

Nader Rezazadeh\* and Touraj Banirostam

# Presentation of ACT/R-RBF Hybrid Architecture to Develop Decision Making in Continuous and Non-continuous Data

https://doi.org/10.1515/jisys-2017-0470 Received September 12, 2017; previously published online May 22, 2018.

**Abstract:** Computational models are based on symbolic architecture. For this reason, computational models function problematically in dynamic, noisy, and continuous environments. The ACT/R (Adaptive Control of Thought-Rational) model is also problematic, as it is purely based on symbolic architecture like other computational models. The ACT/R decision-making process is based on the production operator on the input subject set. This approach firstly does not make a non-linear mapping between input and the decision-making result in ACT/R. Secondly, it is not possible to decide on the input subjects with a continuous input range because of the need to introduce numerous rules. The objective of presenting the ACT/R-radial basis function (RBF) hybrid architecture method was to create a communication network between input concepts in which the reception of and decision making on a combination of subjects and symbols are possible. Moreover, a non-linear mapping between input and the decision-making result can be created. The said capabilities have been obtained by the combination of ACT/R with an RBF neural network and calculation of the decision-making centers in the said network using clustering. The empirical experiments indicate desirable results in this regard.

**Keywords:** Cognitive architecture, connectionism, ACT/R model, RBF neural network.

### 1 Introduction

Decision making is a cognitive process in the mind whose result is to select an alternative among all alternatives based on the available conditions [1]. Nowadays, researchers use cognitive architecture to simulate the decision-making process [25]. One of the advantages of using cognitive architecture in decision-making processes is to investigate all possible alternatives for the elements on which decision making is done [20]. This is possible by relying on the interaction of the knowledge specified in the cognitive model and declarative knowledge [26]. The main problem of the approaches that are based on rational models and decision-making principles is ignoring the decision-making cognitive abilities. In recent years, most of the studies have focused on dimension reduction and extracting high-level features while neglecting the basic cognitive aspect of decision making [17].

Regarding the introduced issues, a model is needed for decision making that takes into consideration the cognitive capabilities with respect to the data classification ability. It should be noted that cognitive decision making is done based on the obtained information from the environment, and it is probable that the results do not have a direct relationship with the early parameters (the relationship between the output and input of the system is completely non-linear). Therefore, a series of measurable parameters are needed to simulate decision making in the computer and make it computational; these parameters are very implicit [4, 30].

<sup>\*</sup>Corresponding author: Nader Rezazadeh, Department of Computer/Science and Research Branch, Islamic Azad University, Tehran, Iran, e-mail: naderrezazadeh1984@gmail.com

Touraj Banirostam: Department of Computer Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran

**a** Open Access. © 2020 Walter de Gruyter GmbH, Berlin/Boston. © This work is licensed under the Creative Commons Attribution 4.0 Public License.

ACT/R (Adaptive Control of Thought-Rational) [5] is one of the modeling methods developed based on cognitive architecture. The decision-making process in ACT/R is done based on cognitive architecture [5]. In the ACT/R architecture, the production operator on the set of subjects is used for decision making [24]. This approach causes the inability for creating a linear relation between decision-making system input and output. Moreover, it is not possible to decide on the subjects with a continuous input range because of the need for numerous rules. As such, this paper sought to use the capabilities of cognitive architecture and eliminate the said problems. As a result, the model would be able to decide on a set of subjects with discrete and continuous input value range. Hence, the proposed method in this paper combines a radial basis function (RBF) neural network [3] with an ACT/R model to implement the decision-making process.

In this method, the RBF neural network helps the ACT/R model to generalize and improve decision making. The educational data centers are saved as procedural knowledge [2] in the ACT/R model. The declarative knowledge is also used to help decision making in this hybrid model. The cluster centers related to the values of the subjects are extracted with an early preprocessing and using an unsupervised clustering method. The cluster center sets are used as decision-making centers in the RBF neural network. If the input is of the needed difference from the saved rules in procedural knowledge, the RBF neural network is used for decision making. The three-dimensional (3D) Gaussian function is used in this model to compare each of the input phrases and the set centers. The numerical representation of the knowledge in a way that it enables the model to decide is another challenge that will be discussed later. In Section 2, the cognitive structure in the ACT/R model and the RBF neural network will be reviewed. In Section 3, the proposed method is explained. Finally, the experiments and the results of the implementation are investigated in Section 4.

# 2 Literature Review

ACT/R is a model of the human cognitive process that is developed and used by cognitive science physicists [2]. ACT/R is a cognitive architecture using cognitive principles for decision making [2]. The ACT/R model presents some theories about simulation and cognition perception in the human brain. The brain structure theory presented by ACT/R seeks to explain the cognition formation in the human brain. The said theory in ACT/R software is able to simulate various samples of task completion in different areas [7]. Although ACT/R is mainly used by researchers of cognitive physiology, the presented theories can be used and developed in the field of modeling in ACT/R and other cognitive architecture. In the current section, the ACT/R architecture and experiment of using neural network in cognitive architecture are briefly reviewed.

### 2.1 ACT/R Architecture

The ACT/R architecture includes a set of modules. Each module performs a special cognitive operation and is independent from other modules. However, the modules can communicate with each other. The relationship between modules is provided by an interface called buffer memory. Each module may include some buffer memory numbers to communicate with other modules.

### 2.1.1 Perceptual-Motor Module System

The perceptual-motor module system (ACT-R/PM [11]) was added to the ACT/R system as a result of secondary modifications. Because of the said modules, the user interactions in the environment can be modeled by ACT/R-PM. In an ACT-R/PM system, there are two perceptual and cognitive motor layers.

### 2.1.1.1 Perceptual-Motor Layer

The perceptual-motor layer is a connector between the cognitive layer and the outer environment. This layer contains modules responsible for handling the input sensors. Moreover, the reaction on the external environment (defined) is made possible by the system perceptual-motor layer.

### 2.1.1.2 Cognitive Layer

In this layer, the input data are processed based on the knowledge available in ACT/R system and cognitive architecture.

### 2.1.2 Knowledge Presentation in ACT/R

There are two methods of knowledge presentation in ACT/R. These two methods provide the basic conditions for doing the final processing. They include declarative knowledge [8] and procedural knowledge [8]. These two kinds of knowledge always interact with each other to do decision making in a cognitive architecture.

### 2.1.3 Knowledge Interaction in the ACT/R Cognitive Layer

The procedural knowledge and declarative knowledge need to interact with each other to do decision making in the cognitive layer. The knowledge interaction in the ACT/R cognitive layer is seen in Figure 1.

In Figure 2, the memory is shown as a rectangle. Memory buffers are also shown as elliptic. The "Retrieval" is the buffer of declarative knowledge memory and the "Goal" is the buffer of Goal memory [24]. The Goal buffer is used for keeping the information of the control the model needs for doing the present tasks. The blue arrow indicates information reception by a module from another module. The procedural knowledge memory always interacts with the buffer of declarative memory (recycling memory) and the buffer of the Goal memory in receiving information related to the requests and sending information.

# 2.2 Artificial Systems Based on the Theories of Mind

The attempts to design of artificial systems capable of simulating important aspects of human cognitive abilities have a long history. In order to achieve this goal, theorists have tried to interpret the mind by using two different theoretical approaches: computationalism [22] and connectionism [24].

#### 2.2.1 Computationalist Model

Computational model followers are trying to implement high-level cognitive functions of the mind through symbolic architecture [19]. Computational theory and symbolic architecture solve the problem of high-level cognitive functions of the mind. The main problem with symbolic architecture is that all information must

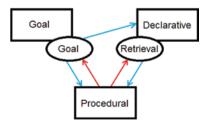


Figure 1: Relationship between Declarative and Procedural Knowledge Memory in the Decision Making Process [6].

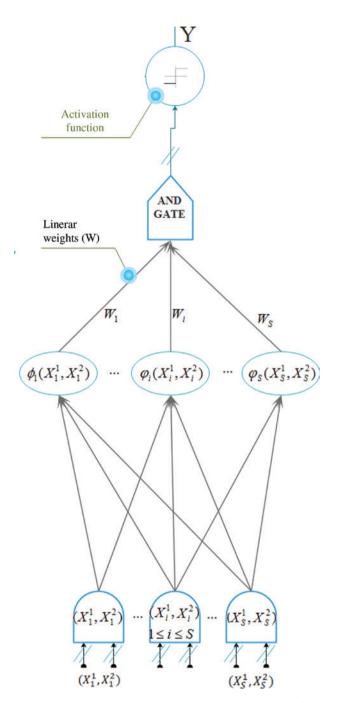


Figure 2: Structure of the RBF Neural Network Used in the ACT/R-RBF Hybrid Model.

be presented in the symbolic form. Thus, with the rise of high-level cognitive functions, it gets into trouble. Recognizing symbols in noisy and dynamic environments is another problem of symbolic architecture [3]. ACT/R clearly belongs to the "symbolic" field [28].

### 2.2.2 Connectionist Model

According to the connectionism theory, the mind is a network of connection. The connectionism theory attempts to describe mental phenomena by interconnected networks of simple and uniform units. The biggest problem with connecting models is the implementation of high-level cognitive function. Followers of the connectionist model focus on biological realism of the neuron model. The most used type of connectionist model is the artificial neural network model [13].

### 2.2.3 Connectionist Computational Model

It is clear that both the computationalism and connectionism theories in the description of the function of the mind have serious structural defects. On the one hand, both theories interpret the important aspects of the mind. Hence, some scholars have tried to merge the computational theory and the connecting theory. Wermter [29] presented a hybrid connectionist natural language processing. Garcez and Lamb [12] proposed a connectionist computational model for epistemic and temporal reasoning. In their opinion, merging of computational and connectionist systems into neural-symbolic systems is more effective than purely symbolic or purely connectionist systems.

# 2.3 Using Neural Network in Cognitive Architecture

Recently, the use of cognitive architecture in neural network has been considered in research papers. One important instance is use of a cognitive neural network for learning and communicating through natural language [13]. In the above research paper, procedural knowledge was used for language communicative interactions. Another important research paper is applying cognitive neural network to cyber security [21]. In the above research paper, declarative and procedural knowledge is also being used to improve the security model. Both papers are based on the human cognitive process. The need for interaction between humans and the neural network model has led to the use of the cognitive model.

# 3 Proposed Method

The ACT/R model also uses symbolic architecture. As previously mentioned, symbolic architecture is problematic in dynamic, noisy, and continuous environments. The reason behind this problem is the lack of symbol definition for an unknown or modified status. Given the above-mentioned issues, symbolic architecture does not have the ability to make proper decisions in continuous data environments. On the other hand, connectional models – such as neural networks in noisy environments – are dynamic, continuous, and even more flexible. Therefore, it has been proposed to combine the ACT/R model with a connectional model to improve the decision-making performance of the ACT/R model. With an increase in the range or continuity of the data set space of a subject, more rules need to be defined to cover all inputs for decision making about the subject. As mentioned in Section 1, even if numerous rules are defined for decision making about a subject in continuous environments, there is the problem of the lack of linear consistency between the rule input and the decision-making result. Therefore, it is necessary to create a communication network between input concepts in which a combination of subjects with continuous input range and symbols can be received and decided upon. Furthermore, the model should be able to create a non-linear mapping between input and decision-making result. In the proposed method, a combination of an RBF neural network and ACT/R cognitive architecture has been used for decision making. The purpose of this is to combine a computational model with a connectional one.

Using a classification method like RBF based on the initial rules in conditions where the input values have a relative difference from initial rules has been defined as a proposed solution. Moreover, in the proposed method, the interaction between the RBF neural network and declarative knowledge has been taken into consideration for redefining input and making a better decision. The RBF neural network uses RBFs as activity functions [15]. The output of this network is a linear combination of RBFs for the input parameters

and neurons. The RBF neural network is used for approximation, prediction, and interpolation of time series [15]. Using non-linear membership functions like the Gaussian membership function provides the possibility for non-linear mapping in this kind of neural network.

### 3.1 Representation of Knowledge in the Proposed Method

The representation of knowledge and using it in the neural network is one of the most important challenges in this study. For doing this, the represented rules and knowledge should be distinctive from other rules and knowledge as much as possible, and knowledge representation should not make any problem in the decision-making process. Declarative and procedural knowledge are two kinds of knowledge used in the ACT/R model and it is sought in this section to introduce a solution for its representation.

### 3.1.1 Representation of Declarative Knowledge

This knowledge is related to obvious concepts we are aware of. In the proposed method, it only suffices to save declarative knowledge including the rules and necessary functions. The format of the used declarative knowledge is provided below.

where  $1 \le i \le N$ ,  $1 \le i' \le N1$ ,  $1 \le j \le M$ ,  $1 \le j' \le M1$ .

The parameter N represents the number of the subjects,  $N_1$  shows the number of the phrases that can be substituted with  $i^{th}$  subject, M shows the number of the propositions, and M, represents the number of the phrases that can be substituted with  $i^{th}$  proposition. To be used in the neural network, the subjects and propositions should be represented in a way that they can be distinguishable. The manner of representation has been provided in the next section.

### 3.1.2 Representation of Procedural Knowledge

As mentioned, procedural knowledge is presented in the form of if-then statements. The presentation format of procedural knowledge is provided below, according to subject and proposition.

If decision making is done based on several rules, the format of the procedural knowledge is presented as below:

$$\frac{\text{Term 1}}{\text{IF } (Subject_1 \text{ is } Proposition_1) \cap ... \cap (Subject_S \text{ is } Proposition_S)} \text{ Then } Y.$$
(3)

In above phrase, *S* is the number of the terms used in a procedural knowledge. To base each term as a decision-making center, it should be put as the set center. To do this, the (Subject, Proposition)  $1 \le i \le S$  pair is put as the center of the membership function used in the neural network and the signed distance function. For example, for the term "IF Water is Low Then Y," the (Water, Low) pair is selected as one of the decisionmaking centers. The manner of numerical representation of the subjects and propositions is one of the most important available challenges. The subjects and propositions of each subject should be valued in a way that they do not interfere with propositions of another subject. It is attempted to classify the subjects proportionally and based on their similarity. Consider four subjects of water, beer, university, and school. An example of the numbers fitted to subjects that have firstly been approximately determined is presented in Table 1.

This method of initialization for the subjects is done at first in a relative and subjective form and is carried out to create a maximum distinction between them. However, in continuing, the values assigned to them are changed at the stage of educating the linear weights in the RBF network again. The secondary changes are in such a way that the risk of final decision making is reduced in the education process. If the propositions are quantity descriptive, the numbers assigned to them should be coordinated with the prepositions. For instance, a sample of the coordination of numbers with the prepositions is presented in Table 2.

In Table 2, the prepositions Very High, High, Medium, Low, and Very Low have been attributed to the numbers in the time slot of 1 to 5. What is of special importance at the beginning of initialization is the interference of assigned values of propositions of one subject and the other ones. Because the values of subjects have been determined in such a way that they could just be differentiated, the  $\sigma$  value related to the subjects should be determined by clustering on the first data if possible, so that the interference of propositions of one subject and the other subjects by Gaussian membership function is reduced. By this method, the propositions of the other subjects do not get a considerable membership value from the membership function of our favorite subject. Most of the times, the prepositions are numeral; so, there is no problem in their representation. However, it should be noticed that, at this time, all the prepositions should be normalized in a certain range.

### 3.2 Configuration of the Proposed RBF Neural Network: Module

The RBF neural network consists of at least three layers. The number of layers can be increased in the RBF network; however, for the reason of using one layer with radial functions, the network should have at least three layers. The RBFs provide the external estimation on the basis of centers of the cluster and the entrance.

### 3.2.1 Training the RBF Neural Network

The RBF networks are usually trained by a two-step algorithm [27]. At the first step, the decision-making centers for RBF functions are selected at the hidden layer. The centers are selectable by two methods. At the first method, the centers are able to be sampled randomly of some of the sets of examples. In the second

Table 1: Initial Values Attributed to Subjects.

Value
1
2
9
10

Table 2: Initial Values Attributed to Propositions.

Proposition	Value		
Very Low	1		
Low	2		
Medium	3		
High	4		
Very high	5		

method, the centers are determined by the use of an unsupervised algorithm. The second method has been used in the RBF neural networks by the proposed method. It means that at first, the centers of clusters (centers of decision making) are extracted by use of the K-means algorithm [27]. Also for this purpose, at first, all the used rules in the membership function have similar effects; all the weights on the link of the input-hidden layer have been regarded 1. At the second step, the linear weights are arranged simply with regard to the output of the hidden layer and purpose value.

### 3.2.2 Membership Function Used in the RBF Network

Usually, the Gaussian normal function is of favorable radial functions in the RBF neural network [10]. Also, in the proposed method, the Gaussian normal function has been used in the RBF neural network. Whereas the input is two dimensional (subject and proposition), the 3D Gaussian normal function [14] has been applied as the membership function. Any term of procedural knowledge is selected as one of the cluster centers. Any input is compared with all the cluster centers to receive the proper membership value. The manner of arranging the 3D Gaussian normal function,  $\varphi_i$ , with the center of (*Subject*<sub>i</sub>, *Proposition*<sub>i</sub>) and the input of  $(X_i^1, X_i^2)$  is presented as follows:

$$\varphi_{i}(X_{i}^{1}, X_{i}^{2}) = \frac{1}{2\pi\sigma^{2}} e^{\frac{-[(X_{i}^{1} - Subject_{i})^{2} + (X_{i}^{2} - Proposition_{i})^{2}]}{2\sigma_{i}^{2}}}.$$
(4)

The membership value that the network gives the vector of input values would be equal to Eq. (5):

$$\varphi_{i}(X^{1}, X^{2}) = \sum_{i=1}^{S} \frac{1}{2\pi\sigma^{2}} e^{\frac{-\left[(X_{i}^{1} - Subject_{i})^{2} + (X_{i}^{2} - Proposition_{i})^{2}\right]}{2\sigma_{i}^{2}}}$$
(5)

where 
$$(X^1, X^2) = (X_1^1, X_2^1), ..., (X_s^1, X_s^2), ..., (X_s^1, X_s^2),$$

where S is the number of terms of procedural knowledge and equal to the number of saved centers in the network. The centers set are also used in the distance calculation module.

#### 3.2.3 Structure of the Proposed RBF Neural Network

First of all, centers  $C_i^1$  and  $C_i^2$ ,  $1 \le i \le S$ , are determined via an unsupervised pre-training process, to determine the membership of the input to the  $i^{th}$  sub-objects and the  $i^{th}$  statements to the training data.  $C_i^1$  and  $C_i^2$  are the centers of decision making in regard of the  $i^{th}$  subjects and  $i^{th}$  propositions in  $i^{th}$  terms of training vectors. Some changes have been considered for the purpose of using the RBF neural network in the process of decision making. The use of AND gate for the multiplication on the rules is one of these changes. This work is done for the purpose of implementing the format of executing the procedural knowledge in the ACT/R model. For this purpose, for external calculation, all the values of the internal layer and the weights related to them are multiplied.

Due to implementation of Eq. (5), the first-layer weights are determined as shown below:

If 
$$i \neq j$$
, Then  $V_{ij} = 1$  else,  $V_{ij} = 0$  (6)

With regard to the used membership function, the first output of the network would be equal to Eq. (7):

where *f* is the activation function that its parameters, as presented in Eq. (8), are arranged in the distance module and RBF radial function.

$$\begin{cases} 1 & Z > Limit_{1} \\ 0 & Limit_{1} \leq Z \leq Limit_{2}. \\ -1 & Z < Limit_{2} \end{cases}$$
 (8)

In fact,  $Limit_1$  and  $Limit_2$  are the amounts of distance from the input to the choices of decision making that on the basis of them, the decision making is assigned to the procedural module or the neural network.

### 3.3 Distance Calculation Module

The membership function and the centers used in the distance calculation module and the RBF neural network are the same. Also, for the purpose of being harmonious in calculating the distance, the  $\sigma$  value is considered the same for the distance calculated on the module and RBF neural network. The amount of distance of input  $X = (X^1, X^2)$  has been presented in Eq. (9) with the regard of the vector of centers of decision making  $C = (C^1, C^2)$  for an input rule with S term.

$$Distance^{i}(X^{1}, X^{2}) = \frac{\sum_{i=1}^{S} \frac{1}{2\pi\sigma^{2}} e^{\frac{-[(X_{i}^{1} - C_{i}^{1})^{2} + (X_{i}^{2} - C_{i}^{2})^{2}]}{2\sigma_{j}^{2}}}{S}.$$
(9)

In Eq. (9), the sum of membership values has been divided on *S* to normalize the distance between 0 and 1.

### 3.4 Proposed Model Architecture

In the proposed architecture, the centers extracted by the K-means clustering method play a key role. At first, the input is compared with the center of clusters. The value of the determined distance of the input from the centers of clusters means the defined difference of the input from the first rules. In this model, D-flip flop [18] is used as a cache memory. In Figure 3, the hybrid ACT/R-RBF architecture model is presented.

In Figure 3,  $L_1$  and  $L_2$  are the limits set for using modules. The input X in the hybrid ACT/R-RBF architecture model is in the format of Eq. (10):

$$X = (X^{1}, X^{2})$$

$$= (X_{1}^{1}, X_{1}^{2}), ..., (X_{i}^{1}, X_{i}^{2}), ..., (X_{S}^{1}, X_{S}^{2})$$
where  $1 \le i \le S$  (10)

In Eq. (9), the pair  $(X_i^1, X_i^2)$  is equal to  $i^{th}$  subject and proposition of the set of the input sentences. In Figure 3, at first, the input is sent to three flip flops (nos. 1, 2, and 4) in addition to the distance module for interim maintenance, so that if needed, by activating them, the input is used for the intended part. The value of input distance from the centers of cluster is extracted by the distance calculation module. If the distance is lower than the determined value,  $L_1$  (*Distance*  $\leq L_1$ ), for the final decision making, the input is directly sent to the

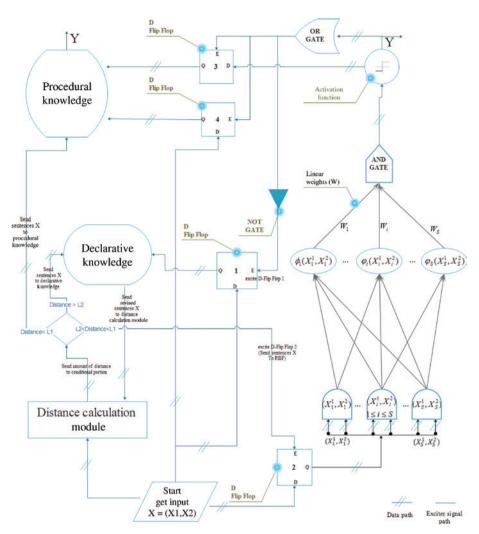


Figure 3: Hybrid ACT/R-RBF Architecture Model.

procedural knowledge module so that the answer is calculated in ACT/R in a conventional way. If the distance is in the determined limit  $(L_1 \le Distance \le L_2)$ , flip flop no. 2 is excited so that the input is sent to the RBF neural network. The RBF neural network determines the output with regard to the centers of decision making. As it was mentioned, the centers of decision making are the same centers of clusters that have been extracted by an unsupervised clustering algorithm in the first preprocessing. In the third mood, if the distance is more than the determined value  $L_2$ , the input rules set is sent to the declarative knowledge module so that the subjects or propositions are exchanged, if possible. With the change of some of input rules, the processes of calculating the distance from the cluster centers and the decision making are performed again. In this model, the interaction of the input with the declarative knowledge has been considered. This interaction is described in Figure 4.

If the neural network present the output 0 (it means finding no answer), flip flop no. 1 is excited and sends the input to the distance calculation module. If the distance is bigger than the determined value, L, (Distance > L<sub>2</sub>), the input is sent to the declarative knowledge module. In this part, if possible, the other substitute is selected for the subject or proposition based on the defined format of that (Section 3.1). With this work, the revised sentence  $X' = (X'^1, X'^2)$  is produced that can result from obtaining the answer from the RBF neural network or even directly from the procedural knowledge module.

The produced answers, if the obtained output is not zero, are saved in the procedural knowledge module by the RBF neural network with the input related to it that has been respectively saved in flip flops no. 3 and

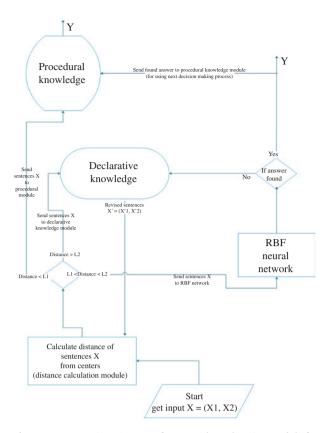


Figure 4: Interaction Diagram of Input with Declarative Module for Recreating Rules of Input Sentence by User of Saved Hypothesis in the Declarative Module.

no. 4 so that they can be used continuously. However, the results of the RBF neural network would play no role in clustering and changing the first centers.

# **4 Experimental Results**

The data set game Deal or No Deal [9] has been selected for the experimentation of the proposed method. In this game, the banker contacts you with regard to the account and presents some suggestions that you can accept (Deal) or reject (No Deal) and continue the game.

All the educational sentences are used as the procedural knowledge in the procedural knowledge module. If the input is determined for each of the sentences saved at the range of distance, the decision making is directly done by the ACT/R model and the procedural knowledge module. For instance, the first row in Table 3, as presented in Eq. (11), is saved in the procedural knowledge module.

IF (Education is College) 
$$\cap$$
 (Gender is male)  $\cap$  (Age is 26)  $\cap$  (StopRound is 4)  $\cap$  (Amount won is 34.9)  $\cap$  (Round is 1)  $\cap$  (Bank offer is 2.9) Then No Deal. (11)

These rules, in addition to the procedural knowledge module, are also used as the decision-making centers in the RBF neural network. For example, the decision-making centers in RBF neural networks have been presented in Eq. (11) based on the centers of clusters that have been extracted from the educational rules after clustering.

IF 
$$(Educationis School) \cap (Gender is male) \cap (Age is 17) \cap (StopRound is 6)$$
  
 $\cap (Amount won is 21.3) \cap (Round is 2.5) \cap (Bank offer is 12.8)$  Then  $Deal$ 

Player	Education	Gender	Age	Stop Round	Amount Won	Round	Bank Offer	Deal or No Deal
1	College	Male	26	4	34.90	1	2.90	ND
2	College	Male	23	4	11.25	4	4.70	ND
3	University	Female	21	4	11.25	1	9.90	ND
4	School	Male	16	4	34.90	4	34.90	D
5	College	Male	26	8	17.50	2	3.80	ND
6	University	Male	22	4	11.25	3	11.85	D
7	School	Female	16	4	34.90	1	17.7	D
8	School	Male	17	4	34.90	3	20.20	ND
9	College	Female	16	8	17.50	4	15.10	D

Table 3: Part of the Training Dataset Used in Determining the Center of Cluster and Procedural Knowledge.

Eight 3D Gaussian membership functions are applied for decision making on the basis of eight terms of the procedural knowledge in Eq. (12). Each of the terms is used as the center in each of the Gaussian membership functions. To continue, the parameters of the RBF neural network and then the used distance module are presented in Table 4.

The approximate value of  $\sigma$  has been determined with regard to the mean of standard deviation in the set of clusters of subject and proposition. The obtained values have been, respectively,  $\sigma^{Subject} = 5.07$  and  $\sigma^{Proposition}$  = 4.27. However, in the experiments, it has been attempted to experience  $\sigma$  about twice the  $\sigma$  of experimental data and also the  $\sigma$  equal to zero. In experiment no. 1, the value of standard deviation for the subject of  $\sigma^{Subject} = 0$  has been done for  $\sigma^{Proposition} = 0$ ,  $\sigma^{Proposition} = 5$ , and  $\sigma^{Proposition} = 10$ . The results of experiment no. 1 are presented in Figure 5.

As it is observed in Figure 5, if  $\sigma^{Subject} = 0$  and  $\sigma^{Proposition} = 0$ , the precision of hybrid model and ACT/R would be the same in the best situation, because with the radius of membership function being zero, a neural network like the ACT/R model is practically changed to the implementer of the terms. In the experiment 1-2, the function of the hybrid model is improved by the selection of a  $\sigma$  near to the value of mean of standard deviation obtained from the clusters of proposition data. In experiment 1-3, the care of the hybrid model is reduced by making distant the value of  $\sigma^{Proposition}$  from the actual value. In the experiments set no. 2, the value of  $\sigma$  has been done for  $\sigma^{Subject} = 5$ ,  $\sigma^{Proposition} = 0$ ,  $\sigma^{Proposition} = 5$ , and  $\sigma^{Proposition} = 10$ . The results of experiment no. 2 are presented in Figure 6.

By making the proper value of  $\sigma^{Subject}$  near to the mean of standard deviation in the clusters of subject, the precision of decision making in experiment 2-1 has been improved in comparison to the similar experiment 1-1. However, the best function is related to experiment 2-2 in which the values of  $\sigma^{Subject}$  and  $\sigma^{Proposition}$  have been selected similar to the values of mean of standard deviation in the set of clusters of subject and proposition. In the set of experiments no. 3, the value of deviation has been done for  $\sigma^{Subject} = 10$ ,  $\sigma^{Proposition} = 0$ ,  $\sigma^{Proposition} = 5$ , and  $\sigma^{Proposition}$  = 10. The results of experiment no. 3 are presented in Figure 7.

As is observable in the set of experiments 3-1, 3-2, and 3-3, the precision of the hybrid model has been decreased in comparison to experiment 2-2. By making distant the values of  $\sigma^{Proposition}$  and  $\sigma^{Subject}$  from the value of the mean of standard deviation in the cluster sets of subject and proposition, the care of the hybrid model

Table 4: Values of Parameters of the RBF Neural Network and Distance Calculation Module.

Parameter	Value
Input nodes	8×8
Output nodes	1
Epoch	30
$\sigma^{Proposition}$	0, 5, 10
$\sigma^{Subject}$	0, 5, 10
Radial basis membership function	3D normal Gaussian function

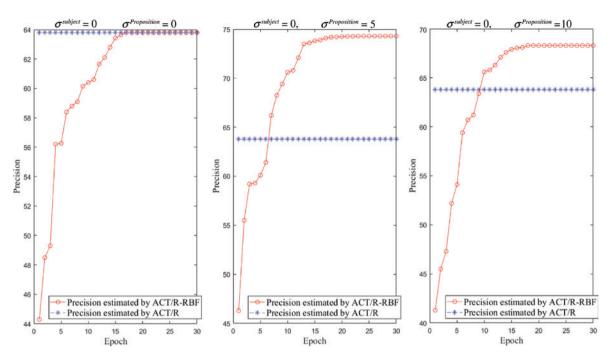


Figure 5: Comparison of the Precision of ACT/R and Hybrid ACT/R-RBF Decision-Making Model for  $\sigma^{Subject} = 0$ .

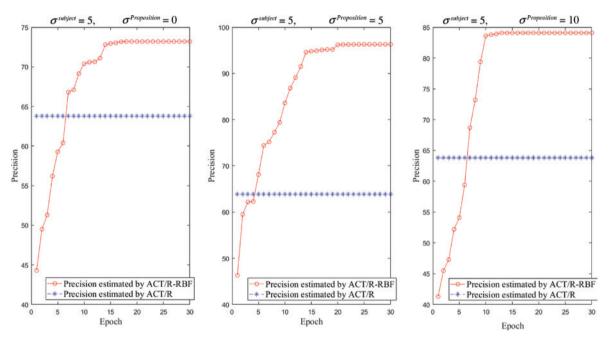


Figure 6: Comparison of the Precision of ACT/R and Hybrid ACT/R-RBF Decision-Making Model for  $\sigma^{Subject} = 0$ .

is also decreased. However, what is observable in all the experiments is that the care of the hybrid model is never lower than the ACT/R model. In the worst situation, the RBF neural model for making a decision like the ACT/R model is changed to an implementer of a set of input terms that, in this regard, the hybrid model would have a care similar to the ACT/R model. Empirical experiments have shown that the ACT/R model is problematic in dynamic and continuous data environments.

Decisions made by symbolic architecture-based models on relatively different inputs with the defined symbols are not always appropriate. Empirical experiments have shown that the RBF neural network can

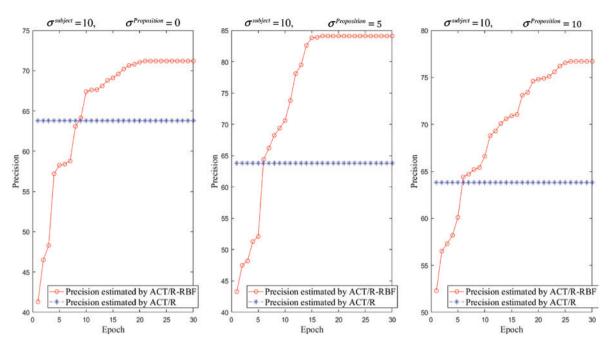


Figure 7: Comparison of the Precision of ACT/R and Hybrid ACT/R-RBF Decision-Making Model for Osubject = 10.

solve the decision-making problem based on features with an unlimited input range by using RBFs. It also has the ability to make decisions on a set of continuous and discontinuous data. Experimental results have indicated that a hybrid architecture can be effective in environments where decisions are made on a set of numbers and symbols. The implementation results have shown that using a connectional model, such as the RBF neural network, can improve the performance of the ACT/R model.

# **5 Final Conclusion**

The proposed method has been designed so as to minimize the symbolic architecture-related shortcomings of the ACT/R model as much as possible. The main weakness of symbolic structure is its inefficacy in dynamic, noisy, and continuous environments. Therefore, it has been tried to use a connectional model in combination with the ACT/R model to improve the performance of the ACT/R model. By doing so, the RBF neural network has been used as a connectional model, as it can make decisions based on the proximity to the data center.

By the increase of input range for the subjects and the existence of one non-linear mapping between the input and output data of decision making, the model based on the ACT/R cognitive architecture would not be useful. The main reason for this inability is the need for the definition of unlimited rules to cover all the situations of input of the studied subjects and the inability in creating a non-linear mapping for the reason of using the implementation rules. Thus, in this article, it has been tried to improve the ACT/R architecture by the use of the RBF neural network and by having the ability of decision making about subjects with continuous and numeral values. One RBF neural network, with regard to the selection of proper parameters, especially the proper radius, can improve the results of decision making in combination with a cognitive architecture such as ACT/R.

In the proposed model, it has been tried to use the features of the ACT/R cognitive architecture, if possible. According to the data set applied in the experiments, the proposed model provides the situation for making a decision based on the rules that the continuous and non-continuous input data have been executed. The need for pre-processing in the RBF neural network is one of the shortcomings of the proposed method. Precise determination of the standard deviation parameter is another shortcoming of the proposed method.

Furthermore, it is not possible to precisely determine the centers of the clusters, especially when there is not enough statistical data available. In such a situation, decisions may be made not based on the actual clusters' centers. Hence, the accuracy of the decisions will be reduced due to the lack of statistical data.

High flexibility and decision making based on a set of continuous data and symbols are among the most important advantages of the proposed method. Structurally, the model used in the proposed method is a computational-connectional model. In addition to maintaining the functionality of the ACT/R model and the symbolic structure, the proposed method can use the connectional capabilities of the RBF neural network. Finally, the proposed method can produce a more flexible model of decision making on a set of continuous and discontinuous data. In summary, the presented research has been able to use machine learning for generalizing and improving cognitive decision making.

# **Bibliography**

- [1] I. Ajzen, The theory of planned behavior, Org. Behav. Hum. Decis. Process. 50 (1991), 179-211.
- [2] R. Anderson, ACT: a simple theory of complex cognition, Am. Psychol. 51 (1996), 355.
- [3] T. Aza and S. Vaidyanathan, eds., Computational Intelligence Applications in Modeling and Control, Springer International Publishing, Switzerland, Europe, 2015.
- [4] T. Banirostam and M. N. Fesharaki, A new approach for biological complex adaptive system modeling and simulation, Life Sci. J. 9 (2012), 2257-2263.
- [5] A. Bargh, The ecology of automaticity: toward establishing the conditions needed to produce automatic processing effects, Am. J. Psychol. 105 (1992), 181-199.
- [6] D. Bothell, ACT-R 7 Reference Manual, Available at act-r.psy.cmu.edu/wordpress/wpcontent/themes/ACT-R/actr7/reference-manual.pdf, Accessed February 2017.
- [7] D. Byrne, ACT-R/PM and menu selection: applying a cognitive architecture to HCI, Int. J. Hum. Comput. Stud. 55 (2001),
- [8] A. T. Corbett and J. R. Anderson, Knowledge tracing: modeling the acquisition of procedural knowledge, User Model. User-Adapt. Interact. 4 (1994), 253-278.
- [9] Deal or No Deal [dataset], https://dataverse.harvard.edu [Online Available], Accessed March 2017.
- [10] R. Debnath and H. Takahashi, Kernel selection for the support vector machine, IEICE Trans. Inform. Syst. 87 (2004), 2903-2904.
- [11] D. Fleetwood and M. D. Byrne, Modeling icon search in ACT-R/PM, Coan. Syst. Res. 3 (2002), 25-33.
- [12] A. S. d. A. Garcez and L. C. Lamb, A connectionist computational model for epistemic and temporal reasoning, Neural Comput. 18 (2006), 1711-1738.
- [13] B. Golosio, A. Cangelosi, O. Gamotina and G. L. Masala, A cognitive neural architecture able to learn and communicate through natural language, PLoS One 10 (2015), e0140866.
- [14] J.-J. Greffet and C. Baylard, Nonspecular astigmatic reflection of a 3D Gaussian beam on an interface, Opt. Commun. 93 (1992), 271-276.
- [15] G.-B. Huang, P. Saratchandran and N. Sundararajan, A generalized growing and pruning RBF (GGAP-RBF) neural network for function approximation, IEEE Trans. Neural Netw. 16 (2005), 57-67.
- [16] A. K. Jain, Data clustering: 50 years beyond K-means, Pattern Recognit. Lett. 31 (2010), 651-666.
- [17] L. Jian, W. Shun-xiang, L. Si-feng and Y. Wang, Adjust decision-making targets based on psychological thresholds, in: International Conference on Grey Systems and Intelligent Services, pp. 396-401, IEEE, 2013.
- [18] W. Kok and Y. C. Tam, D flip-flop, U.S. Patent 7,405,606, issued July 29, 2008.
- [19] P. Langley, An adaptive architecture for physical agents, in: The 2005 IEEE/WIC/ACM International Conference on Web Intelligence, 2005, Proceedings, pp. 18-25, IEEE, 2005.
- [20] P. Langley, J. E. Laird and S. Rogers, Cognitive architectures: research issues and challenges, Cogn. Syst. Res. 10 (2009), 141-160.
- [21] L. Perlovsky and O. Shevchenko, Cognitive neural network for cybersecurity, in: 2014 International Joint Conference on Neural Networks (IJCNN), pp. 4056-4061, IEEE, Beijing, China, 2014.
- [22] G. Piccinini, Functionalism, computationalism, and mental states, Stud. Hist. Philos. Sci. Pt. A 35 (2004), 811-833.
- [23] J. Spencer, M. S. C. Thomas and J. L. McClelland, Toward a New Unified Theory of Development: Connectionism and Dynamical Systems Theory Re-considered, Oxford University Press, England, UK, 2009.
- [24] R. Sun, ed., Cognition and Multi-agent Interaction: From Cognitive Modeling to Social Simulation, Cambridge University Press, England, UK, 2006.
- [25] J. W. Tweedale, A review of cognitive decision-making within future mission systems, Proc. Comput. Sci. 35 (2014), 1043-1052.

- [26] T. t. B. R. van Hezewijk, Procedural and declarative, Theory Psychol. 9 (1999), 605.
- [27] S. E. Vt and Y. C. Shin, Radial basis function neural network for approximation and estimation of nonlinear stochastic dynamic systems, IEEE Trans. Neural Netw. 5 (1994), 594-603.
- [28] H. Wang, X. Liu and J. Fan, Symbolic and connectionist models of attention, in: Cognitive Neuroscience of Attention, M. I. Posner, ed., pp. 47–56, Guilford Press, New York, 2012.
- [29] S. Wermter, Hybrid Connectionist Natural Language Processing, vol. 7, Chapman & Hall, London, 1995.
- [30] X. Xue, Leveraging cognitive science for improving judgment and decision making in construction engineering management, in: Fourth International Conference on Computer Sciences and Convergence Information Technology, 2009, ICCIT'09, pp. 1348-1351, IEEE, Seoul, South Korea, 2009.