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On Virtual Enhancement of Learning Creativity Regarding Computer Aided Instructional Processes (Neural Networks Approach)

Hassan M. H. Mustafa[1], and Nabil El-Sayed Hassan[1]
[1] Educational Technology, and Computer Department, College of Specified Education, Banha University, Banha, Egypt

Abstract: *A growing community represents the field of learning sciences internationally. Many experts now recognize that conventional ways of conceiving knowledge, educational systems and technology-mediated learning are facing increasing challenges in this time of rapid technological and social changes. Since beginning of last decade, Artificial Neural Networks (ANN$^{\underline{s}}$) models have been adopted to investigate systematically critical and challenging educational phenomena. Specifically, this piece of research deals with conceptual analysis and evaluation of quantified learning creativity as an interesting educational phenomenon. In other words, quantitative assessment of learning creativity phenomenon is a rather critical and challenging issue. More precisely, the presented piece of research adopted systematic quantified Investigation of learning creativity phenomenon as an interesting and challenging educational issue. It introduces a novel interdisciplinary approach integrating educational sciences with brain functional modeling across computer simulation of (ANNs), that supported by practical educational field (case study) results. In more details, by adopting realistic ANN^{s} simulation and modeling to quantify learning creativity. Optimal selectivity for values of gain factor, learning rate parameters and number of neurons contributing to learning process are relevant in improving observed quantified learning creativity phenomenon. Interestingly, obtained presented results herein seemed to be valuable and promising for future more elaborate and systematic research in learning creativity as well as other educational phenomena.*

Keywords: *Artificial neural networks, Brain functional modeling, Computer aided learning, learning creativity phenomenon*

1. Introduction

This research work addresses quantified Investigation of an interesting and challenging issue namely learning creativity phenomenon. It introduces an interdisciplinary novel approach associated with educational sciences: simulation computer simulation of brain functions and practical field (case study) results. Realistic simulation for quantifying, learning creativity is suggested by adopting Artificial Neural Networks (ANNs) modeling. optimal selectivity for values of gain factor, learning rate parameters, and/or number of neurons are relevant for improvement of quantified learning creativity phenomenon. This phenomenon considered as an interdisciplinary issue associated with educational field applications and activities. Accordingly, for long time ago and till recently, educationalists as well as psychologists have been cooperatively interesting in systematic searching for quantifying, evaluation, and improvement of that issue. Accordingly, interdisciplinary research work integrating: cognitive and learning sciences, with educational psychology and neurobiology is adopted for quantifying learning creativity phenomenon. This piece of research introduces an interdisciplinary novel approach concerned with evaluation of that interesting issue. Herein, realistically, quantified learning creativity is simulated using (ANNs) modeling. More specifically, presented modeling considers statistically time dependent improvement of learners' achievements (learning convergence time). This work motivated by the interesting interdisciplinary research direction integrating educational sciences with brain functional modeling across computer simulation of Artificial Neural Networks (ANN^{s}), that's shown at next subsection as follows.

1.1 Motivation of Creativity Research

It is referred to the WHITE HOUSE REPORT in 1989; it has been announced in U.S.A. that decade (1990-2000) is named as Decade of the brain [1]. Furthermore, the overwhelming majority of neuroscientists have adopted the concept which suggests that huge number of neurons in addition to their synaptic interconnections constituting the central nervous system with its synaptic connectivity performing dominant roles for learning processes in mammals besides human [2]. More specifically, this motivation is supported by what revealed by National Institutes of Health (NIH) in USA that children in elementary school, may be qualified to learn "basic building blocks" of cognition and that after about 11 years of age, children take these building blocks and use them [3][4]. The extremely composite biological structure of human brain results in everyday behavioral learning brain functions. At the educational field, it is observable that learning process performed by the human brain is affected by the simple neuronal performance mechanism [5]. In this context, neurological researchers have recently revealed their findings about increasingly common and sophisticated role of Artificial neural networks (ANN^{s}). Mainly, this role has been applied for systematic and realistic modeling of essential brain functions (learning and memory) [6]. Accordingly, neural network theorists as well as neurobiologists and educationalists have focused their attention on making interdisciplinary contributions to investigate observed educational phenomena associated with brain functional performance such as optimality of learning processes [7][8].

1.2 Creativity Simulation

Realistic simulation of quantifying learning creativity is suggested by adopting Artificial Neural Networks (ANNs) modeling considering error correction(supervised) paradigm. Moreover, this piece of research considers statistically the time dependent improvement of learners' achievements (learning convergence time). Mainly two design parameters of ANNs proposed for measuring such time improvement of learning creativity. Both parameters are: gain factor (of neuronal sigmoid activation function), and learning rate value. They have effective impact on learning creativity via dynamical synaptic connectivity (brain Plasticity). By either increasing of neurons' number contributing in learning processes or ANNs design parameters. Conclusively, optimal selectivity for values of gain factor, learning rate parameters, and/or number of neurons are relevant for improvement of quantified learning creativity phenomenon. Herein, the introduced research mainly concerned with learning creativity evaluation using realistic neural system models. Specifically, it considers learners' response time during interactive CAL processes. That is measured as average learning convergence time after obtaining results from a case study and running of a computer simulation program. Interestingly, some conclusive remarks are presented after analysis of obtained results. The introduced results seemed very valuable and more promising for future elaborate and systematic research in learning creativity phenomenon. This work motivated by the interesting interdisciplinary research direction integrating educational sciences with brain functional modeling across computer simulation of Artificial Neural Networks (ANNs). Learning creativity phenomenon is a challenging and interesting issue associated with educational field applications and activities [9][10]. So, for long time ago and till recently, educationalists as well as psychologists have been cooperatively interesting in systematic searching for quantifying, evaluation, and improvement of that issue. Accordingly, interdisciplinary research work integrating: cognitive and learning sciences, with educational psychology and neurobiology is adopted for quantifying learning creativity phenomenon [11][12]. This piece of research introduces an interdisciplinary novel approach concerned with evaluation of that interesting issue. Herein, realistically, quantified learning creativity is simulated using (ANNs) modeling. More specifically, presented modeling considers statistically time dependant improvement of learners' achievements (learning convergence time) [13][14]. Realistic simulation of quantifying learning creativity is suggested by adopting Artificial Neural Networks (ANNs) modeling considering error correction(supervised) paradigm. Moreover, this piece of research considers statistically the time dependent improvement of learners' achievements (learning convergence time). Mainly two design parameters of ANNs proposed for measuring such time improvement of learning creativity. Both parameters are: gain factor (of neuronal sigmoid activation function), and learning rate value. They have effective impact on learning creativity via dynamical synaptic connectivity (brain Plasticity). By either increasing of neurons' number contributing in learning processes or ANNs design parameters. Conclusively, optimal selectivity for values of gain factor , learning rate parameters , and/or number of neurons are relevant for improvement of quantified learning creativity phenomenon. Herein, the introduced research concerned mainly with learning creativity evaluation by application of realistic neural system modeling. Specifically, it considers learners' response time during interactive CAL processes. That is measured as average learning convergence time after obtaining results from a case study and running of a computer simulation program. At next section, some clarifications for the relation between learning creativity and brain functions are introduced. The rest of this paper is organized as follows. At section 3, the basic of teaching/learning modeling, and its relation with ANN learning paradigms are presented respectively, at two subsections (3.1&3.2). The basic generalized view for interactive teaching/learning processes is given at subsection 3.1. Additionally, at subsection 3.2, concepts for modeling learning phenomenon using ANN are presented. At the fourth subsect5ion, the obtained learning results (outcomes) have been presented regarding brain's creative performance based on the neurons' number contributing the learning process. These results considered the natural noisy learning environment, in addition to the effect of design ANN parameters on learning performance are Finally, at the last fifth section, some conclusive remarks are introduced.

2. Creativity And Brain Functions

This section is dedicated to introduce a general clarification about what is meant by creativity and its close relation with human brain. Interestingly, by referring to the Three Ring Conception of Giftedness that is displayed in Fig.2.1, This *Three Ring Conception of Giftedness* (Renzulli,) suggests that giftedness involves an interaction between three basic sets of human traits — *above average ability*, *creativity* and *task commitment* — which, like three overlapping rings, create a common area where the most gifted behavior [15]. According to recently published article by Dr.Linda Karges-Bone,[14],it is announced that "creativity is the spark that never burns out". Functionally, true creativity is defined to have a goal, a purpose, and an outcome [16]. Both declared evidences are well supported by more recent research results suggests that fresh neurons arise in the adult brain every day and that the cells ultimately help with learning complex tasks—and the more they are challenged, the more they flourish [17].By more details, thousands of new cells are generated in the adult brain every day, particularly in the hippocampus, a structure involved in learning and memory. Moreover, during a period of two weeks, most of those newborn neurons will die, unless the animal is challenged to learn something new that is a learning task. In other words, by more neural interconnections learning creativity emerges. That is resulting in more extended brain capacity for neural plasticity over time, [18] Recently, some research papers are published describing quantifying of main brain functional phenomena (learning and memory)[19-24]. Moreover, researchers need essentially to know how neurons synapses inside the brain are interconnected together and communication between brain regions,[3][4]. In more details, at any instant brain state (synaptic weight pattern) in neural systems leads to some expected spontaneous behavioral response to any of external stimuli. So, dynamically changes of weight synaptic pattern (vector) measures the learning convergence process in consequence with internal / stored level of intelligence. Consequently, the initial brain state of synaptic connectivity pattern considered as pre-intelligent creativity parameter. Furthermore, to the above clarifications about function of neurons at hippocampus brain area, interesting analysis for the effect of brain Glial cells on learning performance (convergence time factor) is shown at Fig.1, in below. It illustrates mutual inter-communication among Glial cells and typical neuronal brain cells. Noticeably, increasing of synaptic connectivity value is measured as ratio between number of Glial cells versus number of typical neurons. This ratio leads to improvement of learning performance time factor [21] that considered as number of training cycles. For more details, it is referred to [2], and other references therein is recommended.

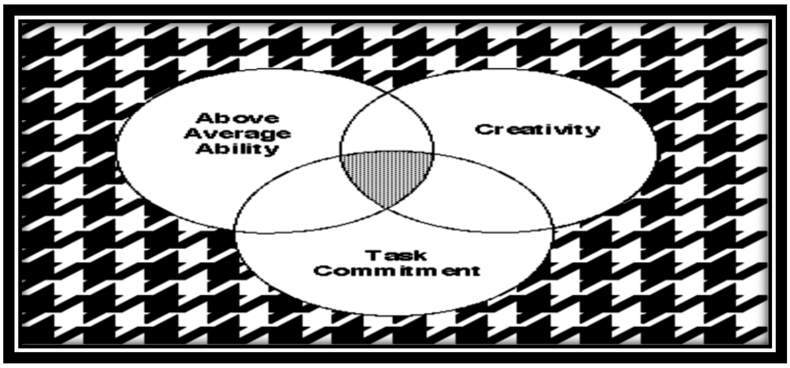

Fig.1 Three-Ring Conception of Giftedness, adapted from [‘15]

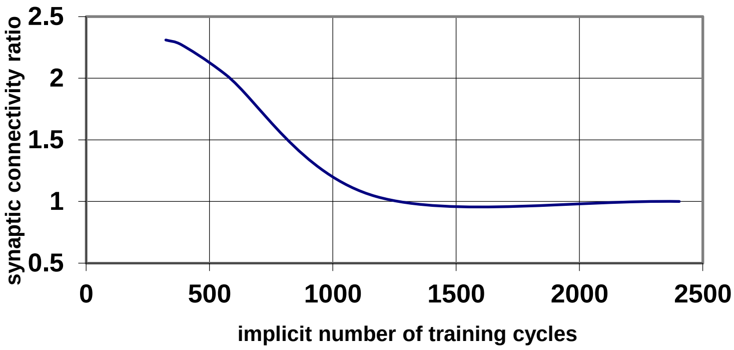

Fig.2 Illustrates the relation between number of training cycles during learning process and the synaptic connectivity (weights) values, adapted from [22]).

3. Basic Interactive Leaning / Teaching Model

Referring to Fig.3 and Fih,4. shown in below, adopted interdisciplinary approach concerned with learning creativity phenomenon is illustrated. Detailed illustrations for both figures have been illustrated at subsections (3.1&3.2) respectively.as follows:

1.3 General View for Interactive Educational Process

Fig.3, an interactive teaching model through stimulating signals (by CAL packages) is well qualified in performing simulation of human brain and /or cognitive functions. at that Figure, Inputs to the neural network learning model are provided by In environmental stimuli (unsupervised learning). 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 tutor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of model pattern input. That is according to tutor’s experience, he provides the model with clear data by maximizing its signal to noise ratio.

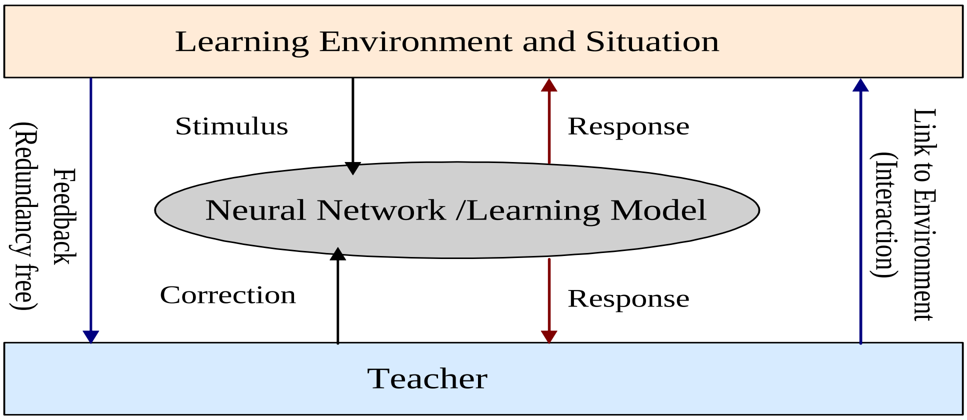

Fig.3. Illustrates a general view for interactive educational process, adapted from [7].

3.2 ANN Modeling Concepts of Learning Phenomenon Analysis

In Fig. 3, generally simulates two diverse learning paradigms. It presents realistically both paradigms: by interactive learning / teaching process, as well as other self-organized (autonomous) learning By some details, firstly is concerned with classical (supervised by tutor) learning observed at our classrooms (face to face tutoring) . Accordingly, this paradigm proceeds interactively via bidirectional communication process between teacher and his learner(s)]. However, secondly other learning paradigm performs self-organized (autonomously unsupervised) tutoring process[14].

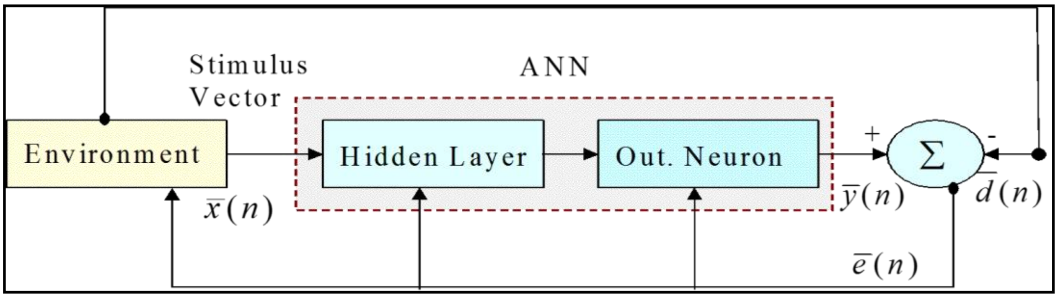

Fig.4: Generalized ANN block diagram simulating two diverse learning paradigms ,adapted from [7].

The mathematical formulation of the Generalized ANN Learning / Teaching Model given at Fig. 2 is given as follows. The error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

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

Where $\bar{e}(n)$ ..... is the error correcting vector that adaptively controls the learning process,

$\bar{y}(n)$ .... is the output obtained signal vector from ANN model, and

$\bar{d}(n)$ ...... is the desired numeric signal vector.

Moreover, the following four equations are deduced:

$$V_k(n) = X_j(n) W_{kj}^T(n) \tag{2}$$

$$Y_k(n) = \varphi(V_k(n)) = (1 - e^{-\lambda V_k(n)})/(1 + e^{-\lambda V_k(n)}) \quad (3)$$

$$e_k(n) = |d_k(n) - y_k(n)| \quad (4)$$

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

Where X is input vector and W is the weight vector. φ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Note that ΔW_{kj} (n) is the dynamical change of weight vector value. Above four equations are commonly applied for both learning paradigms: supervised (interactive learning with a tutor), and unsupervised (learning though student's self-study). The dynamical changes of weight vector value specifically for supervised phase is given by:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \quad (6)$$

Where η is the learning rate value during the learning process for both learning paradigms. At this case of supervised learning, instructor shapes child's behavior by positive/ negative reinforcement Also, Teacher presents the information and then students demonstrate that they understand the material. At the end of this learning paradigm, assessment of students' achievement is obtained primarily through testing results. However, for unsupervised paradigm, dynamical change of weight vector value is given by:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \quad (7)$$

Noting that e_k(n) equation (6) is substituted by y_k(n) at any arbitrary time instant (n) during the interactive learning process. Referring to Fig.1, the correction signal which provided by a teacher should take into consideration the noisy environmental level inside classrooms(such as noisy crowdedness appears as CPE). In other words, that level is quantitatively measured as signal to noise (S/N) ratio or equivalently the additive noise power (σ) to the ideally sensory clear signal. Consequently, the response time response measured by number of training cycles (n) { as defined at the subsection in the above (*B)* by the two equations (6)&(7)}. Noting value of (n) should have been increased until reaching learning convergence instant, when

$$\Delta W_{kj}(n) = 0 \quad (8)$$

That above condition given by equation (8), could be fulfilled only if the desired output learning has been obtained after some number of training cycles (response time) in fulfillment of the two equations (6) & (7).

4. Results

4.1 Effect of Noisy Environment on Creative Learning

Naturally, ideal (noiseless) learning environment is not available in practice. Usually, it environmental learning data is vulnerable to contaminations by either external or internal noisy conditions. So, creative individuals are more capable to be adaptive with environmental noise,[2]. In other words, creative brains are more experienced in building up adaptive connections with noisy data through extended brain capacity [10] Obtained results for optical character recognition under different noise levels are given in a tabulated form as in (Table 1). Noting that, noise effect is measured by signal to noise ratio value (S/N) versus the number of training cycles (T). Conclusively, an interesting remark observed considering relation between number of training cycles values and noisy environmental data for the cognitive(unsupervised) learning. That is convergence time cycle(s) (T), of learning process is inversely proportional to signal to noise ratio value(s) , (S/N).

TABLE 1: Relation between S/N power ratio, noise power, and learning response time

Signal to noise power ratio	5	10	20
Noise power σ at learning environment	0.2	0.1	0.05
Learning response Time (T)	85	62	47

4.2 Effect of CAI Packages' Application Of On Learners' Response Time (Case Study)

Performance evaluation of Educational systems are adopted mainly by using two measurable learning parameters .Namely, both measured parameters are -on the average- learning convergence (response) time and learners' achievements(marks). Herein, error correcting learning paradigm is suggested to simulate the learning principle under supervision with a teacher in nature learning processes observed to converge to some output response value(s) after some number of training cycles. For any case this number observed to differ in a diverse manner following different learning abilities of individuals (students). The application of CAL packages results on improvement of learners' response time as shown at Fig.5.

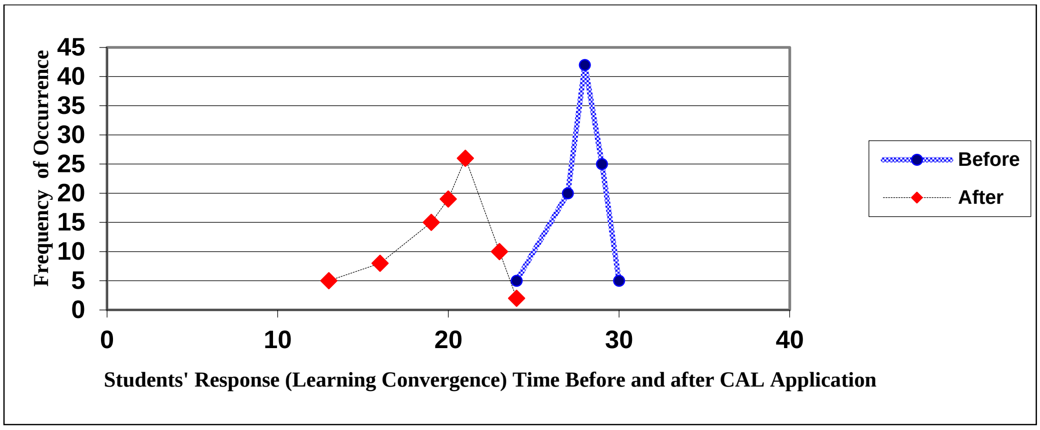

Fig. 5 The effect of suggested CAL package on students' Learning convergence (Response) time (adapted from [13])

4.3 Effect of Learning Rate Values On Learners' Convergence Time

Referring to Fig.4 given in the above, it is worthy note that statistical variations for number of occurrences observed to have approximately bell shape performance versus different values of learning response time (iteration cycles). In other words, the resulting values distribution having a bell form shape seemed to be similar to Gaussian (normal) distribution. Referring to above obtained output results, values corresponding to the learning rate values (0.4,0.3,0.2, 0.1). are given respectively. as (13, 17, 27, 55) cycles on the average for learning convergence (response) time. Conclusively, convergence time (number of training cycles) is inversely proportional to the corresponding learning rate values.

4.4 Effect of Gain Factor Values on Learners' Convergence Time

The obtained results for various gain factor values are comprehensively shown in below at Figure 6. (in a statistical graphical form)

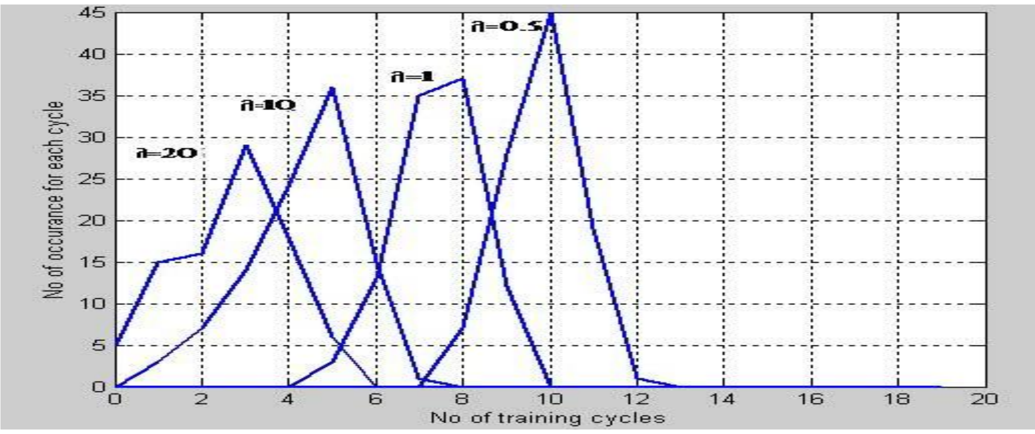

Fig.6. Illustrates improvement of average response time (no. of training cycles) by increase of the gain factor values

The above results illustrate gain factor effect on improving the value of time response measured after learning process convergence, [10]. These four graphs at Fig.6 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, and3) cycles, (on approximate averages). Conclusively, learning creativity is virtually improved by such increase of gain factor values.

4.5 Effect of Neurons' Number on Learning Creativity

Referring to Fig. 7 given in below, as the number of neurons contributing to learning process increases, the better learning creativity obtained. These results seem consistent well with above obtained results shown at Fig.5.

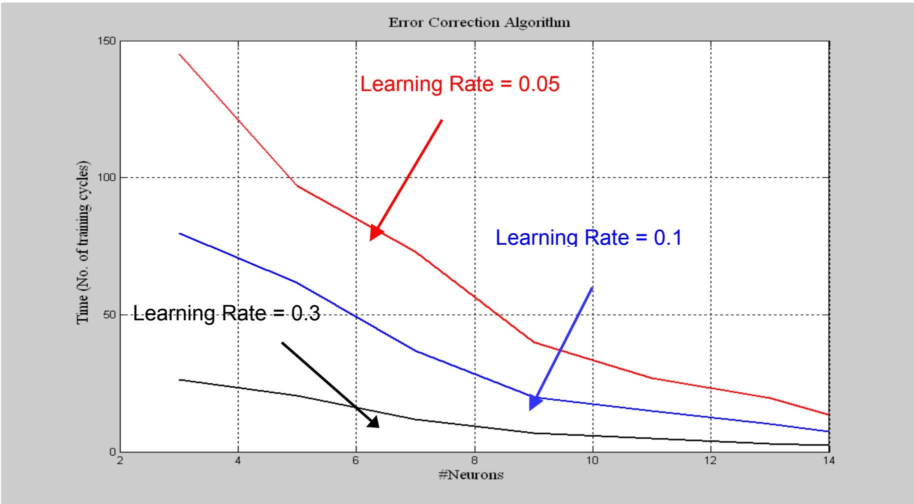

Fig.7 Illustrates the performance of error correction algorithm versus learning convergence time for different learning rate values.

4.6 Comparing of Above Two ANN's Design Parameters

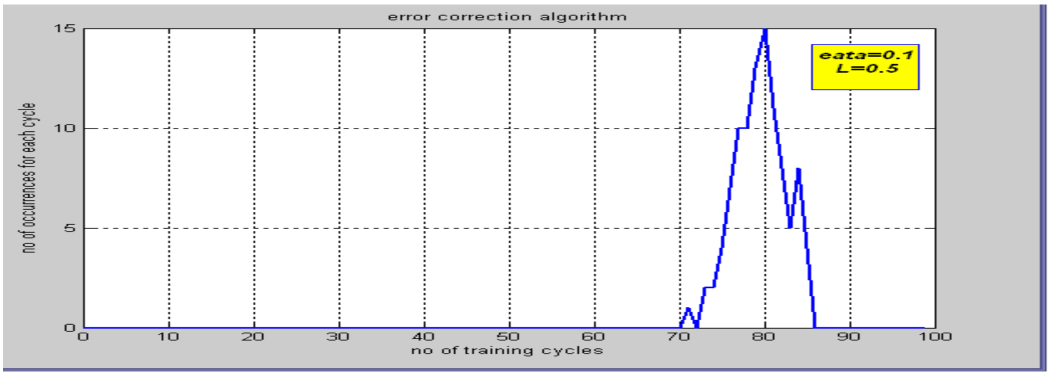

Fig.8. Illustrates the statistical distribution of learning convergence time for learning rate value =0.1, gain factor value=0.5.

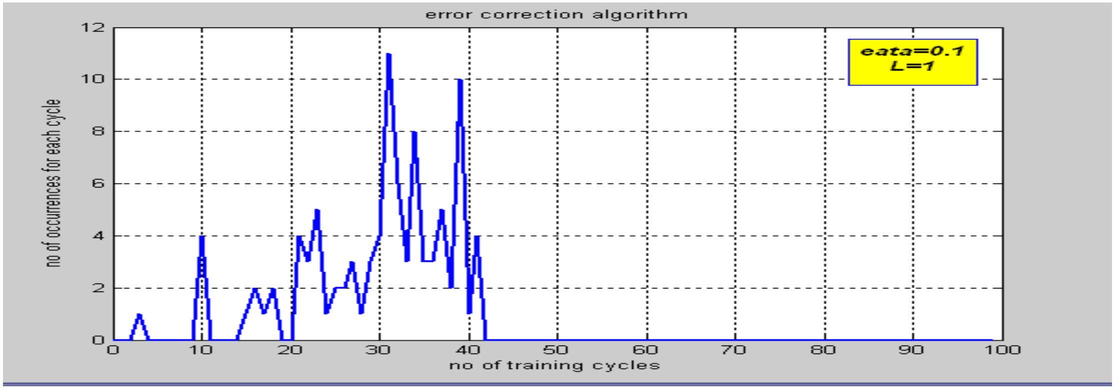

Fig.9 : Illustrates the statistical distribution of learning convergence time for learning rate value =0.1, gain factor value =1.

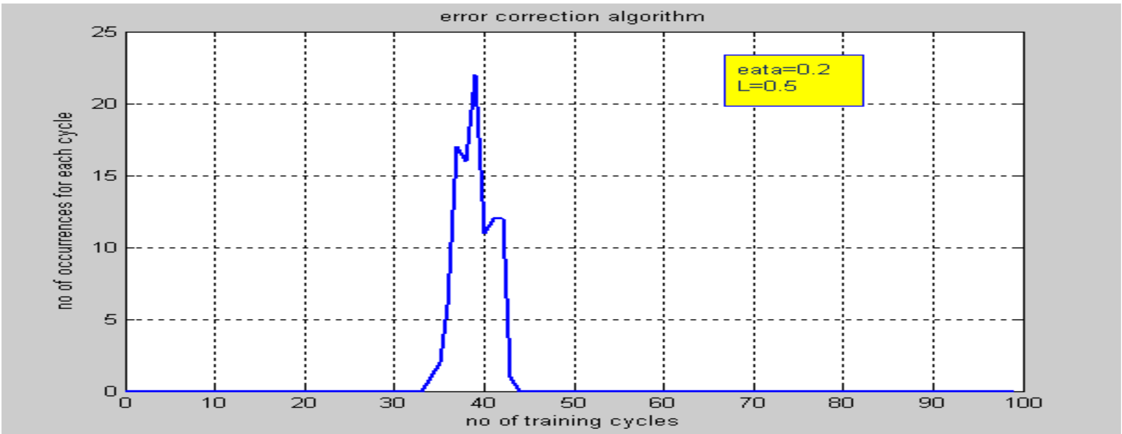

Fig.10: Illustrates the statistical distribution of learning convergence time for learning rate value =0.2, gain factor value =0.5.

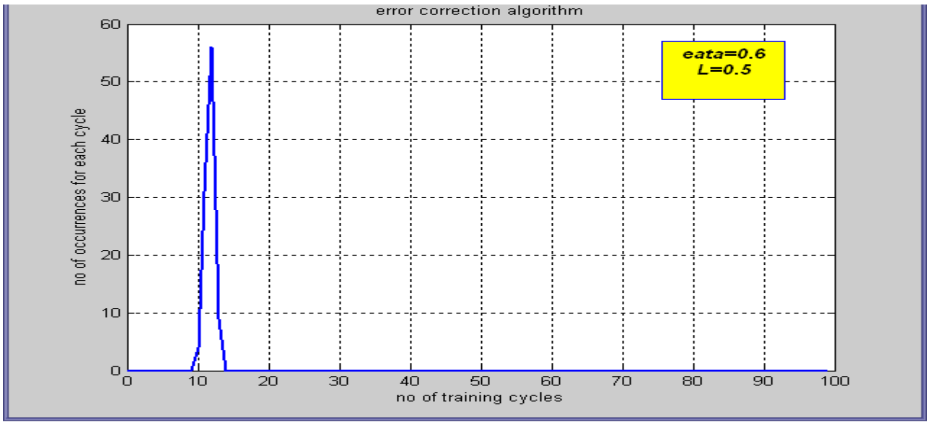

Fig.11 : Illustrates the statistical distribution of learning convergence time for learning rate value =0.6, gain factor value =0.5.

4.7 Comparison samples for two modeling deign parameter presented as follows:

1- Firstly, two samples are given at (Fig.8), and (Fig. 9). 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 at (Fig.10), and (Fig.11) .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 (Fig.10), to 0.6 (Fig.11), the average (normalized) number of training cycles, decreases approximately (on the average), (from 38 to 12) cycles.

4.8 Effect of neurons' number on time response

The following simulation results show how the number of neurons may affect the time response performance. Those graphical presented results show that by changing number of neural cells (14 ,11 ,7 ,5, and 3); during interaction of students with e-learning environment, the performance observed to be improved by increase of number of neuronal cells (neurons). That is shown at figures (12, and 13) respectively; for fixed Learning rate = 0.1 and gain factor = 0.5.

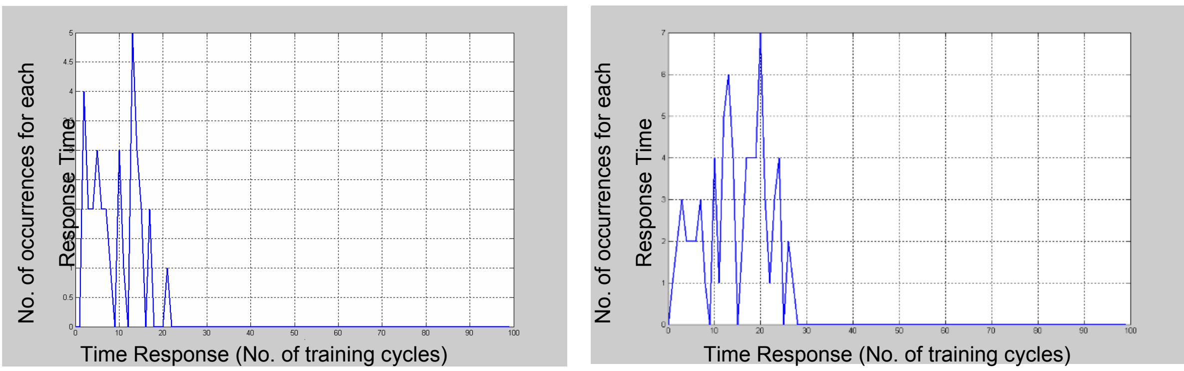

Fig. 12: Illustrate time response performance with #neurons = 14 (left) and with #neurons =11 (right).

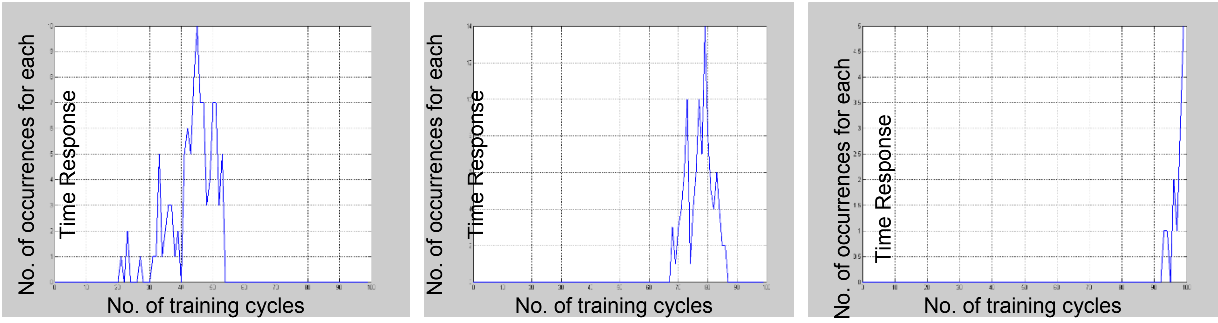

Fig. 13: Illustrate time response performance with #neurons = 7 (left), with #neurons = 5 (middle) and /with #neurons = 3

5. Conclusions

The two design parameters for ANNs modeling (Learning rate, and Gain Factor) in addition to number of neurons, all are considered for **quantifying** learning creativity. In more details, optimal selectivity for values of gain factor, learning rate parameters , and/or number of neurons are relevant for improvement of quantified learning creativity phenomenon. Conclusively, evaluation and assessment of individual differences phenomena is very interesting for educational systems performance referring to main brain functions (learning and memory) . Accordingly, internal (intrinsic) brain state (synaptic connectivity) of students is highly effective on their learning creativity [26]. Recently, referring to [27], more elaborate application of ANN modeling has been introduced. That investigates systematically a real-world instructional problem associated with learning noisy environment, which agrees well with the context of this presented paper.

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