An introduction to brain emotional learning inspired models (BELiMs) with an example of BELiMs' applications

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An Introduction to Brain Emotional Learning inspired Models (BELiMs)
with an Example of BELiMs' Applications

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Abstract Brain Emotional Learning-inspired Models (BELiMs) is a new category of computational intelligence (CI) paradigms. The general structure of BELiMs is based on the neural structure of the emotion system which processes and evaluates fear-induced stimuli, to produce emotional responses. The function of a BELiM is implemented by assigning adaptive networks to different parts of its structure. The primary motivation for developing BELiMs is to address model and time complexity issues associated with supervised machine learning artificial neural networks (ANNs) and neuro-fuzzy methods. One of the applications of BELiMs is chaotic time series prediction problems. A BEliM can be used as a time series prediction model. This paper introduces BELiMs as a new CI paradigm and explains historical, theoretical, structural and functional aspects of BELiMs. I also validate and evaluate the performance of BELiMs as a time series prediction model by examining different variations of BELiMs on benchmark time series data sets and comparing obtained results with different CI models.

1 Introduction

Brain emotional learning-inspired models (BEliMs) [38] and [32] are a class of computational intelligence (CI) models. CI models can solve real-world problems, which cannot easily be answered applying traditional methods such as differential equations (e.g. linear differential equations) or statistical-based methods (e.g., logistic regression), by imitating structural and functional aspect of biological systems. A good example of a CI model is an artificial neural network (ANN) (i.e., has been developed by taking inspiration from neural systems in mammals).

Most CI models have been developed on the basis of human cognition and suffer from high computational complexity[1]. For example, ANNs suffer from high computational complexity because they often need many training iterations to adjust the learning parameters and learn the behaviour of patterns. Thus, the machine learning community aims at solving this issue by utilising new CI models with low computational complexity. It might be useful to consider emotional systems of human (for example the emotional system of fear[2]) as biological systems for the development of new CI models with low model and computational complexity. LeDoux proposed a neural structure (i.e., the fear circuitry)that indicated

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[1] which means that they need a large number of computational resources for solving problems
[2] It is responsible for generating fear reactions and is an essential component of a mammal's survival circuit

what regions in the brain have roles in the fear conditioning behaviour[3] in a rat [25]. The neural structure underlying fear conditioning that was proposed by LeDoux encompasses the amygdala, the sensory cortex and the thalamus[20] and aims at explaining how internal parts of the amygdala can interact with each other and with external regions of the amygdala such as the sensory cortex and the thalamus [20]. Some essential characteristics of the neural structure of fear have been described as the follows: 1) The amygdala plays the main role in processing fear-induced stimuli and providing fear reaction by interacting with other regions of the brain such as the sensory cortex, the thalamus, and the hippocampus. 2) The procedure of processing fearful stimuli and providing emotional reactions is quick. 3) The amygdala not only provides fear responses, but it also learns to predict aversive events by making an association between stimuli.

The above specifications indicate the importance of the emotional system of fear in mammals and some characteristics of the system that make it a suitable choice on which to design CI models. As an attempt to design a CI model by taking inspiration from the emotional system of fear conditioning, brain emotional learning-inspired models (BELiMs) have been developed. The main motivation to present BELiMs has been the development of a new CI model with high performance and the capability to address time and model complexity issues of prior CI paradigms such as ANNs. This paper presents various aspects of BELiMs and describes a BELiM from a diverse perspective, theoretical, historical, structural, functional and application aspects.

After this introduction, the rest of the paper is formed as follows. Part 2 and 3 give a detailed background about theories of emotion and theoretical features of BELiMs by describing some theories of emotion. Part 4 describes the historical aspect of BELiMs. Parts 5 and 6 illustrate how the general structure and function of BELiMs can be defined. Part 7 describes how two different variations of BELiMs have been developed. Part 8 explains one important application of BELiMs and also provides a comparison between the obtained results from BELiMs with other well-known CI models. Finally, Part 9 concludes the paper and provides remarkable notes about the paper.

2 Theories of Emotion

More than 150 theories of emotion have been proposed. They aim at describing emotion from different perspectives [43]. This section just describes four categories of theories as follows:

1) Psychological theories of emotion which explain psychological aspects of emotion processes that lead to bodily responses.

2) Evolutionary theories of emotion which represent evolutionary aspects of emotional behaviours.

3) Anatomical theories of emotion which describe the brain's neural structure, underlying the emotional processes.

4) Cognitive theories of emotion that explain a theory can be classified as cognitive or non-cognitive theories.

2.1 Psychological Theories of Emotion

Psychological theories of emotion are one significant group of theories of emotion that aim to describe emotional behaviour, emotional experience and emotional expression. They include some leading theories of emotion such as the James-Lange theory [16], the Cannon-Bard theory [3], the Schachter-Singer theory [44], the Opponent-Process theory and classical conditioning [40], [14]. In the following, we briefly explain the above theories.

[3] it can be considered as one function of the emotional system of fear, is a kind of behaviour that an organism presents to predict aversive events by learning a connection between an aversive stimulus and a neutral stimulus [25]

James-Lange Theory: The James-Lange theory is one of the old emotional theories, which was suggested by William James (an American philosopher and psychologist) and Carl Lange (a Danish physician). According to this theory, emotional expression happens before an emotional experience, and a human's emotional experience depends on human's physical reactions. Thus, if an event changes the physical state of a person, this event causes that person to experience an emotional feeling. [3] and [11].

Schachter-Singer Theory: The Schachter-Singer theory [44] is another psychological theory of emotion which was presented by Stanley Schachter (an American social psychologist) and Jerome Singer (an American psychologist). This theory states that the emotional experience of one event depends on both personal emotional expressions (e.g. bodily response) and the individual situation at that event and humans have different emotional experiences when they are in different positions; even though they might have similar emotional expressions. If one sees a bear, he runs, and his heart is racing; hence, one might have an experience of fear; in contrast, if one meets a person and the heart is racing, one might have an experience of love. The Schachter-Singer theory indicates that the individual experience of emotion depends on both bodily responses and cognitive interpretation of the event [44].

The Opponent-Process Theory: The Opponent-Process theory [44] was developed by two American psychologists, Richard Solomon and John Corbit. This theory asserts that the emotional experiences of events might be associated with the opposite of emotional feelings of other events. For example, when an individual sees a bear, he might feel fear and begin running to a secure place. However, after being in the safe place, he feels relief, which is an emotional experience that can be considered the opposite of fear.

The Classical Conditioning Theory: Another psychological theory of emotion is the classical conditioning theory [40] which describes how mammals can learn new responses (e.g. emotional responses) via making associations between stimuli via three phases are named as "Before Conditioning", "During Conditioning" and "After Conditioning"[40]. To define these stages, we need to determine three types of stimulus (neutral, conditioned and unconditioned) and two types of responses (conditioned and unconditioned) [40].

1) Before conditioning: A mammal receives an unconditioned stimulus (UCS) and generate a natural response or an unconditioned response (UCR). At this phase, mammals do not provide any answers for a neutral response.

2) During Conditioning: During this phase, a mammal produces an unconditioned response (UCR) to the unconditioned stimulus and the neutral stimulus which have been associated with each other. In this phase, mammal learns to make an association between the neutral stimulus and unconditioned response. After this stage, neutral stimulus is referred to as conditioned stimulus.

3) After Conditioning: The mammal receives a conditioned stimulus and provides a response that is named conditioned response. As mentioned earlier, this part has briefly explained some of the psychological theories of emotion. The next sub-section reviews several critical evolutionary methods of feeling.

2.2 Evolutionary Theories of Emotion

Evolutionary theories of emotion describe evolutionary aspects of emotional expressions, experiences and also anatomical structures undelaying emotional systems.

Charles Darwin Theory of Emotion: This theory is a part of "theory of evolution" [8] and aims to show that the expression of emotions in animals and man are similar and is from experimental results about the similarity and differences between facial expressions in animals and humans. Charles Darwin pointed out that evolutionary aspects of emotional expression have help mammals survive in new environment

[8]. From Darwin's theory of emotion is based on experimental results on facial expressions and the similarity and differences between facial expressions in animals and humans and help psychologists explain why humans have experiences of complicated emotion feelings as well as understand complex facial expressions.

Affect Theory: Affect Theory is another popular theory of evolutionary theories of emotions. Silvan Tomkins introduced affect theory in his book entitled "Affect Imagery Consciousness" and pointed out that humans have nine universal affects (i.e. biological aspects of emotion that are a general, innate mechanism in the human brain [46].) or emotional feelings [46] which are associated with unique emotional expressions. He also stated that affects which are understandable from other people with different cultures and can be categorised into three groups: positive, negative and neutral which include feelings such as surprise, interest, joy, rage, fear, disgust, shame and anguish [46].

Paul Ekman Theory of Emotions: Paul Ekman was influenced by Darwin and Tomkins theories of emotions and developed an "atlas of emotions" to associate emotional feelings and emotional expressions [9]. He asserted that each emotional feeling could be represented with more than one facial expressions and a facial expression can be related to different emotional feelings. He stated that because of the evolutionary aspect of emotions, primary emotional feelings could be linked with universal emotional expressions, but the emotional expressions might also have been represented by different emotional feelings in the different cultures.

Robert Plutchik Theory of Emotions: Robert Plutchik stated a psychological theory to modify affect theory by concentrating on biological, evolutionary and cognitive aspects of emotional expression in humans. He declared that both anatomical structures and physiological mechanisms underlying facial expressions had been modified by both a cognitive procedure and evolutionary adaptation in humans. He stated that humans have eight basic emotions including anger, fear, sadness, disgust, surprise, anticipation, trust, and joy [42] and indicated that each emotional feeling could be associated with its opposite emotional feeling. For example, joy is connected to depression which is its opposite emotional feeling. He also explained that a complicated human emotional feeling is a combination of basic emotional feelings. For example, the feeling of love is the result of trust and joy.

2.3 Anatomical Theories of Emotions

Anatomical theories of emotions have focused on defining underlying neural structures of emotional feelings. These theories have aimed at explaining how different regions of the brain are involved in processing emotional stimuli and providing emotional responses. According to [15], neuroscience studies to understand neural circuits of emotions began in 1840 when Phineas P. Gage was injured during his work and a large part of his brain, in particular, the left part of his prefrontal lobe, was damaged [15] and [6]. Prof. John Martyn Harlow was the first physician who attempted to do surgery on Gage's brain; he published a report about Gage's case in Boston Medical and Surgical Journal [15] and described how the damage to the prefrontal lobe of Gage's brain affected his personality [7].

Another attempt to illustrate the anatomical aspect of emotions goes back to 1920 when Cannon and Bard[4] stated the Cannon-Bard theory. According to the Cannon-Bard theory, mammalians bodily responses cannot guide the brain to categorise emotions. Thus, one particular emotional expression can provide different emotional experiences [3]. In other words, this theory said that an individual has an emotional experience and emotional expression at the same time. The Cannon-Bard theory, is supported by the Cannon-Bard structure. The Cannon-Bard anatomical theory describes the emotional process using

[4] Walter Bradford Cannon was a physiologist at Harvard University, and Philip Bard was a doctoral student of Cannon

three steps. Firstly, the thalamus receives the emotional stimulus, evaluates it and sends the relevant information to both the sensory cortex and the hypothalamus. Secondly, the sensory cortex provides some information regarding emotional experience. Thirdly, the hypothalamus provides emotional expression [45]. As can be observed from Figure 1, the hypothalamus has a central role in the structure, so the Canon-Bard theory sometimes is referred to as the "Hypothalamic theory" [43], Later, in 1937, Papez [5] proposed a circuit to modify the Cannon-Bard structure and, in 1949, Maclean[6] presented the limbic system theory as an improvement of the Papez circuit [6] and [31]. We divide the anatomical theories of emotions into two categories: the first group explains "one single structure of emotions" while the second group describes ‘multiple neural structures’ of feelings" [6]. The former assumes that one unique neural structure is responsible for all emotional expressions and covers the Papez circuit, the Canon-Bard circuit and the limbic system. The latter is based on the assumption that different regions of the brain are responsible for different emotional feelings. Thus, the neural structure of the fear is not similar to the neural structure of the joy.

2.3.1 Single Neural Structure of Emotions

The Cannon-Bard Structure: The Cannon-Bard structure is one of the first anatomical structures of emotions, which was defined by Cannon and Bard [43] and [6] based on their experimental studies of cats. They observed that without connections between cats’ brains and their bodies, they could still experience emotional feelings. Thus, they stated that emotional experiences and emotional expressions in mammals are two separate and independent processes. In other words, mammalians bodily responses cannot guide their brains to categorise emotions. Moreover, one particular emotional expression can provide different emotional experiences [3]. Figure 1 describes the structure and shows the regions (i.e., the role of the thalamus, the hypothalamus and the dorsal thalamus) of the brain that are involved in processing an emotional stimulus, providing emotional experience and expression [43], [6]. and [3].

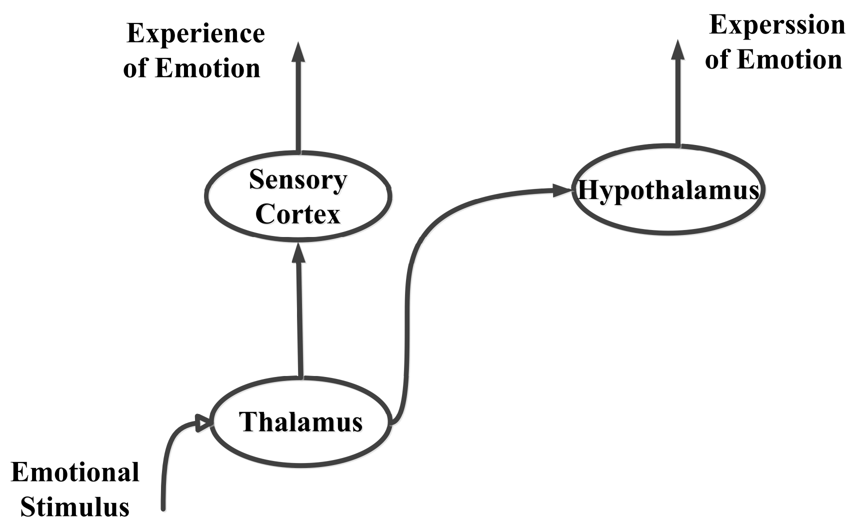

Fig. 1 The Cannon-Bard Anatomical Structure. The thalamus receives the emotional stimulus, evaluates it and sends the relevant information to both the sensory cortex and the hypothalamus that are responsible for providing emotional experience and emotional expression, respectively [45].

[5] James Wenceslas Papez was an American neuroanatomist

[6] Paul D. MacLean was an American physician, and neuroscientist

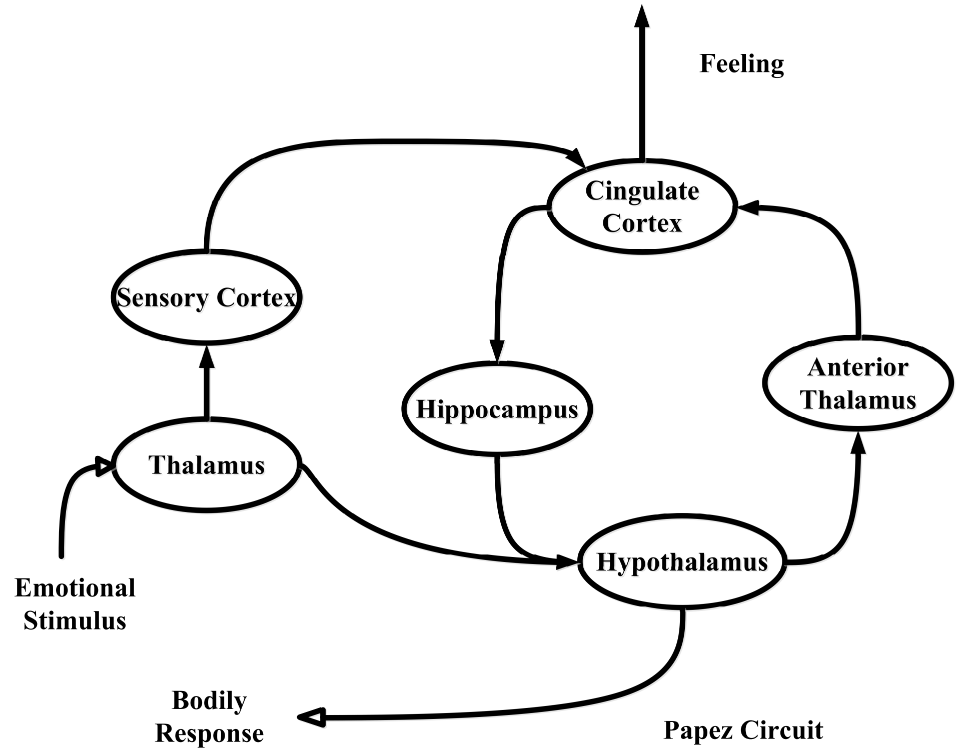

Fig. 2 The neural structure of the Papez circuit represents how different regions of the brain are connected to each other. As it can be observed the thalamus is receiving emotional stimuli and sends it to other parts such as the hypothalamus and the cingulate cortex that provides "emotional experience". The cingulate cortex sends some information about emotional stimuli to the hippocampus and then to the hypothalamus that is responsible for providing emotional responses.

The Papez Structure: Papez modified the Cannon-Bard neural structure by adding other regions of the brain to it and named it as the "Papez circuit" [6], [43] and [45]. The circuit (see Figure 2) consists of the hypothalamus, the anterior thalamus, the cingulate gyrus and the hippocampus. It presents two paths to process the emotional stimulus. The first path is from the thalamus to the hypothalamus and generates the emotional response (emotional expression). The second path is from the thalamus to the sensory cortex, hippocampus, hypothalamus, anterior thalamus and ends in the cingulate cortex; this path is responsible for providing emotional experience [6], [43] and [45]. It should be noted that, more recently, it has been stated that the components of the Papez circuit "have little involvement in emotion" [5].

The Limbic System: In 1952, Paul D. MacLean presented the limbic system (see Figure 3), which is a combination of the neural structure of the Cannon-Bard theory and the Papez circuit. The limbic system which encompasses the areas of the brain such as the thalamus, sensory cortex, cingulate cortex, anterior thalamus, hippocampus, hypothalamus and amygdala is a part of the limbic system theory. The limbic system theory aims to explain how the brain generates emotional expression and emotional experience. The limbic system theory is a popular theory and has been referred to by many studies in neuroscience and psychology [43]. However, many neuroscientists, such as LeDoux, emphasised that the limbic system theory not be able to explain "the emotional brain"[20]. Nevertheless, because of the fundamental role of the amygdala in emotional processing, the limbic system theory has survived.

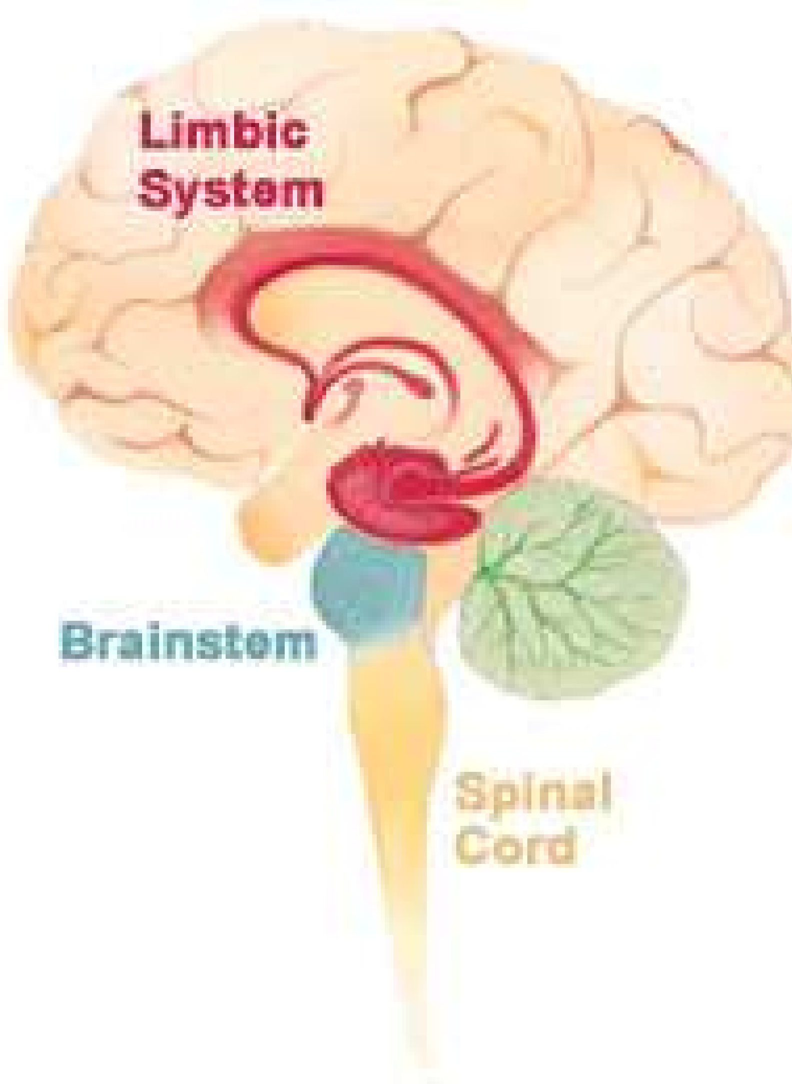

Fig. 3 The regions of the brain mentioned in the limbic system theory. According to this theory, the hypothalamus, amygdala, hippocampus and thalamus are the main regions of the limbic system. They have roles in processing emotional stimuli and providing emotional reactions

2.3.2 Multiple Neural Structures of Emotion

Earlier theories on defining the neural structure of emotion have concentrated on the localisation of emotions in the brain; however, laboratory experiments on mice and humans have verified it is challenging to find a centralised section in the brain as a responsible of generating all emotions [43]. Thus, neuroscientists have focused on finding neural circuits responsible for different emotional behaviours. LeDoux introduced a neural structure of fear conditioning[7], which is a typical behaviour among humans and animals, based on experimental studies on mice. The LeDoux neural structure of fear conditioning [19], which relies on the classical conditioning theory, presents how the amygdala and its internal nuclei, such as the lateral (LA) nucleus, basal (B) nucleus and central (CE) nucleus, interact with each other (see figure 4). These parts are responsible for processing conditioned stimulus (e.g. an auditory stimulus) and making the associations between a conditioned stimulus (e.g. an auditory stimulus) and an unconditioned stimulus (e.g. a foot shock) and providing a conditioned response when the animal receives a conditioned stimulus [19] and [20].

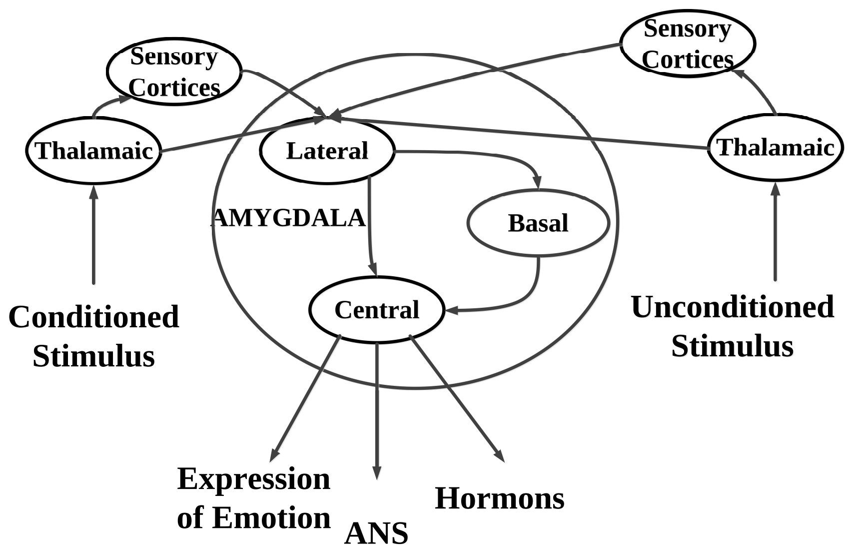

Fig. 4 The neural structure of fear conditioning and the internal parts of the amygdala.

As Figure 4 shows, the central part of the amygdala connects with the hypothalamus, autonomic nervous system (ANS) and hormones to express emotional reactions such as freezing and hormonal responses. Figure 5 describes that the amygdala is receiving emotional stimuli from two paths. The first path is the connection between the amygdala and thalamus and is called the thalamic pathway. From this road, the amygdala receives "quick and dirty representation" [11] of emotionally charged stimuli that help it to provide quick responses. The second path is a connection between the thalamus, sensory cortex and amygdala and provides more sophisticated information about the stimulus. Using the second path, the amygdala can evaluate its initial response.

[7] It is a behavioural paradigm that is used by mammalians not only to predict the occurrence of fearful stimuli but also to learn to avoid the origins of fearful stimuli

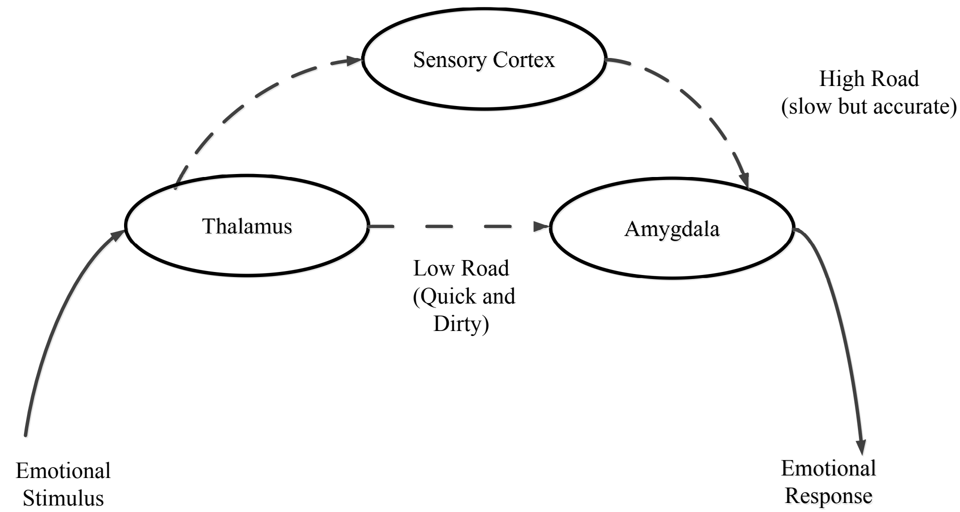

Fig. 5 A circuitry for processing emotional stimulus, in particular, a fear-driven stimulus. First, the received stimulus is sent to the thalamus and the amygdala, which provides an initial response. This path is so-called the low road path. The stimulus can also be processed via sending to the cortical cortex and the amygdala, which provides highly accurate data

2.4 Cognitive Theories of Emotions

Cognitive theories of emotions are another major category of theories of emotions. They have viewed an emotional process as an example of a cognitive procedure and have stated that processing emotional stimuli and providing emotional responses are cognitive procedures. From the perspective of cognitive theories of emotion, emotional processes are complex and high-level processes and consist of cognitive processes that use beliefs, knowledge and goals to trigger emotional responses [16],[20] and [6]. The cognitive theories of emotion can be supported by the fact that different people might have shown different emotional expressions despite receiving similar emotional stimuli. Moreover, an individual can show different emotions for one similar stimulus at various times. Among the above-explained theories, three emotional theories, Cannon-Bard, Schachter-Singer and Opponent-Process theories can be categorised as cognitive theories of emotion. The following discussion provides reasons why the above theories can be considered as cognitive theories of emotion.

1) The Cannon-Bard theory stated that a similar bodily response could express different emotional stimuli; hence, this theory explicitly proposed that a mediated procedure is a bridge between receiving emotional stimuli and providing emotional experience and emotional expression.

2) The Schachter-Singer theory can likewise be considered a cognitive theory because it argues that emotional experience of an event depends on both the individual's emotional expressions (e.g. bodily responses) and the individual's situation at that event. Therefore, this theory also considered that there is a mediated procedure to produce emotional expressions.

3)The Opponent-Process theory can also be classified as a cognitive theory of emotion. In fact, the cognitive method of this theory considers knowledge of emotional experiences and expressions to trigger emotional expressions.

2.5 Non-Cognitive Theories of Emotions

The non-cognitive theories of emotions have proposed that emotional responses not be based on any cognitive procedure. These theories have also stated that emotional responses are direct and automatic responses and are provided based on a hard-wired emotional system. It should be noted that there are two perspectives regarding non-cognitive theories. The first view states that some emotions are generated based on non-cognitive processes. The second aspect claims that all emotions are made based on non-cognitive processes. Fear conditioning theory and evolutionary theories of emotion can be viewed as non-cognitive theories of emotion.

3 Theoretical Aspects of BELiMs

We have developed BELiMs by taking inspiration from the LeDoux neural structure of fear conditioning which has been formed to support the LeDoux theory of emotions. As was mentioned previously, this theory is a non-cognitive theory of emotions, which stated that a direct and quick procedure produces an emotional reaction. Before explaining what has been our motivation to select the LeDoux theory as the foundation theory of BELiMs, we describe fear conditioning.

3.1 Fear Conditioning

Fear conditioning explains how animals, in particular mammals, learn from their previous experiences to predict the occurrence of a fearful situation and how they also learn to avoid the horrible experiences [19]and [21] The fear conditioning not only gives a quick procedure between reception of fearful stimuli and provision of emotional reactions, but it also describes a learning process that is followed by organisms to predict dangerous situations. [19], and [21] hypothesis that was proposed by LeDoux [19].

3.2 The LeDoux Neural Structure of Fear Conditioning

LeDoux proposed the neural structure of fear conditioning on the basis of experimental studies on laboratory rats. The strcture gives an anatomical perspective of fear conditioning theory and highlights regions in a rat's brain that have roles in processing fearful stimuli. The neural structure that was proposed by LeDoux is emphasising the key role of the amygdala not only for "the acquisition of conditioned fear" but also for "the expression of innate and learned fear responses" [19]. LeDoux also explained the internal parts of the amygdala and show it can be divided into two regions: the "evolutionary primitive division" [19], and [21] and the "cortico-medial region"[19]. The former is sometimes referred to as the "basolateral region"[19] and encompasses the lateral, basal and accessory basal regions. The latter, cortico-medial region, consists of two parts, the medial and central nuclei [19]. Figure 6 shows the internal regions and the nuclei of each part and describes how these two regions are connected to each other [19]. The theory has been the foundation of the development of BELiMs, because of the three following essential characteristics of the neural structure that has supported the theory:

1) The amygdala plays the central role in processing fear-induced stimuli and providing a fear reaction. The amygdala interacts with other regions of the brain, such as the sensory cortex, the thalamus and the hippocampus to fulfil the task.

2) The procedure of processing fearful stimuli and providing emotional reactions is quick and straightforward.

3) The amygdala not only provides fear responses, but it also learns to predict aversive events through interacting with other regions.

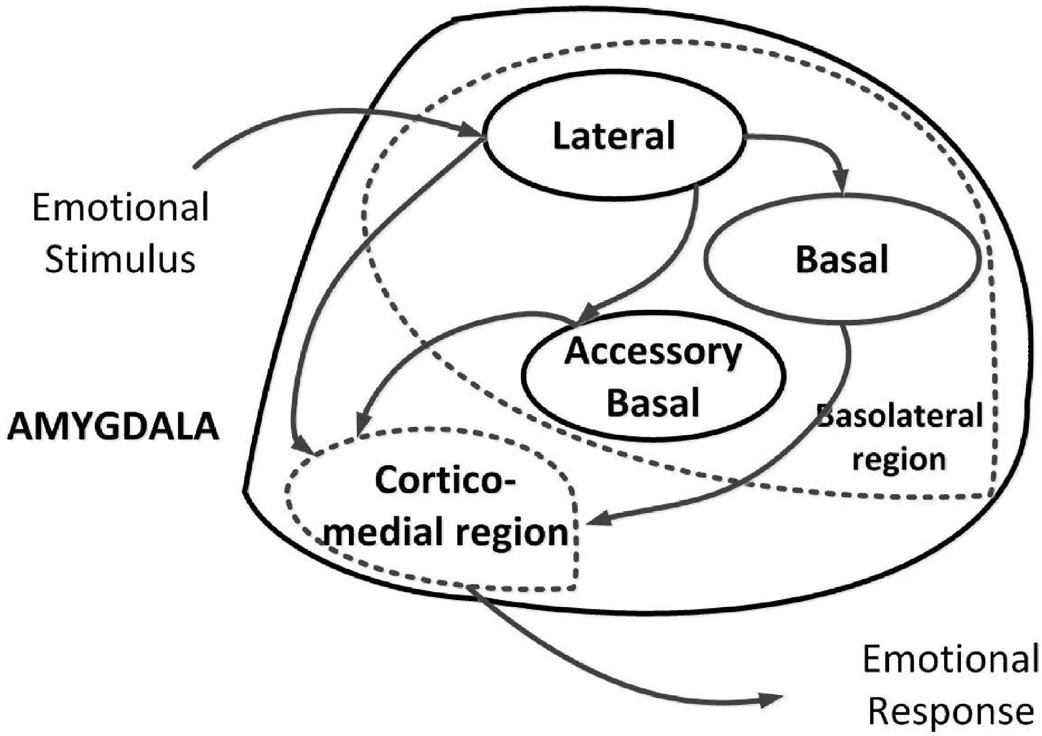

Fig. 6 The schematic of internal parts within the amygdala and their interconnections in receiving an emotional (fearful) stimulus and providing an emotional response; it is notable how different parts of the amygdala are connected to each other. The lateral part spreads this information to other parts, such as the basal and accessory basal parts as well as the cortico-medial regions. The central nuclei part of the cortico-medial regions is an exit point from the amygdala and provides the emotional response.

4 Historical Aspects of BELiMs

Brain Emotional Learning-inspired Models (BELiMs) is a type of Emotion-inspired Machine Learning Models (EMLMs), which is a class of machine learning (ML). EMLMs have been developed by taking inspiration from theories of emotions. Thus, to design an EMLM, a computational model of emotions[8] can be copied. EMLMs have been utilised as predictive models (time series prediction and classification), system identification and intelligent controllers [38] and have mostly been generated from a computational model of emotions called "the computational model of emotional learning" or "the amygdala-orbitofrontal cortex system"[29].

4.1 The Amygdala-Orbitofrontal Cortex System:

The amygdala-orbitofrontal cortex system (i.e., "the computational model of emotional learning") [29] and [28] is a computer-based tool that has aimed at simulating emotional learning (i.e.,"acquisition", "blocking" and "conditioned inhibition" [29]) in the amygdala. Thus, it copies the connection and functionality of the amygdala in evaluating emotionally charged stimuli and learning the emotional acquisi-

[8] Computational models of emotions are simulation tools that aim at proving theories of emotions [45] (for further reading, please refer to [38])

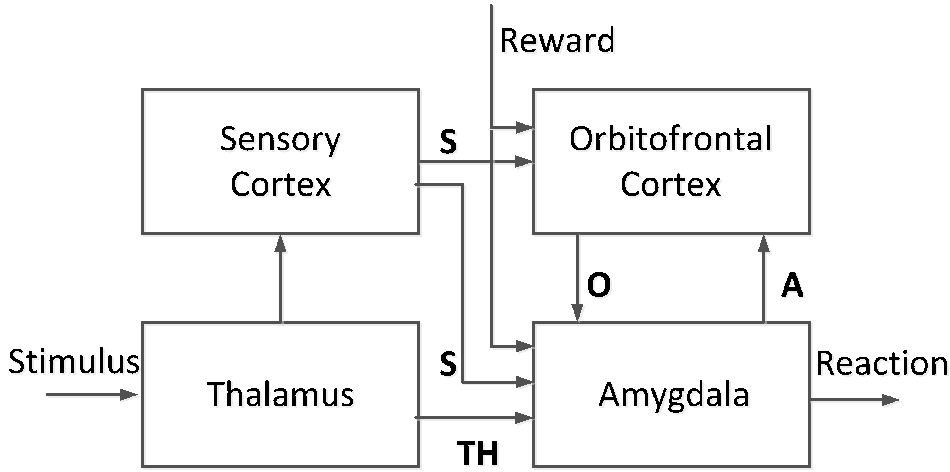

Fig. 7 A block diagram of the amygdala-orbitofrontal cortex system. It has four main parts: sensory cortex, thalamus, amygdala and orbitofrontal cortex. The Thalamus is the first part that receives an emotionally charged stimulus and provides ***TH*** and sends it to the amygdala; it also passes some information to the sensory cortex which is responsible for providing some input (here is shown by ***S*** for the amygdala and the orbitofrontal cortex. Both Orbitofrontal cortex and Amygdala is receiving a reward signal and providing outputs as ***A***, and ***O***. Finally the amygdala provides the reaction to the emotional stimulus.

tion, blocking and conditioned inhibition [29] and [28]. It should be noted that the amygdala-orbitofrontal system is not a computational model of the mammalian emotional systems. Figure 7 shows that the model consists of four parts: thae sensory cortex, thalamus, amygdala and orbitofrontal cortex and presents how these parts are interacting with each other to form the association between the conditioned and the unconditioned stimuli [29]. As can be observed, the design has some advantages, such as simple structure and straightforward implementation to represent the associative learning, but it is not a complete learning system [29] and needs modification to be utilised as a machine learning tool. Moreover, it has been explicitly stated that the two aims of the amygdala-orbitofrontal cortex system are: firstly, to understand the function of the amygdala in the mammalian brain; secondly, to understand the limitations of a computer-based tool for simulating the function of the amygdala [29]. However, the simple structure of the amygdala-orbitofrontal cortex system has been the great motivation for utilising it to develop emotion-based data-driven models such as BELiMs.

4.2 Types of EMLMs

The amygdala-orbitofrontal cortex system has a simple structure with the low number of learning parameters; thus, it can be considered as a foundation of the development of new MLs that have been referred to as EMLMs. This section explains different types of EMLMs.

Emotional Learning Based Intelligent Controller (BELBIC): The Brain Emotional Learning-Based Intelligent Controller (BELBIC) is the first practical implementation of EMLMs and can overcome the uncertainty and complexity issues of classic controller models. BELBIC has been successfully applied for some applications in the field of control systems (e.g., controlling heating and air conditioning, aerospace launch vehicles and intelligent washing machines) [22]. These obtained results have proved that the BELBIC can outperform many other models such as proportional–integral–derivative controllers (PID controllers) and linear controllers concerning simplicity, reliability and stability.

Brain Emotional Learning based Models (BELs): Brain Emotional Learning Models (BELs) includes those models that have been developed by making minor changes in the amygdala-orbitofrontal cortex system. Most BELs have been applied as prediction models, and a popular application of BELs is chaotic time series prediction. However, most BELs have been designed based on two incorrect assumptions, as is described below. First, about the fact that the amygdala-orbitofrontal cortex system is a model for simulating emotional learning in the amygdala, rather than with the purpose of being developed as a data-driven prediction model, to utilise it as a data-driven model, a significant modification is needed. Therefore, assuming the model is a modular neural network, feeding it with input vectors from time series prediction and expecting it to be able to provide an output close to the target would be wrong. Moreover, the weights of the amygdala and the orbitofrontal cortex system are adjusted by rules, but these rules are aimed at adjusting the weights so that the model learns to predict the reward signal that differs from the target signal. However, in most prediction tasks, one needs a data-driven model into which to feed the input, and to predict an output; hence, a learning algorithm to adjust learning parameters by considering the difference between output and target is used.

Because BELs were developed on the above wrong assumption, they could not show excellent results in predicting chaotic time series or classification. The performance obtained is not comparable with advanced ANNs and NFs. A BEL was tested to predict geomagnetic sub-storms, solar activity using sunspot number and the Lorenz time series [2]. The results obtained showed that BEL has the capability to predict peak points of chaotic systems better than neuro-fuzzy and neural networks.

Emotion Motivated Models (EMMs): The second group is referred to as emotion motivate models (EMMs) that has been developed by borrowing the metaphor of emotional signals to modify the loss function and to adjust the learning parameters traditional artificial neural networks (ANNs) or neuro-fuzzy methods (NFs).EMMs includes Emotional Learning Fuzzy Inference System (ELFIS), which is a modification of ANFIS, which tries to find the optimal structure of the Adaptive Neurofuzzy Inference System (ANFIS) by minimising the loss function and has been examined as a prediction model od solar activities and the stock markets [23].

Brain Emotional Learning-inspired Model(BEliMs): The third group of EMLMs is BELiMs [32], [33], [36], [39]. BELiMs comprise models that cannot be considered to belong to any of the above. BELiMs have been developed by combining the neural structure of fear conditioning, the amygdala-orbitofrontal cortex and adaptive networks. In other words, the internal structure of BELiMs is different with the internal structure of the amygdala-orbitofrontal cortex system. The next section will explain how the internal structure of a BELiM has been defined by considering adaptive networks and how its external structure has been designed by considering the internal nuclei of the amygdala and the orbitofrontal cortex system. The obtained results have shown that this type of modification can provide an improvement in the accuracy of the prediction of chaotic systems. BELiMs are suitable to predict solar activities and geomagnetic storms.

5 The Structural Aspect of BELiMs

To design the general structure of BELiMs, we imitate the regions of the brain and connections between them from a summarised neural structure of the brain which has been described by Figure 8. Figure 9 describes the general structure of BELiMs which consists of four main parts, referred to as the THalamus (TH), sensory CorteX (CX), AMYGdala (AMYG), and ORBItofrontal cortex (ORBI). It also depicts the input and output of each part, as well as, the connections between these parts. A BELiM processes an input vector as $\boldsymbol{i}$ via the following steps: 1) The *TH* is the first part of the BELiM that receives the input vector $\boldsymbol{i}$. It provides $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{th}^{AGG}$ and sends these to the *AMYG* and the *CX*, respectively. 2) The

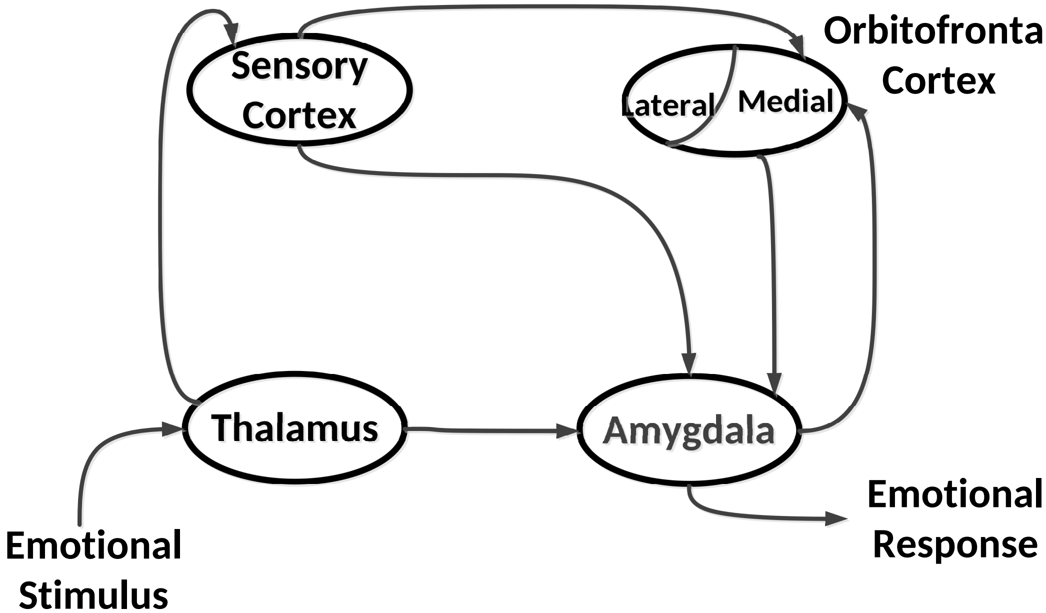

Fig. 8 A summarised structure of regions of the brain that have roles in processing emotional stimuli. It encompasses the amygdala, the thalamus, the sensory cortex and the orbitofrontal cortex.

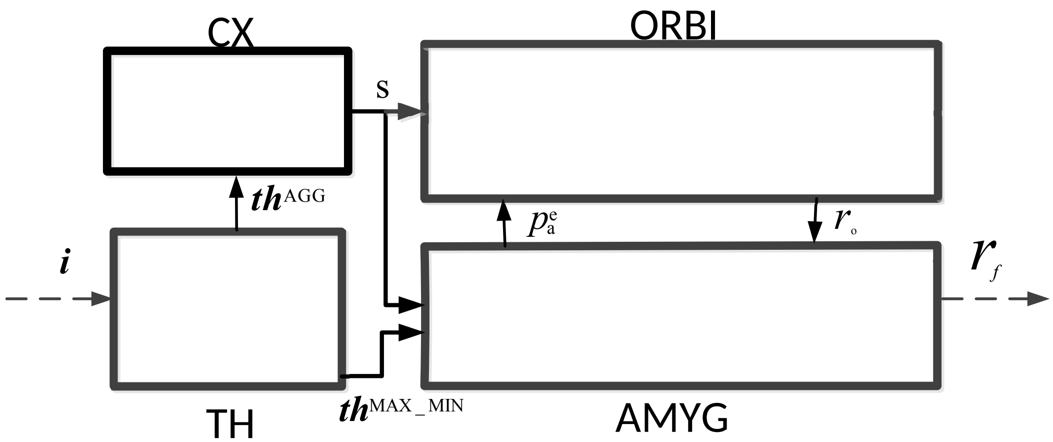

Fig. 9 The outline structure of a BELiM that show different parts are connected to each other.

CX receives $\boldsymbol{th}^{AGG}$ and provides $\boldsymbol{s}$, sending it to *AMYG* and *ORBI*. 3) The *AMYG*receives $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{s}$, and provides the expected punishment, p_a^e which is sent to the *ORBI*, the primary response r_a. The *AMYG* provides the final response, r_f after receiving r_o from the *ORBI*. 4) The *ORBI* has a bidirectional connection to the *AMYG* and provides the secondary response r_o, and sends it the *AMYG*.

To mimic the roles and the connections between the thalamus, amygdala and orbitofrontal cortex regions in the brain, the *TH*, the *AMYG* and *ORBI* of the general structure of BELiM, have been further divided into some internal parts. Figure 10 represents the internal components of these parts and describes the inputs and outputs of each of them.

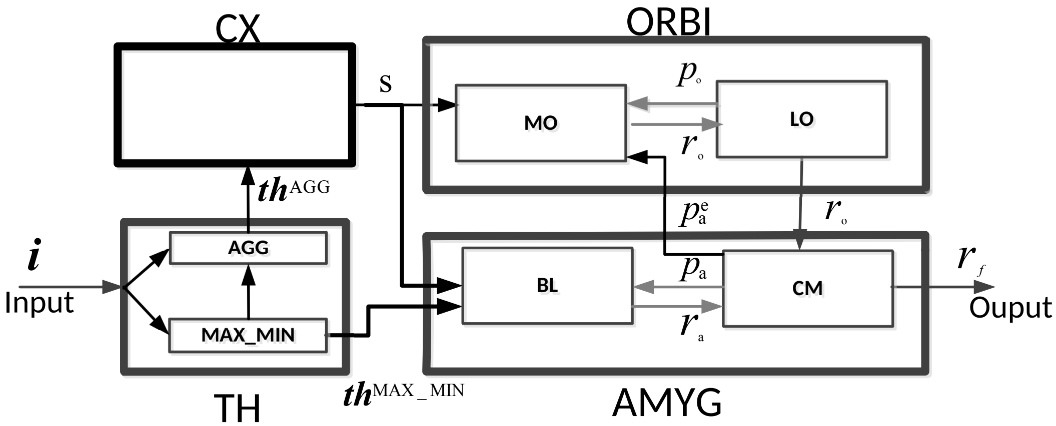

Fig. 10 The internal strcture of a BELiM. There is a bidirectional connection between AMYG and ORBI to exchange the expected punishment of The *AMYG*and the response of he *ORBI*.

1) The *TH* is divided into two subparts: the *MAX_MIN* and the *AGG*.

2) The *AMYG*, which imitates the amygdala regions (lateral, basal, accessory basal and cortico-medial regions of the amygdala and their connections), is divided into two subparts. The first subpart is the *BL* (corresponding to the combination of the basal and lateral parts of the amygdala) and the second part is the *CM* (corresponding to the combination of the accessory basal and cortico-medial regions of the amygdala).

3) The *ORBI* also mimics the role of the orbitofrontal cortex and consists of two sub-parts: *MO* (corresponding to the medial region of the orbitofrontal cortex) and *LO*(corresponding to the lateral region of the orbitofrontal cortex). The input and output of *MO* are the expected punishment (p_a^e) and the secondary response r_o, while the input and the output of *LO* are the secondary response and the punishment, respectively.

By receiving an input as $\boldsymbol{i}$, a BELiM provides the final response, r_f followoing the below steps:

1) The *TH*, which consists of two subparts, ***MAX_MIN*** *MAXimum_MINimum* and *AGG* (AGGregation). The output of *MAXimum_MINimum* can be denoted as $\boldsymbol{th}^{MAX\_MIN}$, while *AGG* receives $\boldsymbol{th}^{MAX\_MIN}$ from MAX_MIN, aggregates $\boldsymbol{i}$ and $\boldsymbol{th}^{MAX\_MIN}$ provides $\boldsymbol{th}^{AGG}$. The *TH* sends $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{th}^{AGG}$ to the *AMYG* and *AGG*, respectively.

2) The *CX* receives $\boldsymbol{th}^{AGG}$ and provides $\boldsymbol{s}$, sending it to the BL part of *AMYG* and to the *MO* part of *ORBI*.

3) The *BL* in *AMYG* corresponds to the basal and lateral parts of the amygdala; it receives $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{s}$, provides the primary response, r_a, and sends the primary response, r_a, to *CM* in *AMYG* , which corresponds to the accessory basal and cortico-medial regions of the amygdala.

4) The *ORBI* consists of *MO* (medial part of the orbitofrontal cortex) and *LO* (lateral part of the orbitofrontal cortex). The *MO* receives $\boldsymbol{s}$ and p_a and provides the secondary response, r_o. LO receives r_o and provides p_o. The *CM* in *AMYG* is responsible for providing the final response, r_f.

6 The Functional Aspect of BELiMs

We implement the functionality of a BELiM by assigning adaptive networks to the different parts of the structure introduced in Figure 10. Thus, the function of a BELiM can be described as the composition of functions of its adaptive networks.

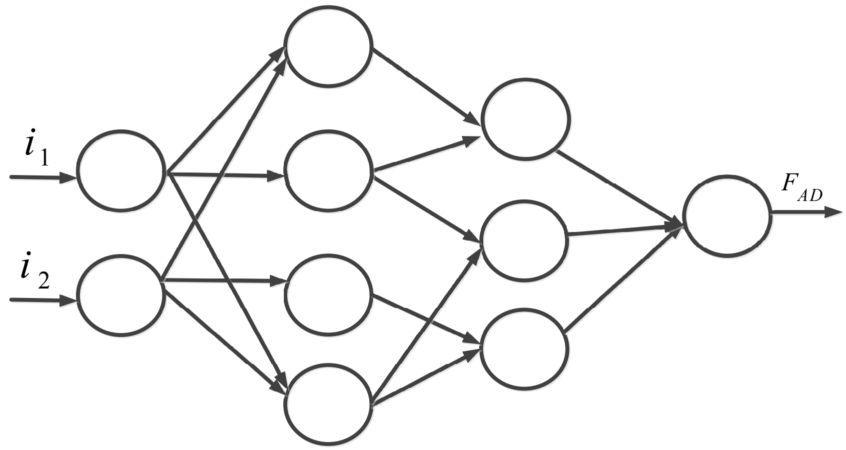

Fig. 11 A simple adaptive network with a two-dimensional input vector and an output. Nodes are connected by directional links.

6.1 What Is An Adaptive Network?

The terminology of adaptive networks (i.e., a network of adaptive nodes) has been defined by Jang [17] and encompasses all types of feedforward/recurrent neural networks that use learning algorithms to adjust learning parameters. Adaptive nodes are building blocks of an adaptive network. The function of an adaptive network depends on the function of its adaptive nodes and the weights of the feedforward or recurrent connections. Note that the learning parameters of an adaptive network are a combination of linear and nonlinear parameters and can be adjusted using learning algorithms [17].In general, the function of an adaptive network, without considering the function of the nodes and its structure, can be denoted as $F_{AD}(i)$. Here i is the input vector of the adaptive network.

Adaptive Node: An adaptive node is an extended version of an artificial neuron (AN) and its output depends on modifiable parameters of this node. Generally, there are two types of adaptive nodes. The first type of node is the circle node, which indicates that it has a fixed function with no parameters to be adjusted. Another type of node is the square node, which has adjustable parameters.

A Simple Adaptive Network: A simple adaptive network (SAN) (see Figure 11), is a type of adaptive network that only consists of circle nodes. The training algorithm of a SAN is limited only to adjusting the corresponding weights of the directional links. A SAN is similar to the early versions of ANNs with a training algorithm that is limited to the weights of connections.

6.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The adaptive neuro-fuzzy inference system, or ANFIS, was introduced in [17]. An ANFIS can be adapted to the Sugeno fuzzy inference system or the Mamdani fuzzy inference system [17]. In the following, we demonstrate a simple example of an ANFIS with two Sugeno fuzzy rules as it has been described by Figure 12. The ANFIS receives a two-dimensional input vector, $\boldsymbol{i} = \{i_1, i_2\}$, and generates an output that is referred to as F_{ANFIS}. Two linguistic labels for the first dimension of input, i_1, are A_1 and A_2 and for the second dimension of input, i_2, are B_1 and B_2. In the following, we explain the rules of the ANFIS and the structure and function of each layer.

Rule 1: If i_1 is A_1 and i_2 is B_1, then $f_1 = q_{11}i_1 + q_{12} + i_2 + q_{13}$.

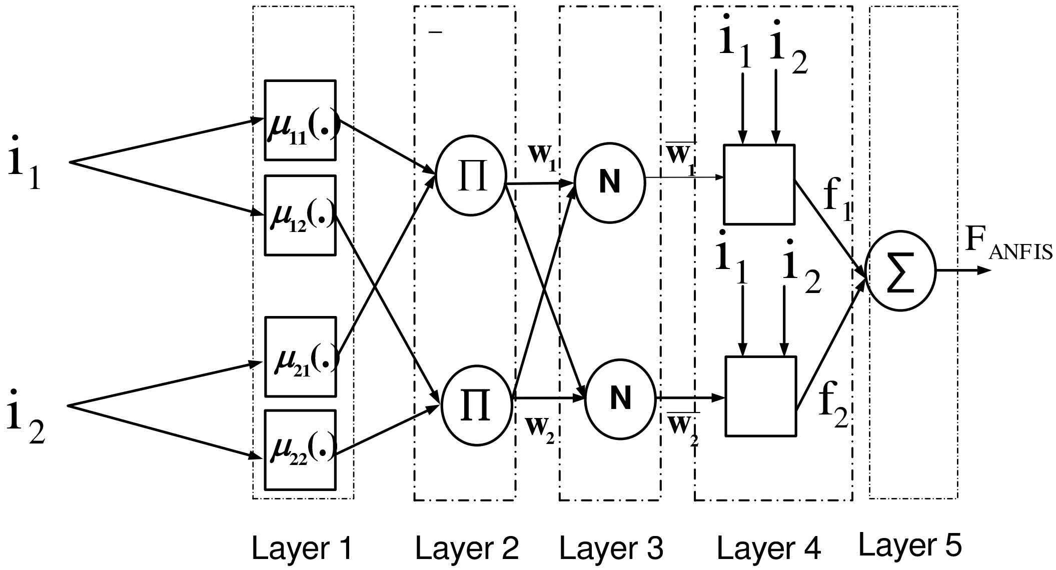

Fig. 12 A simple ANFIS with two rules and five layers; an input vector with two dimension enters the first layer.

Rule 2: If i_1 is A_2 and i_2 is B_2 , then $f_2 = q_{21}i_1 + q_{22}i_2 + q_{23}$.

The parameters $q_{11}, q_{12}, q_{13}, q_{21}, q_{22}, q_{23}$ are "consequent parameters" [17].

Layer 1: The first layer consists of four square nodes; this means that each dimension of input is associated with two linguistic labels (e.g. small, large). The membership function of the first square node can be specified by μ_{11}. It can be defined as a Gaussian (see Equation 1) or a bell-shaped (see Equation 2) function, which determines the degree to which i_1 satisfies the quantifier A_1. Equations 1 and 2 calculate the Gaussian function and the bell-shaped function for μ_{11}. The parameters c_{11},σ_{11} are the centre and the Gaussian RMS (root mean square) width of the Gaussian function, and a_{11},b_{11},c_{11} are the parameters of the bell-shaped function. These parameters are considered to be "premise parameters" [17]. In general, the l^{th} square node of the k^{th} dimension of the input vector is assigned a membership function, μ_{kl}, with the parameters, c_{kl} and σ_{kl}. Equations 3 and 4 calculate the general Gaussian function and the bell-shaped function.

$$\mu_{11}(i_1) = \exp\left(\frac{-1(i_1 - c_1)^2}{2\sigma_{11}^2}\right) \tag{1}$$

$$\mu_{11}(i_1) = \frac{1}{1+ \mid i_1 - \frac{c_{11}}{a_{11}} \mid^{2b_{11}}} \tag{2}$$

$$\mu_{kl}(i_k) = \exp\left(\frac{-1(i_k - c_{kl})^2}{2(\sigma_{kl})^2}\right) \tag{3}$$

$$\mu_{kl}(i_k) = \frac{1}{1+ \mid i_k - \frac{c_{kl}}{a_{kl}} \mid^{2b_{kl}}} \tag{4}$$

Layer 2: The second layer has two circular nodes that are labelled $\prod$ and simply provides the product of its input. The output of the first node and second node are calculated in Equations 5 and 6.

$$W_1 = \prod_{l=1}^{2} \mu_{1l} i_l \tag{5}$$

$$W_2 = \prod_{l=1}^{2} \mu_{2l} i_l \tag{6}$$

Layer 3: This layer has two circle nodes with normalisation functions; each node is labelled N. Assuming this, the output of the first node (which receives W_1 and W_2 from the previous layer) is calculated as Equation 7, while the output of the second node is given as Equation 8.

$$\overline{W_1} = \frac{W_1}{\prod_{l=1}^{2}} W_l \tag{7}$$

$$\overline{W_2} = \frac{W_2}{\prod_{l=1}^{2}} W_l \tag{8}$$

Layer 4: This layer has two square nodes. The functions of the first node and second node are denoted as f_1 and f_2 and calculated by using Equations 9 and 10, respectively. The parameters (q_{ij}) of this layer have been defined as "consequent parameters" [17].

$$f_1(i) = (\sum_{l=1}^{2} i_l q_{1l} + q_{13}) \tag{9}$$

$$f_2(i) = (\sum_{l=1}^{2} i_l q_{2l} + q_{23}) \tag{10}$$

Layer 5: The fifth layer has a single node (circle) that calculates the sum of its input vector values, $\{f_1, f_2\}$, as in Equation 11.

$$F_{ANFIS} = (\sum_{l=1}^{2} \overline{W_l} f_l(i)) \tag{11}$$

The above explanations describe the input and output of each layer for a simple ANFIS with a two-dimensional input vector and two membership functions for each dimension. In the general case, an ANFIS can receive an input vector, $\boldsymbol{i}$, with n dimensions. If its first layer has m membership functions for each dimension of the input vector, the second layer has $K^2 = m^n$ circular nodes that are labelled with $\prod$, the third layer has $K^3 = m^n$ nodes labelled with N, the fourth layer has $K^4 = m^n$ square nodes and the fifth layer has one circle node that is labelled $\sum$ to calculate the output of the ANFIS, which can be referred to as F_{ANFIS} (see Equation 12).

$$F_{ANFIS}(\boldsymbol{i}) = \sum_{l=1}^{m^n} f_l(\boldsymbol{i}) \tag{12}$$

6.3 Recurrent Adaptive Neuro-Fuzzy Inference System (RANFIS)

A recurrent adaptive neuro-fuzzy inference system (RANFIS) is a recurrent adaptive network with the capability to learn from its previous responses. It consists of an adaptive neuro-fuzzy inference system and a recurrent network, as described in Figure 13. The adaptive network takes advantage of the recurrent signal to learn the temporal outputs of the network and uses this type of information to adjust the learning parameters. Figure 13 describes an example of a RANFIS and, as can be seen, a SAN with five layers generates the recurrent signal. In the following, each layer receiving a pair $\{r_f, r\}$ is explained.

Layer 1: This layer consists of a single circle node that has been labelled $\sum$. The input of this layer is r_f (the output of RANFIS) and r (which is the target output).

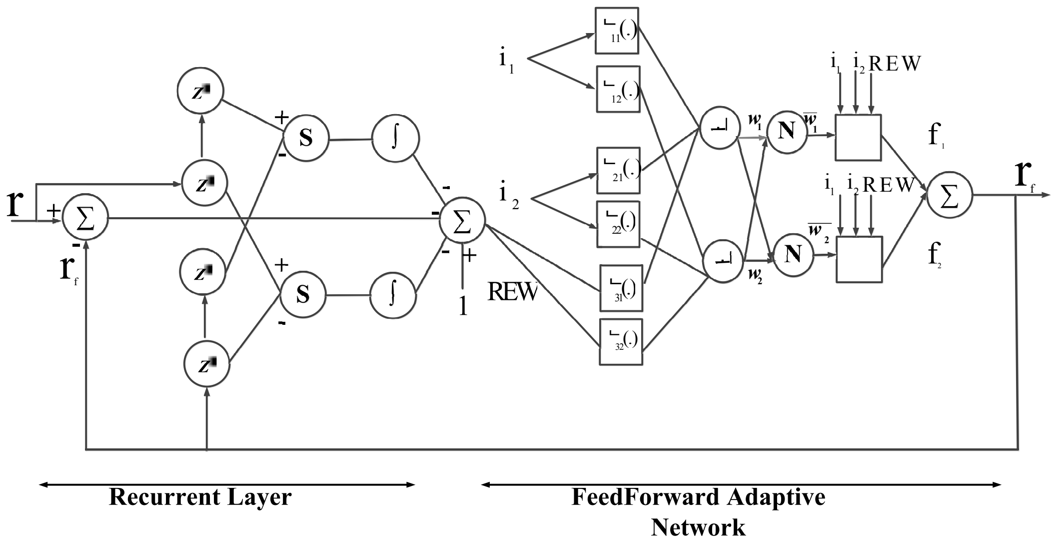

Fig. 13 A recurrent adaptive network.

Layer 2: This layer consists of four circle nodes that are labelled as Z^{-1} (delayed nodes). Two upper delayed nodes add a time delay in r, while two lower nodes add a time delay in r_f.

Layer 3: This layer consists of two circle nodes that are labelled as S. The function of an S node that receives an input, x, is defined as x^2. The upper S node receives $r_f(t-2)$ and $r(t-2)$, and the output of this node is $(r(t-2) - r_f(t-2))^2$. The lower S node receives $r(t-1)$ and $r_f(t-1)$, and the output of this node is $(r(t-1) - r_f(t-1))^2$.

Layer 4: This layer consists of two circle nodes that are labelled as $\int$. Receiving an input, x, at time, t, provides an output, $\sum_{j=1}^{t} x_j$. The upper $\int$ node receives $(r(t-2) - r_f(t-2))^2$ and provides the output, calculated as $\sum(r(t-2) - r_f(t-2))^2$. The lower $\int$ node receives $(r(t-1) - r_f(t-1))^2$ and the output of this node is $\sum(r(t-1) - r_f(t-1))^2$. **Layer 5:** This layer has a circle node labelled $\sum$ and provides the overall output of the recurrent network is defined as in Equation (13).

$$REW = 1 - (r(t-1) - r_f(t-1)) + \sum (r(t-1) - r_f(t-1))^2 + \sum (r(t-2) - r_f(t-2))^2 \qquad (13)$$

7 Different Variations of BELiMs

This section discusses how we can develop multiple variations of BELiMs by focusing on two models that are named as "Brain Emotional Learning Fuzzy Inference System" (BELFIS) and "Brain Emotional Learning based Recurrent Fuzzy Inference System" (BELRFS). We describe functionalities of these models have been implemented by assigning adaptive networks to the components of Figure 10.

7.1 Brain Emotional Learning Based Fuzzy Inference System (BELFIS)

Figure 14 describes brain emotional learning fuzzy inference system (BELFIS) whose function has been implemented by using SAN and ANFIS.

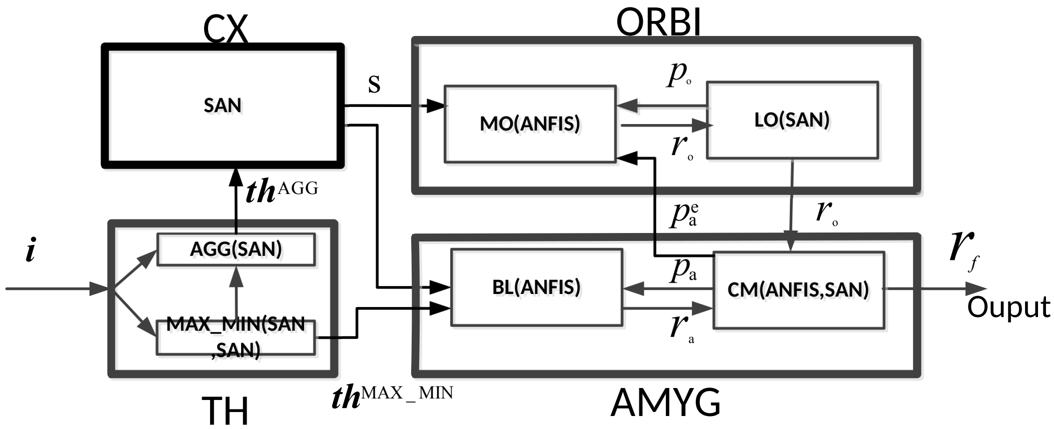

Fig. 14 The internal part of BELFIS, the input and output of each part and the adaptive networks of each part when the BELFIS is fed with a pair of training data samples such as $(\boldsymbol{i}, r)$.

By receiving an input vector as receives $\boldsymbol{i}$, BELFIS starts following the below steps. 1) The *TH* is the first part that receives $\boldsymbol{i}$. The *MAX_MIN* and the *AGG* of the *TH* provide $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{th}^{AGG}$, and send them the *AMYG* and the the *CX* respectively. The function of *MAX_MIN* is implemented by assigning two SANs (simple adaptive networks) that select the absolute maximum and minimum values of $\boldsymbol{i}$. Figure 15 describes the input and output of SANs and functions of adaptive nodes. Let us assume an input vector, $\boldsymbol{i}$=$\{i_1, i_2\}$, with two dimensions; the upper SAN selects the absolute minimum values of $\boldsymbol{i}$ (see Equation 14) while the lower SAN calculates the maximum values of $\boldsymbol{i}$. The *AGG* consists of a SAN that has a role in transforming the input vector, $\boldsymbol{i}$, to the *CX*. Equation 15 calculates the output of the *AGG*.

$$\boldsymbol{th}^{MAX\_MIN} = [\boldsymbol{th}^{MIN}, \boldsymbol{th}^{MAX}] = [F_{SAN}(\boldsymbol{i}), F_{SAN}(\boldsymbol{i})] = [max(\boldsymbol{i}), min(\boldsymbol{i})] \tag{14}$$

$$\boldsymbol{th}^{AGG} = F_{SAN}(\boldsymbol{th}^{(MAX\_MIN)}, \boldsymbol{i}) \tag{15}$$

The step function and linear function of Figure 15 can be defined as $f\_LinearNode(b) = b$ and Equation 16.

$$f\_StepNode(b) = \begin{cases} 1 & if b >= 0 \\ -1 & if b < 0 \end{cases} \tag{16}$$

2) The *CX* receives $\boldsymbol{th}^{AGG}$, provides $\boldsymbol{s}$ and sends it to the *BL* in the *AMYG* and to *MO* in *ORBI*. Note that, in BELFIS, the *CX* does not extensively process what it receives but just passes its received input to other parts. The function of the *CX* is represented by assigning a SAN, as depicted in Figure 15. The output of the *CX* is $\boldsymbol{s}$, as calculated in Equation (17).

$$\mathbf{s} = F_{SAN}(\boldsymbol{th}^{AGG}) = \boldsymbol{i} \tag{17}$$

3) The function of the *AMYG* is implemented by assigning an ANFIS to the *BL*(which receives $\boldsymbol{th}^{MAX\_MIN}$ and $\boldsymbol{s}$) ans a combination of an ANFIS and a SAN to the *CM* (which receives the primary and secondary responses from the *AMYG* and *ORBI*). The ANFIS to the *BL* provides the primary response, r_a and sends it to the SAN of *CM* (which is responsible to provide the expected punishment, ${p_a}^e$, the punishment, p_a, and to the ANFIS (which is responsible to provide the final output, r_f, as in Equation 19)

$$r_a = F^{BL}_{ANFIS}(\boldsymbol{th}^{MAX\_MIN}, \boldsymbol{s}) \tag{18}$$

$$r_f = F^{CM}_{ANFIS}(r_a, r_o) \tag{19}$$

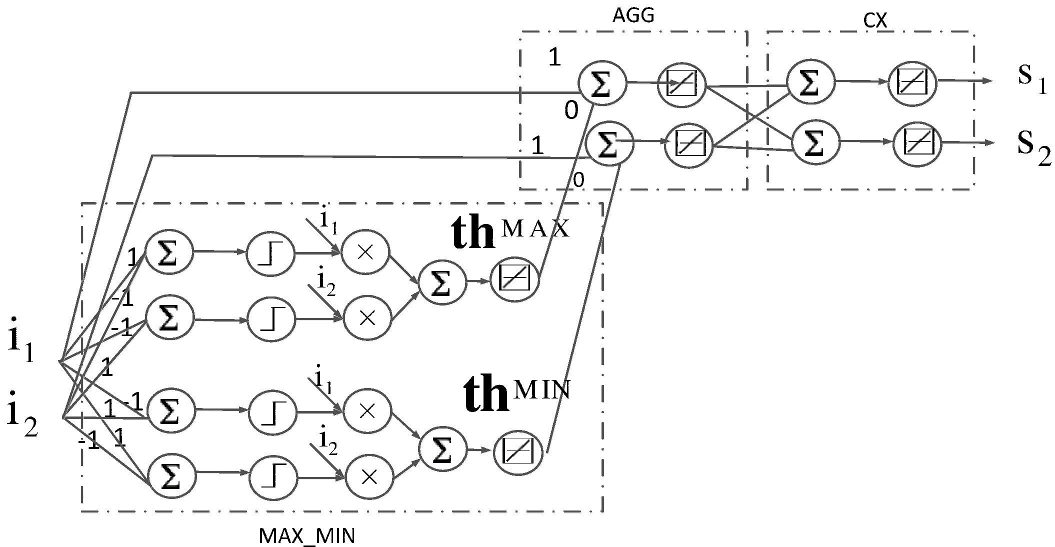

Fig. 15 The adaptive networks of MAX_MIN, AGG.

4) The function of *ORBI* (which receives $\boldsymbol{s}$) is implemented by using an ANFIS to the *MO* (which provides r_o as in Equation 20) and a SAN to the *LO* that provides p_o.

$$r_o = F^{CM}_{ANFIS}(s) \tag{20}$$

7.2 Brain Emotional Learning-based Recurrent Fuzzy System (BELRFS)

The brain emotional learning-based recurrent fuzzy system (BELRFS) is another variation of BELiMs with a slightly different structure with BELFIS. Figure 16 depicts the structure of BELRFS and shows that the function of the *CM* is implemented by assigning a SAN and a RANFIS. The SAN provides the expected punishment, p^e_a , which is sent to the *ORBI*, and the punishment, p_a, that is sent back to the *BL*, while the RANFIS provides r_f, as given by Equation 21. The expected punishment, p^e_a, is sent to ORBI, while the punishment, p_a, is sent back to BL.

$$r_f = F^{CM}_{RANFIS}(r_a, r_o, REW) \tag{21}$$

Note that in the case that the input vector is from the test dataset, the reward signal, REW is calculated by weighted k-nearest neighbour (WkNN) algorithm.

This part describes how two variations of BELiMs can be developed by assigning different adaptive networks to different parts, as in Figure 10.

8 BELiMs as Time Series Prediction Models

This section aims at evaluating the performance of BELFIS and BELRFS (two variations of BELiMs) as time series prediction models. General speaking, a time series prediction model deals with forecasting future values of the time-series based on the previous and the current values of the time series. For example, a BELiM as prediction model of sunspot numbers, uses previous and current values of a number

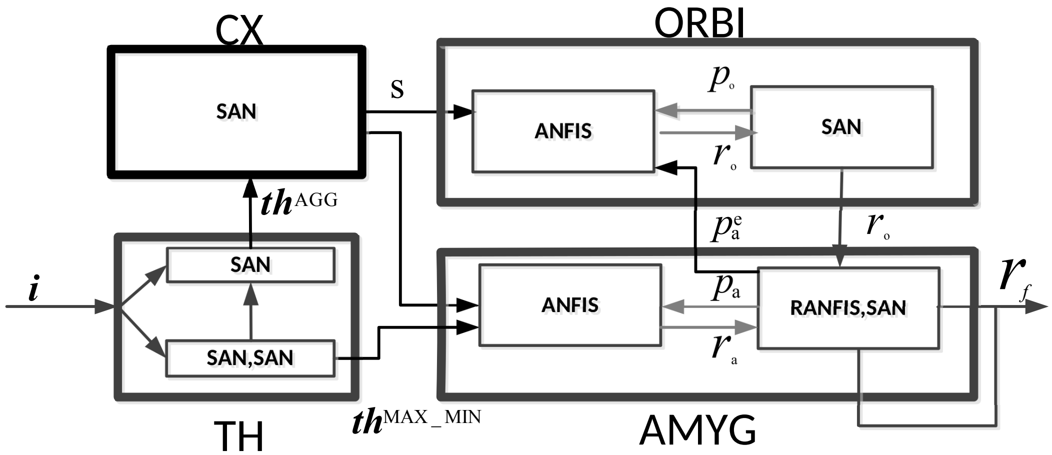

Fig. 16 The internal components of BELRFS when an input vector is chosen from the training data set .

of sunspots to predict its future value. To calculate the performance of these time series prediction models (BELFIS and BELRFS), the normalized mean square error ($NMSE$) as Equation 22 is used.

$$NMSE = \frac{\sum_j^{N_u} (r_{f_j} - r_j)^2}{\sum_j^{N_u} (r_j - \overline{r_j})^2} \tag{22}$$

Here,r_{f_j}, r_j and N_u are referred to as the predicted values, desired values and the number of samples in the test data set, respectively. Parameter $\overline{r_j}$ is the average of the desired values.

8.1 BELiMs for Predicting Lorenz Time Series

Values of $\boldsymbol{x}$ which have been extracted from the Lorenz equation (see Equation 23) [9] is presented by Figure 17.

$$\frac{dx}{dt} = \sigma(y - x) \tag{23}$$

$$\frac{dy}{dt} = x(\rho - z) - y \tag{24}$$

$$\frac{dz}{dt} = xy - \beta z, \tag{25}$$

The Lorenz time series can be reconstructed by using Values of $\boldsymbol{x}$. Two variation of BELiMs (BELFIS and BELRFS) for predicting the time series of $\boldsymbol{x}$ (see Figure 17) have been used. In this example, we have selected 1500 samples from the 30^{th} second to the 45^{th} second as the training data set to train BELFIS and BELRFS. Models are examined predicting values of $\boldsymbol{x}$ variable from the 45^{th} second to the 55^{th} second. Figures 19 and 18, which describes the predicted values of $\boldsymbol{x}$ variable by BELRFS and BELFIS. This figure can verify that these methods can accurately predict Lorenz time series which is a chaotic time series.

[9] where $(x(t), y(t), z(t))$ are coordinates in the 3D space. There are three constants as σ, ρ and β and three variables as $(x(t), y(t), z(t))$

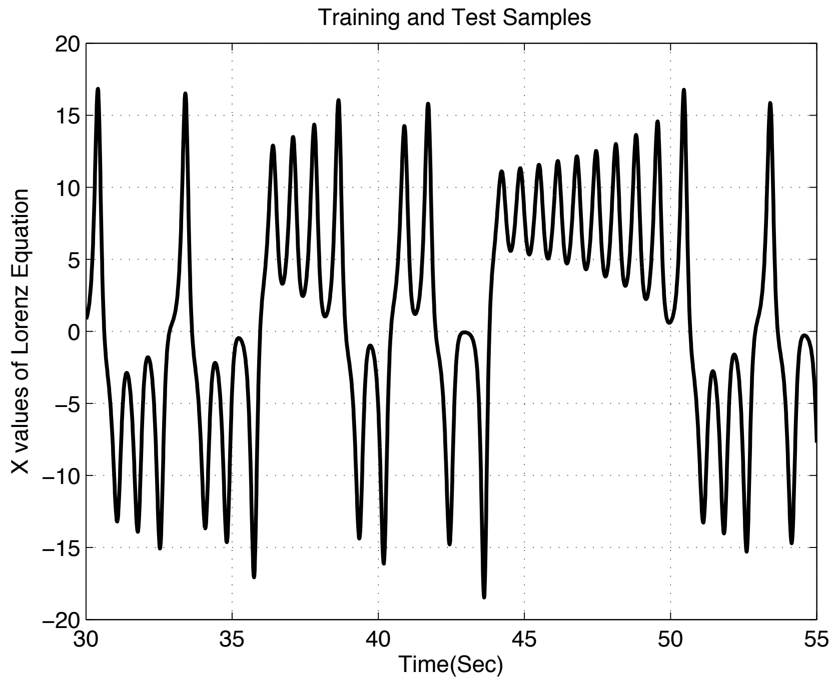

Fig. 17 The values of variable x with the initial values as $x = -15$ over 60 seconds.

For this experiment, Input vector has two dimensions as and different parts of BELFIS have been implemented as follows:

1) The TH is implemented by a three-layered NN that is described in Figure 15.

2) The CX is implemented witha one-layer NN for CX.

3) The BL of AMYG and CM of AMYG are implemented by assigning one-layer NN, an ANFIS with two membership functions for each dimension of the input vector (see Figure12), respectively.

4) While the MO of ORBI and the LO of ORBI are implemented by considering an ANFIS with two membership functions and a one-layer NN, respectively.

BELRFS has been completed similar to BELFIS and the only difference is that the BL part of BELRFS has been implemented by using a recurrent adaptive neural network (RANFIS) as described by Figure 13. Table 1 represents NMSEs obtained from BELRFS and BELFIS. The results of our models are compared by 1) "NARX-Elman" (which is a hybrid NN that combines a four-layer Elman recurrent network with a two-layer "NARX" or Nonlinear autoregressive network with exogenous inputs [1], 2) "ERNN" (an evolving neural network) [24]. It can be observed that obtained NMSEs of BELFIS and BELRFS are 4.4e-10 and 5.11e-10, respectively; They are lower than NMSE of ERNN and higher than NMSE of NARX. It should be noted that the obtained results of NARX is slightly better because of the two following reasons:

1) the NARX-Elman was combined with a preprocessing method to normalize input; 2) its prediction accuracy has been increased by applying it to predict the residuals of chaotic time series. We have not applied any preprocessing method to normalize training samples; we expect that using preprocessing method such as singular spectrum analysis (SSA) BELFIS and BELRFS can provide better results.

Table 1 Examining different methods on one-step ahead of Lorenz Time Series

Specification			
Learning Model	NMSE	Structure	No of training and test samples
NARX [1]	1.9e-10	not specified	1500,1000
BELFIS	4.4e-10	a three-layer SAN, a one-layer SAN, three five-layer ANFISs	1500,1000
BELRFS	5.11e-10	a three-layer SAN, a one-layer SAN, a five-layer RANFIS, two five-layer ANFISs	1500,1000
ERNN [24]	9.9e-10	not specified	1400, 1000

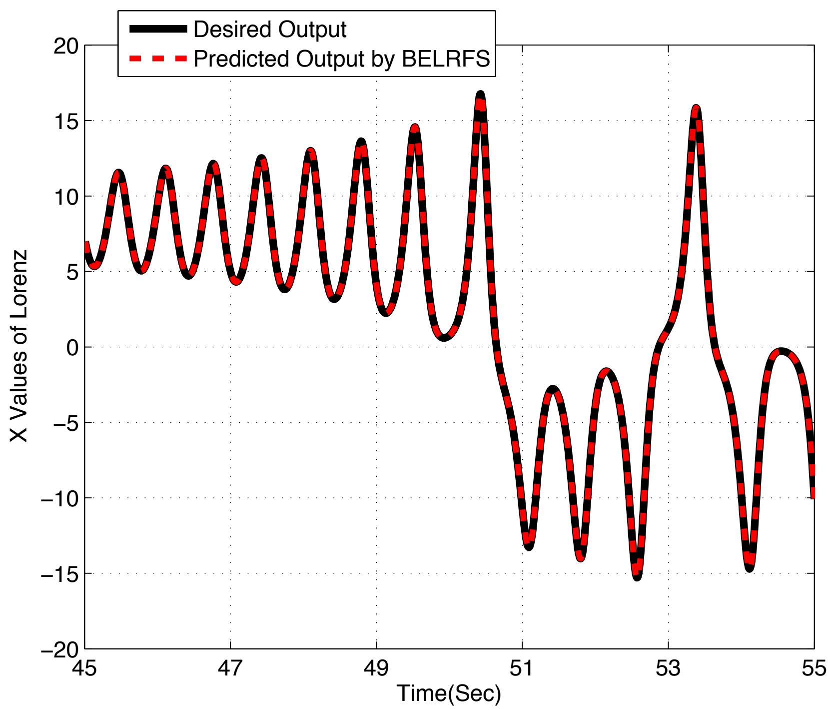

Fig. 18 Predicted values by BELRFS(red dashed lines) versus the observed values.

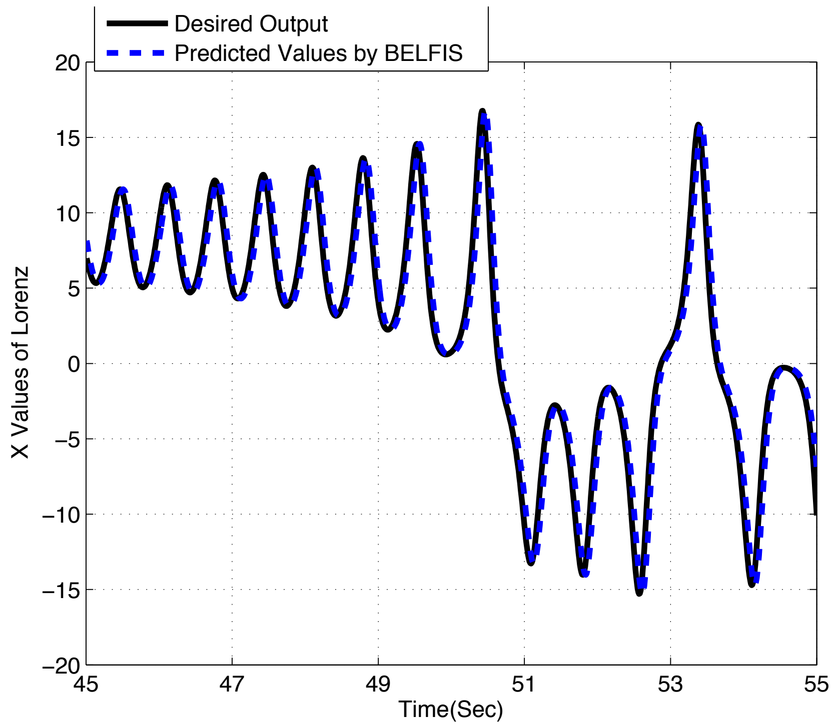

Fig. 19 Predicted values by BELRFS (red blue lines) versus the observed values.

8.2 BELiMs for Predicting Sunspot Numbers

This subsection aims at evaluating the performance of BELFIS and BELRFS by testing them as prediction models of the number of sunspots [10] another public benchmark data set. The number of sunspots is one of the indices of solar activity and has been utilized to forecast solar activity[11].

Yearly sunspot numbers which have been recorded since 1700 are calculated based on the daily sunspot number. While the daily sunspot number is calculated using $R = 10N_g + N_s$, here N_g is the number of spots and N_s is the number of groups counted over the entire solar disk. Since 1981, the Royal Observatory of Belgium is the Sunspot Index Data Center and is responsible for recording the daily, monthly and yearly sunspot numbers. Sunspot number (SSN) time series is constructed using the daily, monthly and yearly sunspot numbers as it has been indicated in Equation 26. Here, t denotes a point in time, $\triangle$ denotes the step ahead (in the yearly sunspot numbers, $\triangle$ indicates year ahead), and D determines the embedding dimension that shows how D samples of sunspot numbers can be mapped to provide one state vector. The elements of a state vector up to t is used to predict the sunspot values at $t + \triangle$.

$$[SSN(t-(D-1)\triangle)..., SSN(t-\triangle), SSN(t); SSN(t+\triangle)] \tag{26}$$

Various CI models such as ANNs and NFs [27], [12], [41] and [26] have been employed to predict SSN time series and forecast cycle peaks. This section presents the results obtained from examining BELFIS

[10] Sunspots are "cool planet-sized areas on the Sun where intense magnetic loops poke through the star's visible surface".[47]

[11] solar activity forecasting is necessary to predict changes in the space environment between the Earth and Sun and protect damages to space weather and ground-based communication tools

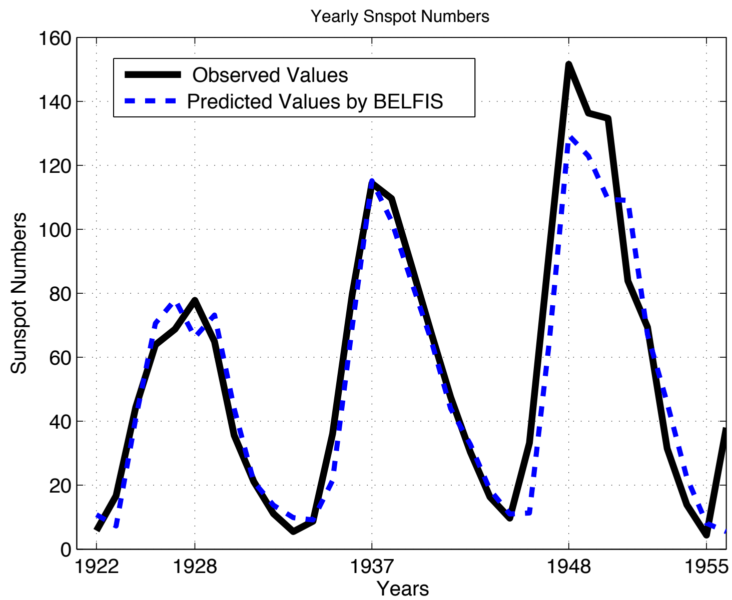

Fig. 20 Predicted values by BELFIS(blue lines) versus the observed values.

Table 2 Examining different methods on one-step ahead of Sunspot Number

Specification			
Learning Model	NMSE	Structure	Learning Models
BELFIS	0.098	16 rules	BELiMs
BELRFS	0.099	20 rules	BELiMs
ANFIS	0.128	4 rules	NF
WNET [23]	0.086	Not Identified	NN
LogF-NN[23]	0.112	Not Identified	NN
DRNN [23]	0.091	Not Identified	NN
MLP [27]	0.140	Not Identified	NN
RBF [27]	0.118	Not Identified	NN
ANFIS [27]	0.111	Not Identified	NF
LLNF[27]	0.070	Not Identified	NF

and BELRFS for predicting the yearly number of sunspots and compares the performance of BELiMs (BELFIS and BELRFS) with the results of other CI methods. To do so, I have considered the yearly SSN time series of solar cycles 16, 17 and 18, which have peaked in 1928, 1937 and 1948, respectively; the training data set has been chosen from 1700 to 1920, and the test set has been selected from 1920 to 1955. Figures 20 and 21 depict the predicted values of BELFIS and BELRFS. By observing the predicted values, we can conclude that these two models have a reasonable performance to predict the peaks of solar cycles.

Table 2 compares the obtained results from BELFIS and BELRFS with different CI models such as WNet (Weight Elimination Feed Forward), an MLP (Multi-Layer Perceptron) with a modified cost

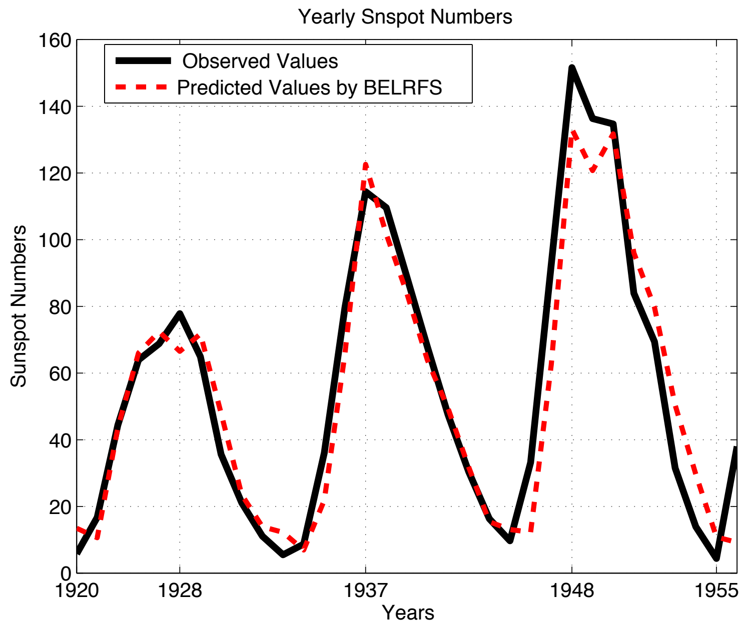

Fig. 21 Predicted values by BELRFS (red lines) versus the observed values.

function, DRNN (Dynamic Recurrent Neural Network) [27] and LogF-NN (gamma Feedback Neural Network) and RBF (Radial Basis Function). Table 2 also specifies the structure (number of neurons or rules) of each model and their obtained NMSE indices. It can be seen that these versions of BELiMs (i.e., BELFIS and BELRFS) are more accurate than the majority of the CI models in Table 2. The structures of BELFIS and BELRFS are similar to the structures of those model in the previous experimental result. In Table 2, we have just determined the total number of fuzzy rules for BELFIS and BELRFS. The obtained results from doing the two above experiments have proved that BELiMs are powerful ML in predicting chaotic time series, and confirmed that the BELiMs have reasonable accuracy, model and computational complexity in comparison with ANNs and NFs that have been well-known MLs for time series prediction.

9 Conclusion

This paper introduced a new class of MLs that is named as BELiMs. We described various theories of emotion to highlight the theoretical aspect of BELiMs. And, we illustrated how the outline structure of a BELiM has been developed by taking inspiration from anatomical theories of emotion. This paper just presented two variations of BELiMs (they are named as BELFIS and BELRFS) and demonstrated a straightforward method to implement functions of those models. We also evaluated the performance of those models by examining them as prediction models to forecast time series and compared their obtained results with other traditional MLs such as ANNs and NFs. or future research, we aim at improving the performance of BELiMs by modifying the general structure and functionality of BELiMs.

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