

On Assessment of Brain Function Adaptability in Open Learning Systems Using Neural Networks Modeling (Cognitive Styles Approach)

H. M. Mustafa and Saeed. M. Badran

Faculty of Engineering, Al-Baha University, Al-Baha, KSA
mustafa_hasan47@yahoo.com & sbadran@bu.edu.sa

Abstract: The piece of research presents a conceptual overview on diverse cognitive styles reflections in adaptable Open Learning systems. The main goal of this approach is quantitative forecasting the performance of adaptable Open Learning (equivalently e-learning) Systems using cognitive Neural Network modelling. Furthermore, analysis of interactive two diverse learners' cognitive styles with a friendly adaptable teaching environment (e-courses material). Consequently, presented paper provides e-learning systems' designers with relevant guide for learning performance enhancement. Additionally, it supports e-learners in fulfilment of better learning achievements during face to face tutoring. Accordingly, quantitative analysis of e-learning adaptability performed herein, via assessment of matching between learning style preferences and the instructor's teaching style and/or e-courses material. Interestingly, application of two realistic cognitive models using Artificial Neural Network gives an opportunity to experience well assessment of adaptable e-learning features. Such as adaptability mismatching, adaptation time convergence, and individual differences of e-learners' adaptability.

[H .M. Mustafa and Saeed. M. Badran, **On Assessment of Brain Function Adaptability in Open Learning Systems Using Neural Networks Modeling (Cognitive Styles Approach)**. Journal of American Science 2011; 7(9): 238-247]. (ISSN: 1545-1003). <http://www.americanscience.org>.

Keywords: E-learning Systems; Cognitive Learning Style; Artificial Neural Networks; Learning performance parameters.

1. Introduction

The field of the learning sciences is represented by a growing community internationally. Many experts now recognize that conventional ways of conceiving knowledge, educational systems and technology-mediated learning are facing increasing challenging issues in this time of rapid technological and social changes. Furthermore, due to recently excessive progress in information technologies and computer applied at the field of the learning sciences, some complex interdisciplinary educational issues arise in practice. More specifically, this research work adopts an innovative trend concerned with assessment of learners' adaptability at Open Learning Systems (OLS) or equivalently e-learning systems. Assessment of adaptability in e-learning systems is an interesting interdisciplinary issue motivated by researchers at the fields of education, cognitive science, and psychology. So, it is a rather critical and challenging issue concerned with realistic behavioral brain modeling. Also, it is associated with learners' ability to match their learning styles with instructor's teaching style and/or e-courses material.

This paper adopts an investigational approach dealing with e-learning systems' adaptability considering learners' cognitive styles. So, by using ANN modeling, a novel realistic simulation is presented herein for learning adaptability

phenomena taking into consideration learners' diverse performance with different cognitive styles. At educational field practice, both learners' styles are called as Field Dependent (FD), and Field Independent (FI) cognitive styles [1],[2]. Briefly, adopted approach herein, is a mapping of interactive e-learners' cognitive styles with adaptable e-learning systems into realistic domain to ANN modeling.

Conclusively, investigational objectives of this work are fulfilled using two different learning paradigms inspired from ANN models to simulate relevantly learners' cognitive types [1]. In more details, the FD cognitive style is simulated as error back propagation learning rule as one type of supervised learning paradigm [3]. However, to simulate other FI cognitive style, Hebbian learning rule is adopted as one of unsupervised learning paradigms [3]. Interestingly, obtained results shown to be agree well with results obtained by practical educational experimental work [4]. Finally, it is worthy to note that presented approach opens well an interdisciplinary research area to evaluate realistically observed educational phenomena concerned with adaptation of deferent learners' cognitive styles.

The rest of this paper is organized as follows. At the next second section, a general adaptability model in e-learning system is presented. A description of Neural Network Model of

Adaptability is shown at the third section. That model represents realistic simulation of two contradictory (FD and FI) cognitive styles. At The fourth section adaptability in behavioral animal learning is presented. It illustrates analogy between behavioral learning (a mouse inside figure 8 maze) and adaptability in e-learning systems. This analogy motivates measurable simulation program of adaptability performance parameters. At the fifth section, after running of adaptability simulation programs, assessments of obtained results are given in details at three subsections (5.A,5.B, and 5.C). They presents respectively: details of graphical results obtained for adaptability mismatching, its time convergence, and analysis of individual differences of learners' adaptability. Some valuable conclusive remarks and suggestions for future research work are suggested at the last sixth section. Finally, at the end of this paper three appendices are attached as following: At APPENDIX I, a simplified flowchart describing in algorithmic steps for adaptability convergence time is presented. Considering individual learners' differences, two programs listing for measuring matching between learning style preferences and the instructor's teaching style are given at the two APPENDICES (II&III).

2. General Adaptability Model

In general, the adaptation in systems is classified as either adaptable systems or adaptive systems [5]. Adaptable systems allow the user to change certain parameters and adapt the systems' behavior accordingly. On contradictory, adaptive systems adapt to the users automatically based on the system's assumptions about the users' needs [6]. Herein, assessment of adaptable e-learning systems is considered. Such systems facilitate learners to change there own specific parameters individually. These changes needed to be adaptable with instructional teaching styles (system inputs). Practically, at educational field, adaptable instructional methodologies are varying much. Such methodologies' variations range from either oral lectures presentation, demonstrations, focusing on principles or emphasizing on memory [7]. Herein, all of instructional methodologies assumed to be virtually in correspondence with various values of learning rate factor. Matching between instructional teaching styles and learners' preferred learning style increased comfort level and willingness to learn, which provides practice and feedback in ways of thinking and solving problems [7]. In most of OLS, all learners are capable to control accessing of some E-course materials in accordance with their own learning objective(s). In other words, such controlled

accessibility is attained through fixable navigation via e-learning system's materials available to all of e-learners (students). Generally, individual learners adopt preferable learning strategy. An individual's collective strategies for learning are his or her "learning style." A learning style includes strategies for cognitive (mental), affective (emotional), social (interpersonal and cultural), and physiological (physical) components of learning [8].

This piece of research concerned mainly with two e-learners' cognitive styles while interacting with their tutors besides e-course learning materials. By more details, in practical educational field ; performing of learning process supported essentially by two e-learners' multimedia brain functions. Both functions are required to perform efficiently learning / teaching interactive process as follows. Firstly, pattern classification function for e-course material given through (visual / audible) interactive signals. Referring to neural networks' point of view that function originated for signals' perception, and essentially needs supervisor's (tutor's) intervention (face to face interactive tutoring) to converge learning process. Secondly, associative memory function which is originally based on classical conditioning motivated by Hebbian learning rule. It belongs to the principle of learning without a teacher (unsupervised). In other words, from educational view, learning process performed either by interaction with a teacher (face to face learning) or with computer aided learning software[9],[10],[11].

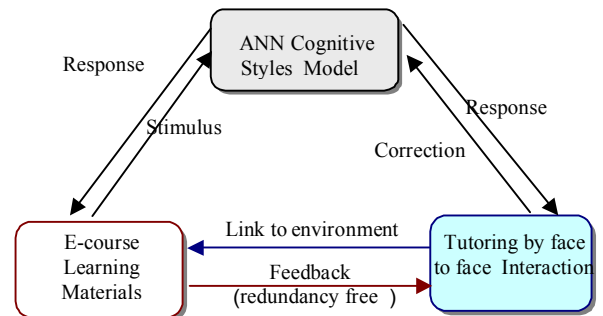


Figure 1. A general adaptability model for e-learning system with diverse cognitive learners' styles

At Fig.1, a qualified teaching/learning adaptability model is illustrated to perform realistic simulation of above mentioned adaptable brain functions,(referred to next section). Inputs to neural network cognitive style model are provided by environmental stimuli (supervised E-course learning material). The correction signal for the case of learning with a teacher is given by responses outputs of the model will be evaluated by either the

environmental conditions (unsupervised learning) or by the teacher. Finally, the teacher plays a role in improving the input data (stimulating the learning) by reducing noise and redundancy of the model input. That is according to the teacher's experience, he provides the model with clear data with maximum signal to noise ratio. However, that is not our case which is based upon unsupervised Hebbian self-organized (autonomous) learning.

3. Neural Network Model of Adaptability

Diverse cognitive styles are classified into either field dependent (FD) or field independent (FI) cognitive style [1]. The shown model at Fig.2 presents adaptability of FD cognitive style is considered. Error correction learning rule is adopted to simulate learner's adaptability towards coincidence with instructional environment. In other words, this coincidence state implies the occurrence of matching

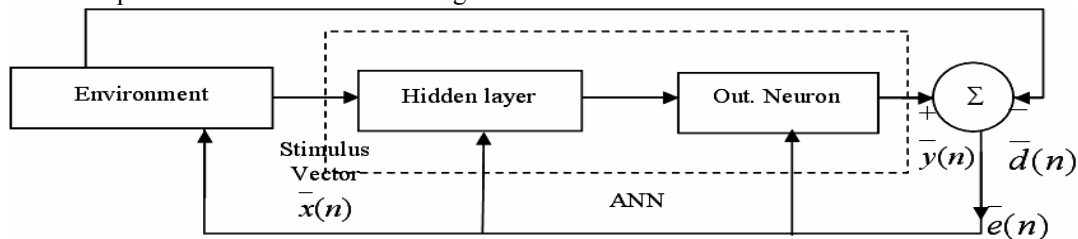


Figure 2. Block diagram of adaptability Model for FD cognitive style

The error vector at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \quad (1)$$

Where

$\bar{e}(n)$: Error correcting signal controlling adaptively

$\bar{y}(n)$: The output signal of the model

$\bar{d}(n)$: Numeric value(s) of the desired /objective parameter of learning process (generally as a vector). Referring to above figure 1., following equations are considered:

$$V_k(n) = X_j(n)W_{kj}^T(n) \quad \square$$

$$Y_k(n) = \phi(V_k(n)) = (1 - e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \quad \square$$

$$e_k(n) = |d_k(n) - y_k(n)| \quad \square$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \quad \square$$

Where X is input vector, W is the adaptable weight vector, ϕ is an odd sigmoid (activation) function characterized by λ as gain factor and Y as its output, e_k is the error value, and d_k is the desired output. Noting that $\Delta W_{kj}(n)$ is the dynamical change of adaptable weight vector value connecting the k^{th} and j^{th} neurons. Equations (2 to 5) are commonly applied for both FD and FI cognitive styles.

between students' learning style preferences and the instructor's teaching style.

Furthermore, presented ANN model in below gives attention to simulate of student's personality indicator that influences his/her way of adaptable learning after Myers-Briggs Type Indicator (MBTI) [12]. This MBTI based on Jung's theory of psychological types [13]. It has been recently adopted for learning style analysis and evaluation in engineering education [14]. Therein, based on (MBTI), simulation of students' individual characteristics are given by (extroversion/introversion). An extrovert attitude represents interaction with learning environment is relevantly simulated by learning rate. Whereas learner's introvert's preferred focus is on his/her own thoughts and ideas (Intrinsic neuronal weight parameters).

So, dynamical changes of adaptable weight vector values for FD style are given by equation:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \quad \square$$

where, η is the learning rate value during learning process for both FD and FI cognitive styles. However, dynamical change of adaptable weight vector values in case of FI cognitive style are given by equation:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \quad \square$$

Noting that $e_k(n)$ in (6) is substituted by $y_k(n)$ at any arbitrary time instant (n) during learning process.

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Noting that $e_k(n)$ in (6) is substituted by $y_k(n)$ at any arbitrary time instant (n) during learning process.

4. Adaptability in Behavioral Animal Learning [16],[17]

A. Revising of Solving reconstruction problem

Referring to [15], the timing of spikes in a population of neurons (at rat's hippocampus brain area), can be used to reconstruct a physical variable is the reconstruction of the location of a rat in its environment from the place fields of neurons in the hippocampus of the rat. In the experiment reported here, the firing part-terns of 25 cells were simultaneously recorded from a freely moving rat, [16]. The place cells were silent most of the time, and they fired maximally only when the animal's head was within restricted region in the environment called its place field [17]. The reconstruction problem was to determine the rat's position based on the spike firing times of the place cells. Bayesian reconstruction was used to estimate the position of the mouse in the figure-8 maze shown in above figure 2, that according to [16]. Assume that a population of N neurons encodes several variables (x_1, x_2, \dots) , which will be written as vector x . From the number of spikes $n=(n_1, n_2, \dots, n_N)$ fired by the N neurons within a time interval τ , we want to estimate the value of x using the Bayes rule for conditional probability:

$$P(x|n) = \frac{P(n|x)P(x)}{P(n)} \quad (8)$$

Assuming independent Poisson spike statistics, the final formula is written as:

$$P(x|n) = kP(x) \left(\prod_{i=1}^N f_i(x)^{n_i} \right) \exp\left(-\tau \sum_{i=1}^N f_i(x)\right) \quad (9)$$

Where k is a normalization constant, $P(x)$ is the prior probability, and $f_i(x)$ is the measured tuning function (i.e. the average firing rate of neuron i for each variable value x). The most probable value of x is thus obtained by finding x that maximizes $P(x|n)$. It is written as:

$$\hat{x} = \arg \max_x P(x|n) \quad (10)$$

By sliding the time window forward, the entire time course of x can be reconstructed from the time varying-activity of the neural cells population.

B. Adaptability of Rat's behavioral Learning

This subsection illustrates how a mouse becomes well adaptable with its learning environment (Figure 8 maze) by increasing of number on neuronal cells at its hippocampus brain area. The results obtained after adaptable solving reconstruction (pattern recognition) problem by a mouse in 8 figure maze are given at [16], [18]. That measured results given at Table 1 & Fig.5, are derived from activities of pulsed neuron spikes at hippocampus of the mouse brain as shown in the above subsection 4.1. Accordingly, the error values (see Table 1), are shown to decrease similar to exponential decaying curve reaching to some limit value versus number on neuronal cells (place field).

Table 1. Relation between number of neuronal cells and mean error in solving reconstruction problem

| No. of neuron cells | 10 | 14 | 18 | 22 | 26 | 30 |
|---------------------|----|-----|-----|----|-----|----|
| Mean error (cm) | 9 | 6.6 | 5.4 | 5 | 4.5 | 4 |

Furthermore, by referring to Fig.5, it is noticed that, the mean error value converges (by increasing of neuronal cells number) to some limit, excluded as Cramer-Rao bound. Noting that limiting bound is based on Fisher's information given as tabulated results in the above and derived from [18]. The performance of the shown graph at Fig.5 obeys the Least Mean Square learning algorithm which presented recently as basic concept of Behavioral Learning [19].

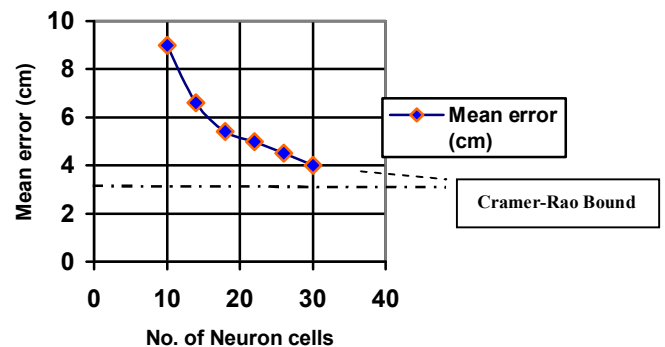


Figure 3. The dashed line indicate the approach to Cramer-Rao bound based on Fisher information adapted from [18].

The above presented mouse behavioral learning adaptability results motivate simulation measurement for adaptability mismatching as well as time convergence of e-learners' adaptability as given at subsections (5.A&5.B).

5. Assessment of Adaptability Simulation Results

A. Adaptability Mismatching [1]

Referring to above section the rat performs adaptable behavior versus fixed external learning environment (Figure 8 maze) [16],[17]. The errors at Fig.4 and Fig.5 shown to have inverse proportionality with the adaptability time convergence (number of cycle). Moreover, these errors represent a measurement degree of mismatching between the rat's behavioral learning vector and solving reconstruction problem at Figure 8 maze. The set of graphs shown at Fig.4 and Fig.5 represent graphical simulation results obtained after running of some

computer program. That results simulate realistically, learners' cognitive style FD, and FI as presented in accordance with equations (6),(7),given at previous section, respectively. Noting that, at Fig.4, external learning environment is considered as a teaching agent selected to perform supervised learning in case of simulating FD learners' cognitive style. However at Fig.5, that teaching agent considered as self organized learning while simulating FI style, as Hebbian Learning Rule illustrated.

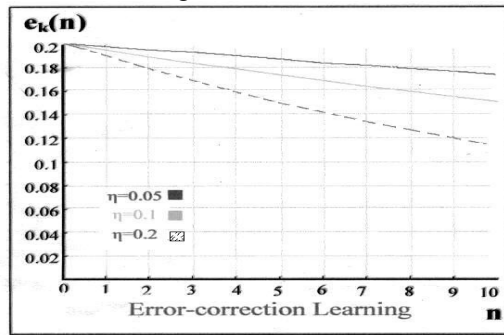


Figure 4. Adaptability performance concerned with FD learners' cognitive style.

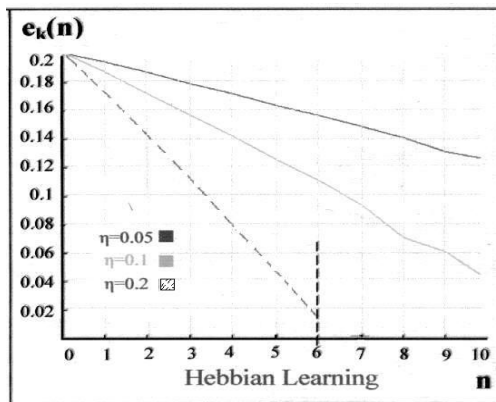


Figure 5. Adaptability performance concerned with FI learners' cognitive style .

B. Adaptability Time Convergence [20][21]

The two sets of graphs shown in below at Fig.6 and Fig.7 are following equations (6),(7), respectively. Both represent graphical simulation results obtained after running a computer program model (Its flowchart is given at APPENDIX I). Noting that learning environment is considered as input vector having the same dimension as learners' self-intrinsic weight vector. Also, it represents one of the teaching methodologies (learning rate value) selected to measure behaviors of FD and FI learners' cognitive styles. Additionally, both sets of obtained graphical results (at Fig.6 and Fig.7) simulate realistically students' behavioral learning by increasing number of neurons (dimension of weight vector) contributing to adaptability dynamics. These

results presented for both cognitive style FD, and FI, which corresponds to error correction and Hebbian learning paradigms, respectively. .

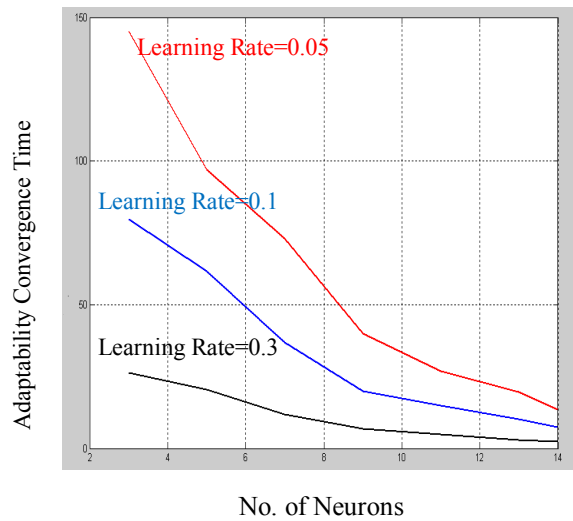


Figure 6. Adaptability convergence time considering three different teaching methodologies corresponding to learning rates: 0.05,0.1,and 0.3 (for FD learners' cognitive style).

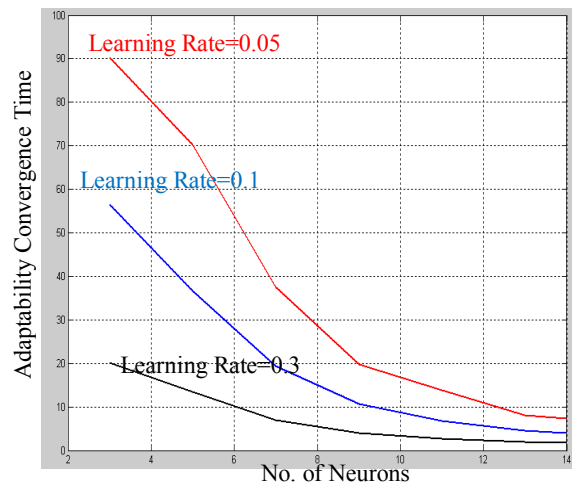


Figure 7. Adaptability convergence time considering three different teaching methodologies corresponding to learning rates: 0.05,0.1,and 0.3 (for FI learners' cognitive style).

C. Adaptability Versus Individual Differences [22][23]

Simulation results to quantify learning adaptability are shown at the two figures (Fig. 8&9) represent Field Dependent and Field Independent learning cognitive styles respectively. Additionally, two learning cognitive styles are considered in fulfillment of some fixed matching target value

(90%). The results depicted at both figures are obtained by running of two computer programs written using of MATLAB Version 6 software. Algorithms of both computer programs presenting FD and FI learning cognitive styles are respectively given at Appendix II & Appendix III.

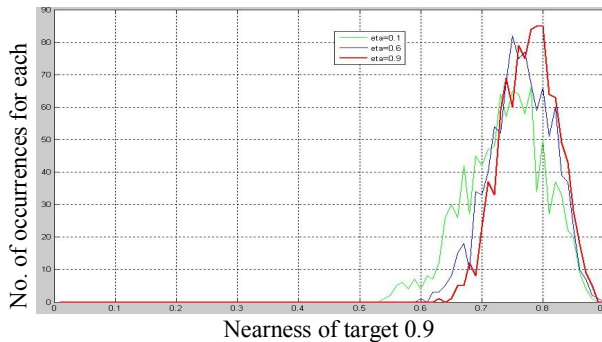


Figure 8. Statistical distribution of adaptability matching individual learners' differences with F D cognitive style after running of computer program given at APPENDIX II.

By referring to set of graphs shown at figures 8&9, some interesting interpretations concerned with quantifying learning adaptability are investigated. The nearness of learners' styles towards the instructor's style vector measured on the abscissa (with 90 %). However on the ordinate axis, it is shown frequency of occurrence (probability) for various matching values. Briefly, referring to Fig.8, value by improvement of learning rate factor -for FD cognitive styles- results in very slightly increase in average matching value which measures quantitatively learning adaptability. Conversely, referring to Fig.9, improvement of learning rate factor -for FI cognitive styles- results in well observed increase in average measured adaptability matching values.

Conclusions

Analysis and evaluation of adaptability in e-learning systems is an interesting interdisciplinary issue motivated at the fields of education, cognitive science, and psychology. It is a rather critical and challenging concerned mainly with e-learners' brain function resulting in ability to match there preference learning styles with instructor's teaching styles (E-courses material). This work motivated by the trend suggested by M. Caudill that "if you are more biologically inspired, you will reach more optimal solution". In other words, going towards optimal problem solving (for an engineered based application), by implementations or simulations utilizing biologically inspired principles [24].

So, presented approach inspired by analysis and evaluation of biological adaptability published after observable behavioral learning data in animals (as shown at section 4). Accordingly, herein the main attention has been developed towards neural networks' realistic dynamic modeling to simulate e-learners' adaptability via interaction of there brain functions with open learning systems' environment. That suggested innovative approach agrees well with results obtained from recent application of ANN for learning styles' recognition in e-learning environment [25].

The statistical analysis of obtained results illustrated is presented by curves shown at (Fig.8 and Fig.9) for different learning rate values (eta) and considering 1000 samples of virtual students (see Appendices II&III). Interestingly, these curves have bell shapes which are closely near to Gaussian (normal) distribution. The suggested ANN model assumed that different instructional methodologies to be virtually in correspondence with various values of learning rate factor. Furthermore, the model samples are subjected to testing for Field Dependent and Field Independent learners' cognitive styles, resulting in superiority of Field independent samples. The obtained results declared that quantified learning adaptability is dependant upon learners' self intrinsic factors to be more adaptable (matched) with instructor's teaching style and/or e-courses material.

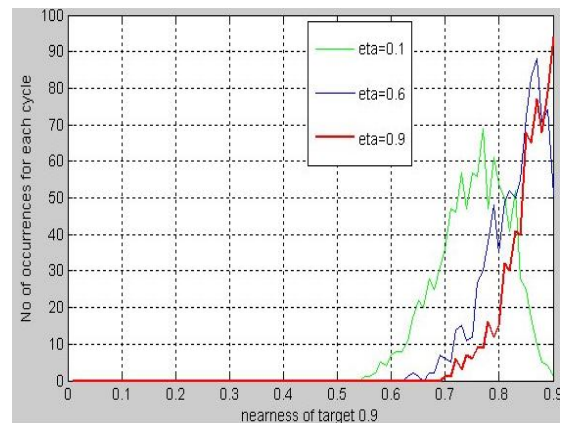


Figure 9. Statistical distribution of adaptability matching individual learners' differences with Field Independent cognitive style after running of computer program given at APPENDIX III.

As an extension of presented work, more elaborate assessment is urgently needed for learning adaptability as well as adaptivity phenomena at OLS. That mainly aims to investigate mystery of brain adaptation observed at educational field. Which possibly carried out by considering the effect of either dynamical changing of learners' internal

weights of brain status via ANN modeling (self-intrinsic gain factor of Sigmoid function), or external learning environment (instructor's teaching style) via different learning rate values. Additionally, future research work has to consider other observed learning phenomena. Such phenomena would have subjected to investigational analysis and evaluations. One of very recently considered learning phenomenon which based on cognitive psychology and neuroscience. That is considerate computing applied to modify learning systems. These systems have to monitor interruption phenomena carried out by students following computer screen (VDU) activities [26]. Consequently, sensing attention mainly exculpated to perform the function of future considerate learning computer systems [26]. That equipped by attentive appliances which are responsible for gaze detection function during learning by video conference systems [26] [27].

Corresponding author

H. M. Mustafa

Faculty of Engineering, Al-Baha University, Al-Baha, KSA

mustafa_hasan47@yahoo.com

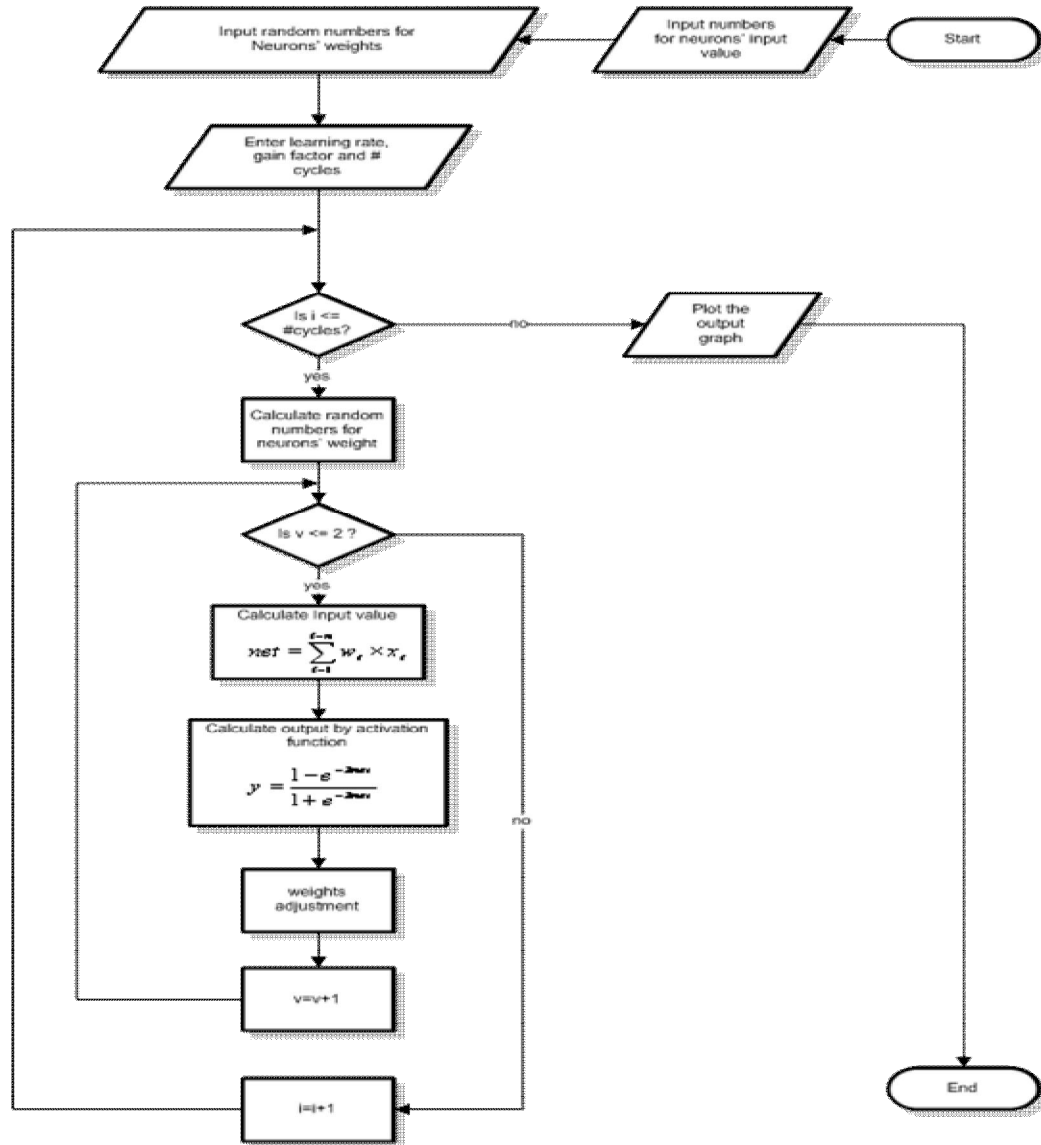
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APPENDIX I

The shown figure in below presents a simplified macro level flowchart describing in brief algorithmic steps for realistic simulation learning program using Artificial Neural Networks . After running that program, three graphs time response results are obtained as shown at two above figures (Fig.6&Fig.7).



APPENDIX II

Modeling of Field Independent Cognitive Style Using Error Correction Learning Algorithm. The obtained results shown as set of graphs at Fig. 8.

for i=1:1000

w1=w(1,i); w2=w(2,i);w3=w(3,i);

for v=1:2 %constant no of itr.

% no(i)=no(i)+1;

net=w1*x1+w2*x2+w3*x3;

y=1/(1+exp(-1*net));

e=0.9-y;

w1=w1+eta*e*x1;

w2=w2+eta*e*x2;

w3=w3+eta*e*x3;

```

end
  p=uint8((y/0.9)*90);
  nog(p)=nog(p)+1;
end
i=0:89;

```

```

plot((i+1)/100,nog(i+1),'linewidth',0.5,'color','blue')
xlabel('nearness of target 0.9')
ylabel('No of occurrences for each cycle')
title('error correction algorithm')
grid on
hold on

```

APPENDIX III

Modeling of Field Dependent Cognitive Style Using Hebbian Learning Rule Algorithm. The obtained results shown as set of graphs at Fig.9.

```

w=rand(1000,1000);
x1=0.8; x2=0.7;x3=0.6; l=10; eta=0.3;

for g=1:100
  nog(g)=0;
end

for i=1:1000
  w1=w(1,i); w2=w(2,i);w3=w(3,i);
  for v=1:2      %constant no of itr.
    % no(i)=no(i)+1;

```

```

net=w1*x1+w2*x2+w3*x3;
  y=1/(1+exp(-l*net));
  %e=0.9-y;
  w1=w1+eta*y*x1;
  w2=w2+eta*y*x2;
  w3=w3+eta*y*x3;
end
  p=uint8((y/0.9)*90);
  nog(p)=nog(p)+1;
end

i=0:89;
plot((i+1)/100,nog(i+1),'linewidth',1.5,'color','black')
xlabel('nearness of balance point')
ylabel('No of occurrences for each cycle')
title('Hebian algorithm')
grid on
hold on

```