On Analysis of Quantifying Learning Creativity Phenomenon Considering Brain Synaptic Plasticity

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Abstract: *Generally, Analysis of learning creativity phenomenon is an interesting and challenging issue associated with educational practice. Moreover, that phenomenon is tightly related to main human brain functions (Learning and Memory). So, creative individuals are characterized by their distinct capabilities in performing both brain functions. Additionally, educationalists as well as psychologists, for a long time ago and until recently, have been interesting in searching for quantitative investigation of that challenging issue. In the field of education, practical evaluation of learners' performance, - during tutoring session(s) - may result in observation of creativity phenomenon. Herein, this work introduces an interdisciplinary novel approach concerned with analysis of quantifying learning creativity phenomenon. That is fulfilled by adopting Artificial Neural Networks modeling for realistic simulation of synaptic connectivity dynamics (equivalently, synaptic plasticity). By some details, presented work considered two main design parameters of Artificial Neural Networks. Namely they are, gain factor (of neuronal sigmoid activation function), and learning rate value. Both parameters Synaptic Plasticity inside the brain. Obviously, individuals characterized by various values of gain factor value as well as learning rate parameter are well relevant to quantify there learning creativity. Conclusively, obtained results motivate future research for systematical investigational study in depth considering the effect of congenital and/or hereditary factors on learning creativity phenomenon.*

Keyword: *Artificial neural network modeling, learning creativity phenomenon, synaptic plasticity, and brain functional modeling.*

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1. Introduction

Generally, learning creativity is an interesting phenomenon considered under investigations by researchers working in interdisciplinary fields of education, cognitive science, and psychology. So, searching for quantitative analysis and evaluation of learning creativity phenomenon is a rather critical and challenging issue [1, 2]. In our classrooms, tutors observe that some learners perform better than other colleagues during teaching sessions. Noting such tutors' observations considered under less noisy educational environment [3].

Consider the dynamics of synaptic connectivity via two neuronal design factors. Namely, gain factor (slope) of neuronal activation function (sigmoid) as to measure time for learning convergence. Additionally, the model considers statistical study for the effect of learning rate factor (value) on learning time responses. Also, it gives attention for supervised learning paradigms (error correction learning), rather than unsupervised one. [6]. Finally, some other interesting comments are given considering the effect of initial state of synaptic connectivity (weights) pattern (inside brain state), on learning convergence process, and consequently, on observed learning creativity, [4]. Moreover, some other comments concerned with the effect of the other half of the brain (Glial cells) on creativity are introduced [7, 8].

By some details, creative individuals (learners) are mainly characterized by their distinct capabilities (learning performance). So, they are capable of performing intelligent brain functions (learning and memory) with better observed response, [4, 5].

This work presents an approach based on Artificial Neural Network (ANN) modeling to simulate realistically the process of quantifying learning creativity. Through the statistical analysis for a sample composed of 100 creative learners population, distinct achievements proved to agree with Gaussian (normal) distribution(similar to bell shape distribution) . It is of interest note that this paper belongs to the interdisciplinary research discipline (frame work), entitled: "building up bridges for natural inspired computational models across behavioral brain functional phenomena; and open learning systems". That is currently performed by research team of Arab Open University (KSA Branch). For more details see appendix I.

The paper is composed of five sections organized as follows. In the second section, the adopted model description is given in details. That model considers tight coupling between axonal output of neurons (activation function) and synaptic connections (weights) dynamics. The effect of gain factor on learning convergence time is presented at the third section, considering individuals with different activation functions outputs. In the fourth section, detailed results and listing of applied simulation programs are introduced along with relevant descriptive graphical results, and comments. Some interesting conclusive remarks are given in the last fifth section. Finally, two appendices are presented related to adopted interdisciplinary research frame work this paper employed.

2. Quantified Learning Creativity Modeling

The adopted neural model for simulation of quantified learning creativity follows the most common type of ANN. It is worthy to notice that basic building unit for neural systems is a single biological neuron. By referring to the figure in below Figure 1, a schematic illustration for a single neuron is presented. For more details concerned with the function of any biological neuron, it is recommended to review a mathematical comprehensive foundation at reference [10].

At Figure 2, a Feed Forward Artificial Neural Network (FFANN) model is illustrated schematically by eight circles (4-3-1). They are arranged in three groups (equivalently neuronal layers) representing eight biological neurons: four Input neurons , three neurons for hidden layer and one output neuron.
Generally, the function of FFANN is briefly given as follows:

1. The activity of the input units represents the raw information that is fed into the network.
2. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.
3. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

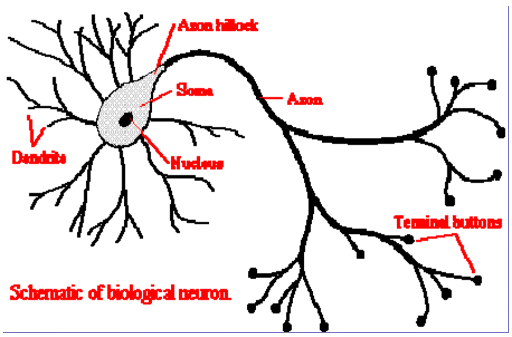

Figure 1. A simplified schematic illustration for a biological neuronal model (adapted from, [10]).

More precisely, a general block diagram given in below at Figure 3 adopted to simulate quantitatively learning creativity phenomenon. This diagram simulates realistically learning process performed by FFANN model. By some details, it presents an ANN model adopted to evaluate two diverse learning cognitive styles namely: Field Dependent (FD) and Field Independent (FI) learning cognitive styles, [6]. More recently; it is applied for investigational analysis of two learning parameters while quantifying learning creativity [1].

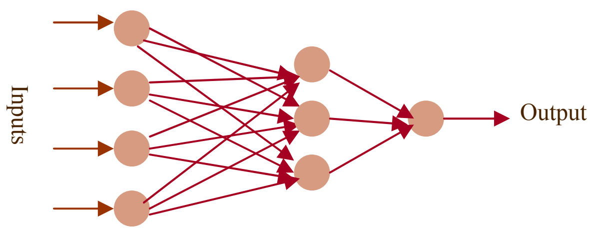

Figure 2. A simplified schematic diagram for a (FFANN) model (adapted from, [9]).

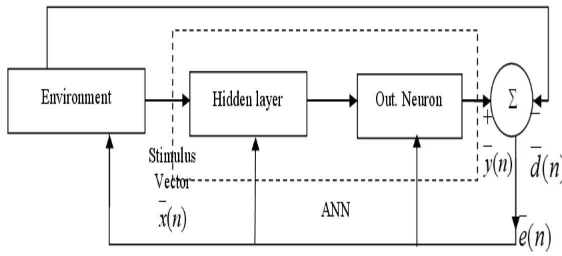

Figure 3. Block diagram for an ANN model adopted for quantifying creativity (adapted from, [2]).

Referring to above figure, error vector at any time instant (n) observed during learning processes is given by:

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

here $\bar{e}(n)$ is an error correcting vector controlling learning adaptation process. $\bar{y}(n)$ is an output signal of the model. $\bar{d}(n)$ is a numeric value(s) of the desired /objective parameter of learning process (generally as a vector). Referring to Figure 2 shown in the above, following equations are considered:

$$V_k(n)=X_j(n)\, W^T_{kj}(n) \tag{2}$$

$$y_k(n)=\varphi(V_k(n))= (1-e^{-\lambda v_k(n)}) / (1+e^{-\lambda v_k(n)}) \tag{3}$$

$$e_k(n)=|d_k(n)-y_k(n)| \tag{4}$$

$$W_{kj}(n+1)=W_{kj}(n)+\Delta W_{kj}(n) \tag{5}$$

where X is an input vector, W is a weight vector, φ is the activation function, y is the output, e_k the error value, and d_k is the desired output. Noting that $\Delta W_{kj}(n)$ the dynamical change of weight vector value.

The above four equations are commonly applied for two different learning cognitive styles FD and FI learning cognitive styles. Recently, both styles are simulated considering supervised and unsupervised learning paradigms, respectively [6]. The dynamical change of weight vector value specifically for FD cognitive style (supervised paradigm) is given by equation:

$$\Delta W_{kj}(n) = \eta\, e_k(n)\, x_j(n) \tag{6}$$

where η is the learning rate value during learning process for both learning paradigms.

However, for FI cognitive style (unsupervised paradigm), dynamical change of weight vector value is given by equation:

$$\Delta W_{kj}(n) = \eta\, y_k(n)\, x_j(n) \tag{7}$$

3. Effect Of Gain Factor On Learning Convergence Time

Referring to [5, 11], learning by coincidence detection is considered. Therein, angle between training weight vector and an input vector have to be detected. Referring to [12], the results of output learning processes considering Hebbian rule are following the equation:

$$y = (1 - e^{-\lambda t}) \tag{8}$$

The above equation performs analogously to gain factor (slope) in classical sigmoid function [9].

$$y(t) = \frac{1}{1 + e^{-\lambda t}} \tag{9}$$

However, equation 8 performs versus time closely similar to odd sigmoid function given as:

$$y(t) = \frac{1 - e^{-\lambda t}}{1 + e^{-\lambda t}} \tag{10}$$

For $0 \le t \le \infty$

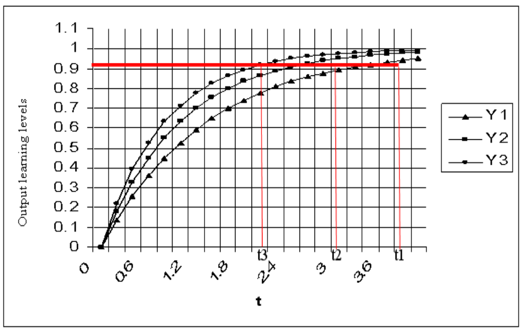

Figure 4. Illustrates three different learning performance curves Y_1&Y_2 and Y_3 that converge at time t_1& t_2 and t_3 considering different gain factor values λ_1 & λ_2 ,and λ_3.

At Figure 4, which adapted from [11], the three curves shown represent different individual levels of learning. Curve (Y_2) is the equalized representation of both forgetting and learning factors [11]. However curve (Y_1) shown the low level of learning rate (learning disability) that indicates the state of angle between synaptic weight vector and an input vector . Conversely, the curve (Y_3) indicates better learning performance that exceeds the normal level of learning at curve (Y_2). Consequently learning time convergence decreases as shown at Figure 3, (t_1 & t_2, and t_3) three different levels of learning performance curves representing: normal, low, and better cases shown at curves Y_1 & Y_2 and Y_3, respectively.

4. Results

This section is devoted to presenting detailed and complete programming process associated with obtained graphical results. Detailed description of obtained results is given via next four subsections as follows:

4.1. First Program Listing

The following program illustrates all mathematical equations given in the above considering learning under supervision paradigm. It is written using MATLAB software -version 6- programming language.

```
w=rand (3,100);
x1=0.8;x2=0.7;x3=0.9;l=0.5;eata=0.1;
for i=1:100
   w1=w(1,i);w2=w(2,i);w3=w(3,i);
   net=w1*x1+w2*x2+w3*x3;
   y=(1-exp(-l*net))/(1+exp(-l*net));
   e=0.8-y;
   no(i)=0;
   while e>0.05
      no(i)=no(i)+1;
      w1=w1+eata*e*x1;
      w2=w2+eata*e*x2;
      w3=w3+eata*e*x3;
      net=w1*x1+w2*x2+w3*x3;
      y=(1-exp(-l*net))/(1+exp(-l*net));
      e=0.8-y;
   end
end
for i=1:100
   nog(i)=0;
   for x=1:100
      if no(x)==i
         nog(i)=nog(i)+1;
      end
   end
end
i=0:99;
plot(i,nog(i+1),'linewidth',1.5)
xlabel('no of training cycles')
ylabel('no of occurrences for each cycle')
title('error correction algorithm')
grid on
% hold on
```

4.2. Result Samples

Four samples of obtained results after running of above computer program are shown at appendix II. These samples illustrate effect of different values of gain factor; and learning rate values on learning convergence (response) time. Moreover, performing some slight modifications for the computer program shown in section 4.1 , obtained results for various gain factor values are comprehensively shown in below at Figure 5.

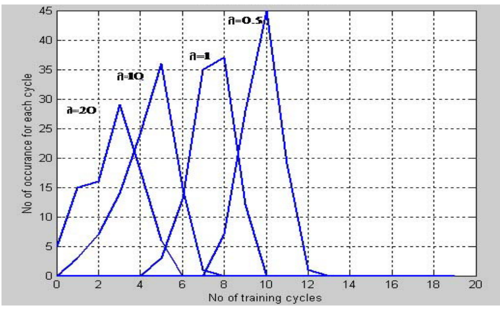

Figure 5. Illustrates improvement of average response time (no. of training cycles) by increase of the gain factor values

The above results illustrate gain factor effect on improving the value of time response measured after learning process convergence [5]. These four graphs at Figure 5 are concerned with the improvement of the learning parameter response time (number of training cycles). That improvement observed by increasing of gain factor values (0.5, 1, 10, and 20) that corresponds to decreasing respectively number of training cycles by values (10, 7.7, 5, and 3) cycles, (on approximate averages).

4.3. Second Program Listing

The following program is written using MATLAB software-version6- programming language. It illustrates mathematical equations for error correction learning algorithm, given in the above by equation (6), (considering learning under supervision paradigm). That for changeable learning rate values eta [η=(0.1,0.2,0.3,0.4)]

```
w=rand(1000,1000);
x1=0.8; x2=0.7;x3=0.6; l=1; eta=0.4;
for g=1:100
nog(g)=0;
end
 for i=1:1000
    w1=w(1,i); w2=w(2,i);w3=w(3,i);
    net=w1*x1+w2*x2;
    y=1/(1+exp(-l*net));
    e=0.9-y;
    no(i)=0;
   while e>0.05
      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*e*x1;
       w2=w2+eta*e*x2;
       w3=w3+eta*e*x3;
    end
  end

for i=1:100
    nog(i)=0;
    for x=1:1000
      if no(x)==i
       nog(i)=nog(i)+1;
      end
    end
end
i=0:99;
plot((i+1),nog(i+1),'linewidth',1.0,'color','black')
xlabel('Itr. number')
ylabel('No of occurrences for each cycle')
title('error correction algorithm')
grid on
hold on
```

4.4. Results

After running of a computer simulation program shown at the above subsection *C.*, obtained results are given in below Figure 6. This figure illustrates a comprehensive view for learning rate effect on learning time response (number of iteration cycles), indicating quantification of creativity phenomenon. In other words, the resulting values distribution have bell form shapes, seemed to be similar to Gaussian (normal) distribution. Referring to Figure 6 obtained output results, values corresponding to the learning rate values (0.4, 0.3, 0.2, and 0.1), are given respectively as numbers (13, 17, 27, and 55) for iteration cycles (on the approximate averages), for learning convergence/response time.

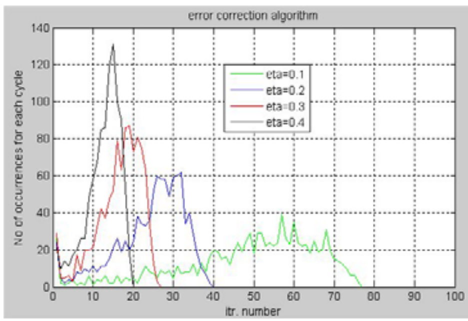

Figure 6. Illustrates the statistical distribution of learning convergence time for different learning rate values eta, (Adapted from [2].

5. Conclusion

Generally, creativity is an interesting phenomenon considered under investigations mainly by educational researchers, [13]. This work concerned mainly with time response parameter of learning convergence processes. In other words, it presents specifically brain synaptic plasticity that affects directly learners' performance during tutoring session(s) in our classrooms. So, quantitative analysis of learning creativity phenomenon is well performed considering synaptic plasticity. ANNs modeling is our adopted approach to simulate realistically synaptic plasticity inside brain. By some details, it is clearly illustrated that synaptic plasticity – given by above equation 6 - improved implicitly and explicitly by increasing values of gain factor learning rate parameter, respectively. Hence, as convergence response time decreases (shown as iteration number of cycles), improvement of learning creativity is observed.

Consequently, this paper obviously is considered as an extension for some recently published work dealing with learning and memory brain functions, that are commonly associated to each other [11, 12, 14, 15]. The statistical analysis illustrated in the above by curves (shown at Figure 5), for samples of 100 virtual students, proved to have near to Gaussian (normal) bell shape distribution. The suggested model considers the learning rate factor of dynamical neuronal connectivity to measure learning convergence time as to quantify learning creativity. The model samples are subjected to testing for field dependent rather than field independent learning cognitive styles. The obtained results declared that congenital factors seem to be more effective than acquired one for quantifying learning creativity. Referring to [3] and [4] published over one decade ago, an interesting overview impact on learning creativity is observed as follows. Firstly, by referring to [3], creative students have distinct ability for learning under noisy data conditions. i.e., they are capable of performing filtration function for input information signal contaminated with environmental noise. Hence, they can process acquired information inside there brains with better signal to noise ratio. Consequently, results obtained after biological processing simulation proved to have better (decreased) learning convergence time (i.e., better learning creativity). Secondly, by referring to [4], Application of improved synaptic connectivity with random weight values is highly recommended in order to perform medically promising treatment of mentally disable students. Conversely, for creative students, they should have distinct patterns of synaptic connectivity (weights). By those patterns, learning process converge to desired output during less time period indicating learning creativity of such students. The issue of glial cells is noticed by increase of synaptic connectivity value measured as ratio between numbers of glial cells and neurons brain. That ratio leads to improving of learning performance conditions, [7, 8]. For more details, referring to [7], and other references therein is recommended.

Finally, more elaborate evaluation and assessment of learning creativity phenomena urgently needed in future aiming, that to investigate mystery of brain creativity observed at educational field. That is possibly carried out considering the effect of either congenital/hereditary internal (intrinsic) brain status of students, or external environmental factors. Conclusively, this work seems to open future research for more evaluation and elaborated studies which aim to achieve better optimized strategies concerned with other interdisciplinary educational issues.

References

[1] Hassan H., "On Quantifying Learning Creativity Using Artificial Neural Networks (A Mathematical Programming Approach)," *Published at CCCT 2007*, USA, 2007.

[2] assan H., Al-Hamadi A., and Ben Al-Mohaya F., et al. "On Quantifying Learning Creativity Using Artificial Neural Networks (A Nero-physiological Cognitive Approach)," published at *National Conference on Applied Cognitive Psychology*, India, 2007.

[3] Ghonaimy M., Al –Bassiouni, A., and Hassan, H. "Leaning Of Neural Networks Using Noisy Data," *Second International Conference on Artificial Intelligence Applications*, Egypt, PP. 387-399, 1994.

[4] Ghonaimy M., Al –Bassiouni, A. and Hassan H., "Learning Ability in Neural Network Model," *Second International Conference on Artificial Intelligence Applications*, Egypt, PP-400-413, 1994.

[5] Hassan H. "Evaluation of Learning / Training Convergence Time Using Neural Network (ANNs), " *published at international conference of Electrical Engineering*, pp.542-549, , 2004.

[6] Hassan H. "On Simulation of Adaptive Learner Control Considering Students' Cognitive Styles Using Artificial Neural Networks (ANNs)," *Published at International Conference on Computation Intelligence for Modeling Control and Automation CIMCA)*, IEEE Press, Austria, 2005.

[7] Hassan H. "On Behavioral Dynamics Evaluation of Glial Cells Role in Comparison with Brain Neurons Functions Using Artificial Neural Networks," *(Conceptual view) Published at ICCS*, India, 2005.

[8] Douglas R., 'The other half of the brain," *Scientific American*, vol. (21), no. 1/2: pp 46-55, 2005.

[9] peter.andras@ncl.ac.uk,www.staff.ncl.ac.uk/peter.andras/lectures Artificial Neural Networks (Application).

[10] Haykin S., *Neural Networks*, Englewood Cliffs, NJ: Prentice-Hall 1999.

[11] Hassan H., "On Quantitative Mathematical Evaluation of Long Term Potentiation and Depression Phenomena Using Neural Network Modeling," *published at SIMMOD 2005*, pp 237-241, 2005.
[12] Freeman, J., *Simulating Neural Networks with Mathematica*, Addison-Wesley Publishing Company, 1994.
[13] Mousa A. et.al. "Lectures on Education", Psycho-educational Dpt., College of Education Zagazig University, Benha branch 1992, pp.90-110, and references therein
[14] Tsien J., " Building a brainier Mouse," *Scientific American*, Majallat Aloloom, vol. 17, No. 5, pp. 28-35, 2001.
[15] Hassan H. , Al-Hamadi A., and Michaelis B., "Evaluation of Memorization Brain Function Using a Spatio-temporal Artificial Neural Network (ANN) Model," *Published at CCCT 2007 conference*, USA, 2007.

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Appendix I

Research Frame Work Suggested by Arab Open University (KSA)

Building up bridges for natural inspired computational models across behavioral brain functional phenomena; and open learning systems

The main topics of this suggested research frame work belong to some interdisciplinary research direction adopted recently. Namely, it is concerned with building up theoretical connections between neuroscience cognitive science, and swarm intelligence to enhance educational decisions and/or learning performance. In particular, such theories would be capable of evaluating learning performance tasks, in addition to optimal complex educational decisions. So, those research topics are performed via realistic dynamical modeling of some educational / learning phenomena. They associated with main brain functions (Learning & memory) using artificial neural networks and swarm intelligence systems. in brief, some of these learning phenomena are learning creativity, individual differences, and diverse learning cognitive styles.

The proposed frame work timely planned learning as to be composed of three phases in details. These phases are motivated by dynamical learning mechanism and technologies and started by June 2007. Each of frame work phases, planned to elapse for (approximately) 15-18 months as follows:

1. Simulation and Modeling of Behavioral Learning Performance, individual differences and Quantified Creativity Phenomenon Using Artificial Neural Networks
2. Modeling of Creativity Phenomenon observed in Ant Colony Systems and comparison with human learning creativity.
3. Comparison between obtained results by the above two phases with recent research work related to modeling of brain functions. That is considering analysis and comparisons among various Learning phenomena considering Ant Colony System Optimization and Artificial Neural Network modeling of behavioral learning.

Finally, it is worthy note that, above work currently started by A.O.U. research team. It is planned to elapse for (45 up to 54), months. Until now, that work results in a set of interdisciplinary recently published papers interacting Neurobiology & AI & experimental Psycho-learning, and swarm intelligence as follows:

1. "On Quantifying Learning Creativity Using Artificial Neural Networks (A Nero-physiological Cognitive Approach)", published at National Conference on Applied Cognitive Psychology held in India, Calcutta, 29 –30 November, 2007.
2. "Towards Evaluation of Phonics Method for Teaching of Reading Using Artificial Neural Networks (A Cognitive Modeling Approach)", published at IEEE Symposium on Signal Processing and Information Technology Seventh Symposium held in Egypt-Cairo during 15-18 December 2007.
3. "On Optimal Selection of Software Learning Packages Using Artificial Neural Networks' Modeling (Educational Simulation Approach)", published at IEMS 2008-International Conference on Industry, Engineering, and Management Systems Cocoa Beach, Florida March 10-12, 2008.
4. "On Comparison between Swarm Intelligence Optimization and Behavioral Learning Concepts

Using Artificial Neural Networks (An over view)", to be published at the 12th World Multi-Conference on Systemics, Cybernetics and Informatics: WMSCI 2008 The 14th International Conference on Information Systems Analysis and Synthesis: ISAS 2008 June 29th - July 2nd, 2008 – Orlando, Florida, USA.

5. On Comparative Evaluation of Thorndike's Psycho-Learning Experimental Work Versus an Optimal Swarm Intelligent System", published at IEEE conference, CIMCA 2008 Vienna, Austria (10-12 Dec. 2008).

Appendix II

Four samples of obtained results after running of computer program presented at sub-section (4.1). These samples are given as follows:

1. Firstly, two samples are given below at Figure 7, and Figure 8. These two figures are concerned with the improvement of the learning parameter response time (number of training cycles), observed by increasing of gain factor (from 0.5 to 1), for fixed learning rate value (0.1). Respectively, the number of training cycles decreased approximately -on the average from 80 to 30 cycles. Both figures indicate gain factor effect on improving time response values measured (after learning process convergence).
2. Secondly, other two samples are shown in below at Figure 9, and Figure 10 .Both figures consider changes of learning rate parameter (for fixed gain factor value (0.5)). By some details, as the value of learning rate parameter increases from 0.2 Figure 9, to 0.6 Figure 10, the average (normalized) number of training cycles, decreases approximately (on the average), (from 38 to 12) cycles.

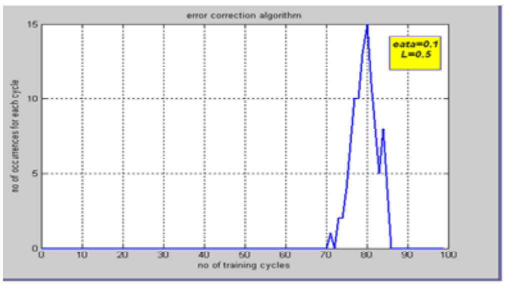

Figure 7. Illustrates the statistical distribution of learning convergence time for learning rate values =0.1, gain factor =0.5.

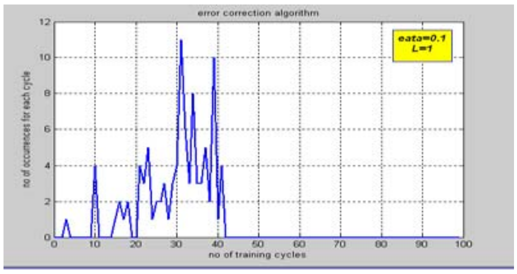

Figure 8. Illustrates the statistical distribution of learning convergence time for learning rate values =0.1, gain factor =1.

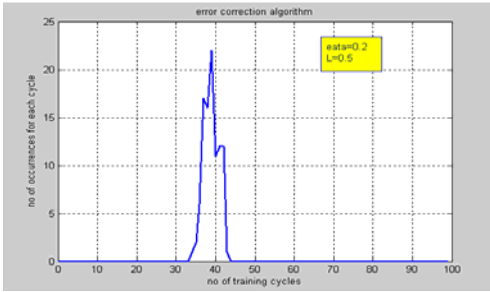

Figure 9. Illustrates the statistical distribution of learning convergence time for learning rate values =0.2, gain factor =0.5.

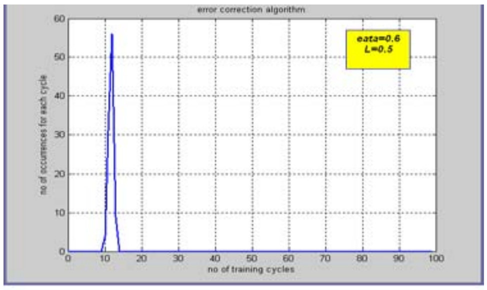

Figure 10. Illustrates the statistical distribution of learning convergence time for learning rate value =0.6, gain factor =0.5