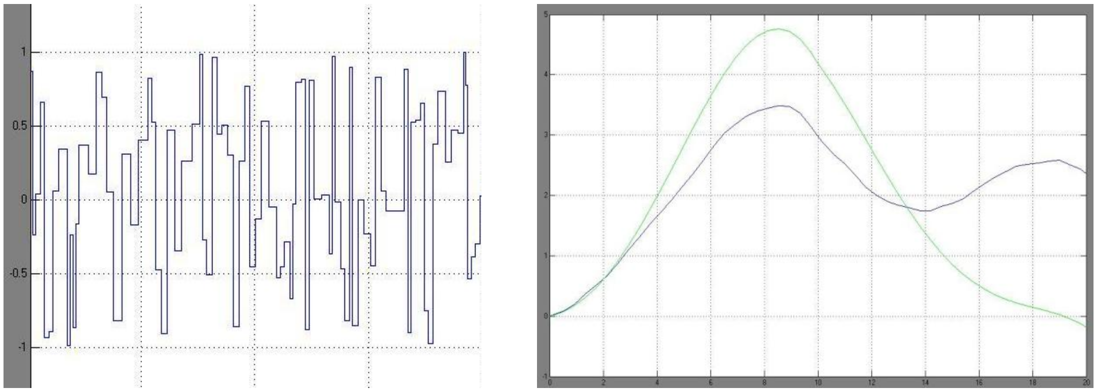


Fig 6.23 (a) disturbance (b) plant and model output without controller

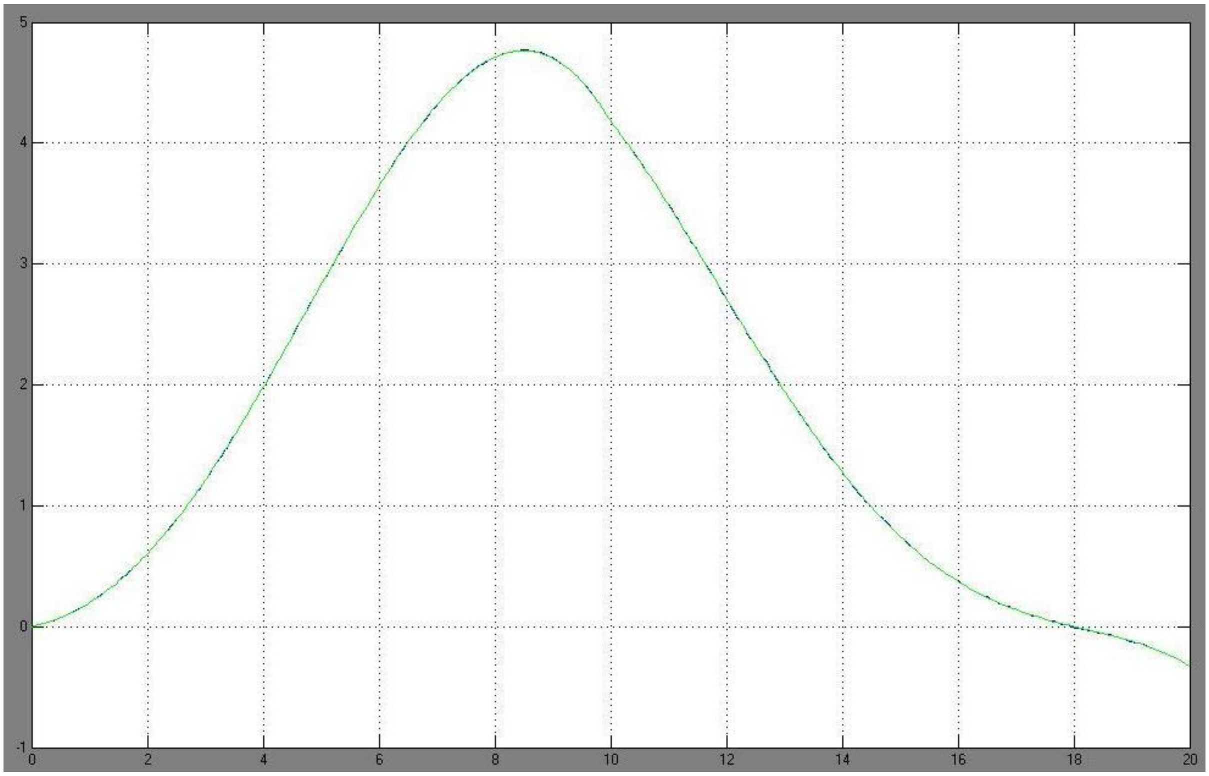


Fig 6.23 (c) plant and model output with controller.

Chapter 7
Conclusions and future work

7.1 Conclusion

This research was dealing with different aspects in applying a biomorphic system to an engineering problem. The first few chapters furnished a review of similar works in which the biologically motivated algorithms are used to solve different types of problems, the basic background on the emotional processes and the architecture of the Limbic system which is believed to be responsible for emotional processes in the brain.

In the chapter 3, we furnished more specified descriptions of the limbic system and its main components of: Thalamus, Sensory Cortex, Amygdala and Orbitofrontal Cortex.

The next step was establishing a computational model where to do that, we made some simplification assumptions to be able to do the modeling. For example, we modeled the Sensory Cortex as a block with computational delay, because other biological tasks of this component were not easy to capture in a mathematical formulation.

Consequently in chapter 6, we presented the applications of the BEL model in control problem. The main issue in applying the model for different applications is defining the sensory and emotional signals in such a way that appropriately represent the state and objectives of the system. The model is adapted for applications in control systems and the applicability of the model is verified by simulating it in controlling different systems with increasing complexity and results show that BEL controllers have an amazing performance and the error is almost 0(zero) in all the situations.

7.2 Future work

This study has mainly developed the idea of using a computational model of the learning in the brain limbic system for engineering applications and for control systems in particular. However, different aspects of this problem are still in their infancy stages and can motivate further research works. Among the different issues, here are some more important topics to be considered:

Analytical Study

To develop any (learning) control algorithm and to evaluate its functionality, the first issues would be the questions on how fast does the controller converge, how stable it is and how the performance indices are, e.g. time-domain performance indices. However, some preliminary studies on the model are performed in this thesis, but more comprehensive works are required to establish the bases for performance of the system.

Systematic Design Procedure

Current design procedure of the BEL controller does not have a systematic routine, i.e., to design the controller for each application, different values of the gain are tried to obtain suitable design parameters. This task can generally be cumbersome in some applications. So, it is advantageous to establish a systematic way to design the system parameters. In particular, this can be a self-tuning algorithm to determine the gains of the controller and corresponding weights in the emotional and sensory signals.

Advanced Study of the Components of the System

As it is particularly mentioned in the sections 2.3 and 3.2, the current structure of the limbic system and the model developed based on that are simplified models of the limbic system. In fact, there are some other components in the real limbic system which directly affects the functionality of the system, but they are not included in the current model. Furthermore, the models currently assumed for some of the components are too simple or inappropriate and are required to be enhanced. In particular, the current models of the Thalamus and Sensory Cortex include the minimum properties of these components and efforts should be made to enhance these models. Also the proper source and the proper way of generation of emotional signal is still unknown which makes it a topic for enormous research as its performance shows that it is one of the best controllers which can be designed by a control engineer.

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