On Simulation of e-Learning Convergence Time Using Artificial Neural Networks

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ABSTRACT

This paper addresses a challenging and critical issue of how to evaluate dynamically e-Learners' performance. That is by considering their learning response (convergence) time to reach desired output answer. More precisely, this piece of research aims to investigate realistically performance of e-educational phenomenon associated with e-learners' brain response time. Moreover, presented work integrates neuronal sciences and computer technology into e-educational environment as an interdisciplinary research direction to study realistically e-learning performance issue. Accordingly, Artificial Neural Networks (ANN^S) models are suggested for realistic performance evaluation of timely dependant response till reaching learning process convergence. So, response time is adopted as an appropriate candidate parameter for e-learning systems' evaluation. Herein, analysis of response time parameter considers individual learners' differences while performing learning process. Additionally, evaluated effect of contributing neurons on e-learning processes performance is presented. Finally, after running of suggested realistic simulation programs, some interesting results are introduced.

Keywords: Artificial neural network modeling, E-Learning Performance Evaluation, Synaptic Connectivity, learning paradigms.

1 Introduction

The field of 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 challenges in this time of rapid technological and social changes. Since beginning of last decade, Artificial Neural Networks (ANN^S) models have been adopted to investigate systematically mysteries of human brain, the most complex biological neural system, [1]. Additionally, modeling of human brain functions considered as recent interdisciplinary evaluation trend by educationalists in learning science incorporated Nero-physiology, psychology, and cognitive science, [2].

Generally, evaluation of learning systems performance is an interesting challenging issue, considered under investigations by educational researchers working at interdisciplinary field integrating educational environment with computer technology and neural science. Some research work considers the basic implementation of an adaptive e-Learning system . More specifically , integrating machine intelligence technique such as ANN seems to make e-Learning more attractive by ensuring on flexibility, adaptability and modularity [3]. Essentially educationalists need to know how neurons synapses inside the brain are interconnected together to perform communication among brain regions, [4]. By this information they can fully understand how the brain's structure gives rise to perception, behavioral learning, and consequently, they can investigate well in very details how learning phenomenon proceeds.

The presented paper is an interdisciplinary piece of research that aims to simulate appropriately performance evaluation issue in e-learning systems with special attention to face to face tutoring phenomenon. That purpose fulfilled by adopting an appropriate metric parameter to evaluate learners' interaction with e-learning course material(s) during face to face tuition. Herein, learner's response (convergence) time is recommended as metric learning parameter. Practically, it is measured as learner's elapsed time till accomplishment of a pre-assigned achievement level (learning output) [5-8]. This paper presents ANN modeling approach for getting insight with e-learning evaluation issue considering learner's response (convergence) time. Mainly, ANN^S models are motivated by synaptic connectivity dynamics of neuronal pattern (s) inside brain which equivalently called as synaptic plasticity while coincidence detection learning (Hebbian rule) is considered, [5-6]. By some details, at any time instant; the status of synaptic connectivity pattern inside e-learner's brain supposed to be presented as timely dependent (changes) of weight vector. This status pattern expected to proceed spontaneously towards learner's output answer (response).Obviously, the number of contributing neurons (inside e-Learner's brain) has a significant effect on evaluated performance of any e-Learning process dynamics. Consequently, after successful timely updating of dynamical state (weight) vector, pre-assigned achievement is accomplished in accordance with coincidence learning [8].

This piece of research consisted of six sections rather than an introductory one. Accordingly, the rest of presented work is organized as follows. At the next second next section, a brief review about biological function of a single neuron is presented along with its mathematical modeling function. A general overview about performance evaluation technique is presented at the third section. This section introduces also two relevant selectivity criteria those are realistically applicable for e-learning systems At the fourth section, a generalized block diagram for an ANN model to simulate e-learning performance is given in addition to simulation results presented the effect of gain factor and learning rate on learning convergence (response) time . At the fifth section the effect of two ANN design parameters and number of neurons on e-learning systems' performance is introduced by graphical and tabulated results. At the last sixth section some interesting conclusive remarks are presented.

By the end of this paper , an appendix is presented for generalized mathematical formulation along with graphical presentation for different values of ANN two design parameters. Moreover, analogy between number of neurons' activities and Ant Colony Optimization ACO (number of ants)is given

2 LEARNERS' BRAIN FUNCTION

During last decade, it had been announced (in U.S.A.) to call it Decade of the brain,[9]. Consequently, neural network theorists as well as neurobiologists have focused there attention on making a contribution to investigate systematically biological neural systems (such as the brain), functions. There is a strong belief that making such contribution could be accomplished by adopting recent direction of interdisciplinary research work, combining ANN [S] with neuroscience. Consequently, by construction of biologically inspired artificial neural models it might have become possible to shed light on behavioral principles and functions concerned biological neural systems.
Additionally, recent biological experimental findings have come to interesting results for evaluation of intelligent brain functions (Learning and memory)[7],[10], and[11] .However, about quarter of a century ago, in practical neuroscience experimental work carried out by many biologists declared results that even small systems of neurons are capable of forms of learning and memory [9]. Recently, the relation between number of neurons and information-processing capacity; and efficiency at hippocampus brain area of mice is published at [12].
By some details about both features are tightly coupled to each other and they basically defined as follows:
1) Learning: is the ability to modify behavior in response to stored experience (inside brain synaptic connections).
2) Memory: is that ability to store that modification (information) over a period of time as well as to retrieve spontaneously modified experienced (learned) patterns.
Moreover, some recently published work (based on neural network modeling) illustrated the tight mutual relation between learning and memory [13],[14]. Additionally, about one decade ago two other published research articles[15], [16], have account , respectively to the effect of brain synaptic plasticity on learners' ability, and the effect of not well prepared tutors on learning convergence time.

2.1 A Single Biological Neuron Function
It is well known that human brain structure is internally composed of excessively great number of neurons; mutually interconnected via patterns of their axons and synapses [17] .By some details, inside a learner's brain cerebral cortex structure, synaptic connectivity patterns among vast number of neurons relay upon biological information processing conducted through communication among neuronal axonal (outputs) to other neurons' synapses (inputs). At Fig.1, given in below an illustrative schematic drawing is shown for the basic structure of a single biological neuron. As given in above, this neuron presents the building block for biological information processing inside learner's brain structure. Consequently , performance improvement of many building blocks (neurons) conducts inevitably a significant enhancement of global brain function is .For more details concerned with function and mathematical modeling of biological neurons ,it is recommended to review a comprehensive foundation reference book ,[17] .Thus , enhancement of e-learners' intelligence (learning and memory) could be attained via enhancement of neuronal

activation (response) function. The following subsection presents a detailed mathematical formulation of a single neuron function.
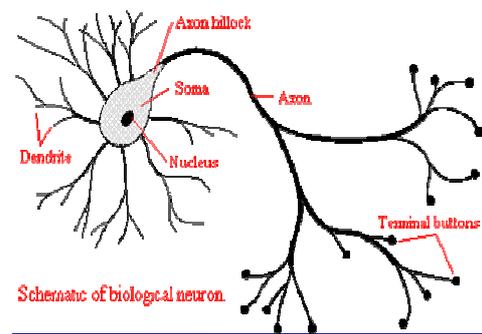

Fig.1 A simplified schematic illustration for a biological neuronal model (adapted from, [18]).

2.2 Mathematical Formulation of a Single Neuron Function
Referring to T.Kohenen's work [19], the output neuronal response signal observed to be developed following what so called membrane triggering time dependent equation. This equation is classified as a complex non-linear partial deferential. Its solution works to provide us with the physical description of a single cell (neuron) membrane activity. However, considering its simplified formula, which equation may contain about 24 process variable and 15 non-linear parameters. Following some more simplification of any neuron cell arguments, that differential equation describing electrical neural activity has been suggested, as follows:

$$\frac{dz_i}{dt} = \sum_{j=1}^{n} f(y_{ij}) - j(z_i) \qquad (1)$$

Where,
y_{ij} represents the activity at the input (j) of neuron (i) ,
$f(y_{ij})$ indicates the effect of input on membrane potential,
$j(z_i)$ is nonlinear loss term combining leakage signals, saturation effects occurring at membrane in addition to the dead time till observing output activity signal.
The steady state solution of the above simplified differential equation (1), proved to be presented as transfer functions. Assuming, the linearity of synaptic control effect, the output response signal is given by the equation:

$$Z_i = \phi\left(\sum_{j=1}^{n} w_{ij} y_{ij} - \theta_i \right) \qquad (2)$$

Where, ϕ is a function having two saturation limits. That ϕ may be linear above a threshold and zero below or linear within a range but flat above.
θi is the threshold (offset) parameter , and
wij synaptic weight coupling between two neuron *(i)* and *(j)*.
Above function *(φi)* has been Specifically, recommended to obey sigmoid signal activation function [1], presented by equation y(U) as follows:

$$y(U) = \frac{\left|1 - e^{-\lambda(U-\theta)}\right.}{\left|1 + e^{-\lambda(U-\theta)}\right.} \qquad (3)$$

Where

$$U = \sum_{i=1}^{m} w_i x_i$$

λ .... is the gain factor value.

$\theta\iota$ .... is the threshold value.

By referring, to the weight dynamics described by the famous Hebb's learning law, the adaptation process for synaptic interconnections is given by the following modified equation:

$$\frac{d\,\omega_{ij}}{dt} = \eta\,z_i\,y_{ij} - a\,(z_i)\omega_{ij} \qquad (4)$$

Where, the first right term corresponds to the unmodified learning (Hebb's law [4]) and η is the a positive constant representing learning rate value. The second term represents active forgetting; a (z_i) is a scalar function of the output response (z_i). The adaptation equation of the single stage model is as follows.

$$w\,\dot{}_{ij} = -a w_{ij} + \eta z_i\,y_{ij} \qquad (5)$$

Where, the values of η, z_i and y_{ij} are assumed all to be non-negative quantities [20].The constant of proportionality η is less than one represents learning rate value, However a is a constant factor indicates forgetting of learnt output [4],[19], (it is also a less than one).

2.3 Brain Functions versus ANN$\underline{s}$ Models

Development of neural network technology is originally motivated by the strong desire to implement systems contributing tasks similar to human brain performance. Basically such systems are characterized by their smartness and capability to perform intelligent tasks resembling human. Objectively, after a completing of training of well designed neural system models it is expected to respond correctly (in smart manner) and spontaneously towards input external stimuli. In brief, these systems well resemble human brain functionally in two ways:

1- Acquiring knowledge and experience through training / learning through adaptive weights neurodynamic.

2- Strong memorizing of acquired knowledge /stored experience within interconnectivities of neuronal synaptic weights.

Consequently, adopting of neural network modeling seems to be very relevant tool to perform simulation of educational activity phenomena. To implement realistically some simulated educational activities we should follow the advice that such models needed to be with close resemblance to biological neural systems. That resemblance ought to be not only from structural analysis but also from functional characterization. In other words understanding learning / training process carried out by ANN is highly recommended for increasing efficiency and effectiveness of any simulated educational activity. The statistical nature of training/learning time of convergence for a collection group (of ANN models) observed to be nearly Gaussian. This simulates a group of students under supervised learning. Additionally, the parameters of such Gaussian distribution (mean and variance) shown to be influenced by brain states of student groups as well as educational instrumental means. The well application of educational instrumentation during proceeding of learning / training processes improves the quality of learning performance (learning rate factor). Such improvements are obtained in two folds. By better neurodynamic response of synaptic weights and by maximizing signal to noise ratio of input external learning data (input stimuli). So, any assigned learning output level is accomplished if and only if connectivity pattern dynamics (inside learner's brain) reaches a stable convergence state. i.e. following Hebbian learning rule, connectivity vector pattern associated to biological neuronal network performs coincidence detection to input stimulating vector.

3. PERFORMANCE EVALUATION TECHNIQUES [22]

The most widely used techniques for performance evaluation of complex computer disciplines similarly to e-learning systems are: experimental measurement, analysis and statistical modeling, and simulation [22]. Herein, special attention is given to quantitative evaluation of timely updated performance of learners' brain functions. That is carried out by using ANN modeling based on error correction (supervised) learning, supposed output delivery of a pre-assigned learning level. More precisely , inside a learner's brain , dynamical changes of synaptic connectivity pattern (weight vector) modified adaptively after during response (convergence) time period , so as to develop (output desired answer) . Accordingly, superior quality of evaluated e-leaning system performance attained via global decrease of response time (on the average). Consequently, response time value needed - to accomplish pre-assigned learners' achievement- is a relevant indicator towards quality of any -under evaluation- learning system.

3.1 Selecting an Appropriate Learning Parameter

Referring to some educational literature one of the evaluating parameter for learning processes is learning convergence time (equivalently as response time) [23].By more details, at e-educational field practice while a learning processes proceeds , e-learners are affected naturally by technical characterizations as well as technological specifications of the interactive learning environment. Thus, learners have to submit their desired achievements (output learning levels) finally, by successive timely updated interaction with learning environmental conditions. This is well in agreement to the unsupervised (autonomous) learning paradigm following Hebbian rule [21], [24], in case of self-study learning. Conversely, considering the case of second learning way concerned with supervised learning (with a teacher) paradigm. It would be relevant to follow error correction learning algorithm as an ANN model [16], [24]. Accordingly, two ANN models (supervised and unsupervised), are recommended for realistic simulation of both face to face learning phases (paradigms): from tutor and from self-study, respectively [26]. Herein, special attention is developed towards supervised learning phase.

3.2 Examinations in E-Learning Systems

In fulfillment of an e-learning system performance evaluation, time response parameter applied to measure any of e-learners' achievement. Thus e-learner has to subject to some timely measuring examination that is composed as Multi choice questions (MCQ). Hence, this adopted examination discipline is obviously dependant upon learners' capability in performing selectivity of correct answer to questions they received. Consequently, to accomplish a pre-assigned achievement level, stored experience inside learner's brain should be able to develop correct answer up to desired (assigned) level. Referring to neurobiological point of view, selectivity function proceeds (during examination time period) to get on either correct or wrong answer to received questions spontaneously. Consequently, assigned learning output level is accomplished if and only if connectivity pattern dynamics (inside learner's brain) reaches a stable convergence state. In other words, connectivity vector pattern associated to biological neuronal

network performs coincidence detection to input stimulating vector. i.e. inside a learner's brain, dynamical changes of synaptic connectivity pattern (weight vector) modifies adaptively convergence time, so as to deliver (output desired answer) .Hence, synaptic weight vector has become capable to respond spontaneously (delivering correctly coincident answer) to its environmental input vector (question) [5-6]. Accordingly, at next section the argument of selectivity functions is considered as the synaptic pattern vector (inside brain) is modified to post training status.

3.3 Selectivity Criteria applied for e-Learning

Referring to the above descriptive analysis for dependence of obtained achievement by e-learners on brain synaptic weight dynamics, one selectivity criterion is suggested to simulate adaptivity in e-learning performance, [3]. Therein, Kohonen's Self Organizing Maps (SOM) algorithm is presented for Clustering of Learner Profiles. It introduces a method in which NN modules can be easily integrated into the existing eLearning system. SOM is a variant of ANN competitive learning. In details as given at references [27-30], the basic idea of this method is in the arrangement of the neurons (nodes) into an x - dimensional array. A vector (weights of neuron) with the dimension of the original data space is assigned to each node. During the training of the map, not only the weights of the winner neuron are modified -- as in case of a simple competitive network, but also the weights of its neighbors in the original array. This process can be imagined as stretching the elastic net on the training data set. After training, the vectors assigned to the neighbors in the two-dimensional array are also neighbors in the input data space. Therefore, it results both the input data set quantization and its representation in a two- (or one-) dimensional map. Similarly, autonomous learning by interaction with environment has been suggested for selective optimal response (spontaneously), after receiving some input stimuli to an unsupervised ANN model [31].

Additionally some selective criteria are given at, [14]. In this section, a special attention is developed to modelling of grandmother selectivity criterion [32].This criterion is based on a simple sorting system constructed using a set of grandmother cells (neurons).The basic building block of this model is motivated by biological neuronal model shown in the above (Fig.1) with input synaptic pattern and output axonal signal. Referring to Fig.2 in below, analogy between biological versus artificial neurons is clarified. That implies, each neuron should be well trained in order to respond exactly (correctly) to one particular input synaptic pattern. In other words, each neuron has become able (after training) to recognize its own grandmother. Appling such models in real world, they have been characterized by two features. Firstly, a lot number of grandmother cells are required to implement such grandmother model. That is due to the fact each cell is dedicated to recognize only one pattern. Secondly, it is needed to train that simple sorting network possible grandmother pattern to obtain correct output response. Consequently, all synaptic weight values at this model have to be held up unchanged (fixed weights). Hence, it is inevitably required to either add new grandmother cell(s),to recognise additional new patterns or, to modify weights of one or more existing cells to recognise that new patters.
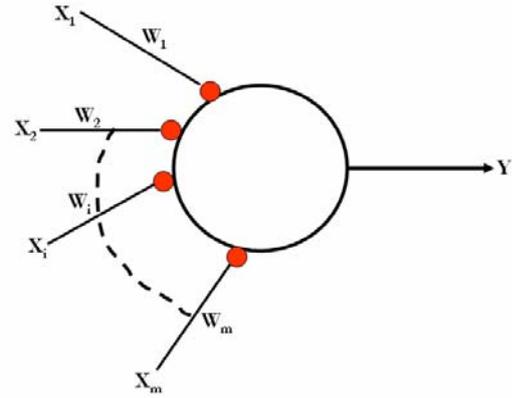

Fig.2 Illustrates a single grandmother cell (artificial neuron) that works as processing element

The above grandmother model could be described well by following mathematical formulation approach.
The output of any grandmother cell (neuron) is a quantizing function defined as follows:
It is worthy to note that selectivity condition considers a network model adopting artificial neurons with threshold (step) activation function as shown as a quantizing function defined as follows:

$$\phi(a) = \begin{cases} 0 & when \quad a < 0 \\ 1 & when \quad a \geq 1 \end{cases} \qquad (6)$$

Then the output y is represented by

$$y = \phi(U - \Theta) \qquad (7)$$

Where U is defined as

$$U = \sum_{i=1}^{m} w_i x_i \qquad (8)$$

4 A Generalized ANN Learning Model

This section presents a general block diagram for realistic modeling performance of e-learning processes. More precisely, herein an ANN is suggested to simulate performance of two face to face tutoring phases: supervised and self (unsupervised) learning. It is shown in below at Fig.2 a schematic block diagram of suggested ANN model. This model has been adopted to simulate realistically both diverse learning phases (paradigms) [26].More recently; this model has been adopted for investigational analysis of quantifying learning creativity using the two design parameters, [12]. (See Appendix I)
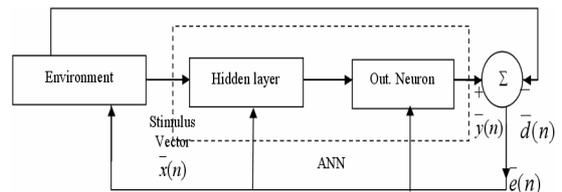

Fig.3 Block diagram for an ANN model adopted for quantifying creativity, adapted from [33].

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

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \qquad (9)$$

Where

$\overline{e}(n)$: Error correcting vector controlling learning adaptation process.

$\overline{y}(n)$: Output signal of the model.

$\overline{d}(n)$: Numeric value(s) of the desired /objective parameter of learning process (generally as a vector). By referring to Fig. 2, following four equations illustrate simplified synaptic weight dynamics of any learning process.

$$V_k(n)=X_j(n)\ W^T_{kj}(n) \tag{10}$$
$$y_k(n)=\varphi(V_k(n))=1/(1+e^{-\lambda v_k(n)}) \tag{11}$$
$$e_k(n)=|d_k(n)-y_k(n)| \tag{12}$$
$$W_{kj}(n+1)=W_{kj}(n)+\Delta W_{kj}(n) \tag{13}$$

Where: X input vector, W weight vector, φ is the activation function, y is the output, $e_k(n)$ the error value at the n th learning cycle , and d_k is the desired output. Noting that $\Delta W_{kj}(n)$ the dynamical change of synaptic weight vector value.

The above four equations (10, 11, 12, and 13) are commonly applied for two different e-learning phases. Namely: Field Dependent (FD) learner for supervised learning, and other Field Independent (FI) one for self-learning phase. Recently, both phases are realistically simulated considering supervised and unsupervised learning paradigms respectively,[17]. The dynamical changes of weight vector values specifically for FD phase (supervised paradigm) is given by equation:

$$\Delta W_{kj}(n)=\eta\ e_k(n)\ x_j(n) \tag{14}$$

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

However, for FI phase (unsupervised paradigm), dynamical changes of weight vector values is given by equation:

$$\Delta W_{kj}(n) =\eta\ y_k(n)\ x_j(n) \tag{15}$$

Hebbian learning and error correction algrithms are adopted for realistic simulation of both above mentioned leaning phases. Obtained simulation results are given at next two sections (fourth and fifth) in below.

4.1 Effect of Gain Factor On Learning Convergence Time
Referring to [8}, learning by coincidence detection is considered. Therein, angle between training weight vector and an input vector have to be detected. Additionally, by referring to [6], results of output learning processes considering Hebbian rule are following the equation:

$$y = \left(1-e^{-\lambda t}\right) \tag{16}$$

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

$$y(t) = \frac{1}{1+e^{-\lambda t}} \tag{17}$$

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

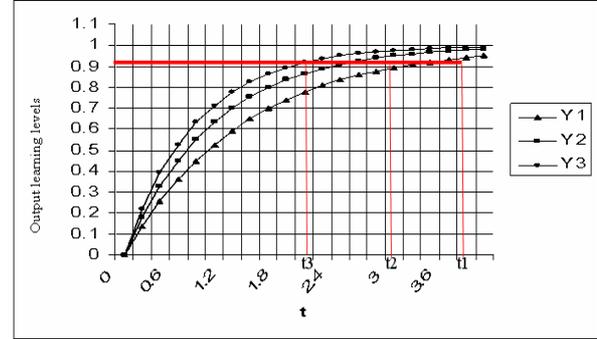$$y(t) = \frac{1-e^{-\lambda t}}{1+e^{-\lambda t}} \qquad \text{For } 0 \le t \le \infty \tag{18}$$

Fig.4 Illustrates three different learning performance curves Y1, Y2 and Y3 that converge at time t1, t2 and t3 considering different gain factors: $\lambda 3$, $\lambda 2$, $\lambda 1$.

At Fig. 4 , that adapted from [6],the three curves shown represent different individual levels of learning. Curve (Y2) is the equalized representation of both forgetting and learning factors [11],[20]. However curve (Y1) 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 (Y3) indicates better learning performance that exceeds the normal level of learning at curve (Y2). Consequently learning time convergence decreases as shown at Fig.4, (t1, t2, and t3) three different levels of learning performance curves representing: normal, low, and better cases shown at curves Y2, Y1, and Y3 respectively.

4.2 Improvement of Convergence Time by Gain Factor Increase [34]
The graphical results shown in below (at Fig.5); illustrate gain factor effect on improving the value of time response measured after learning process convergence, [34]. These four graphs at Fig.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,and3) cycles, (on approximate averages). Gain Factor Value (λ) and average response (learning convergence time) in reaching some desired output learning level.
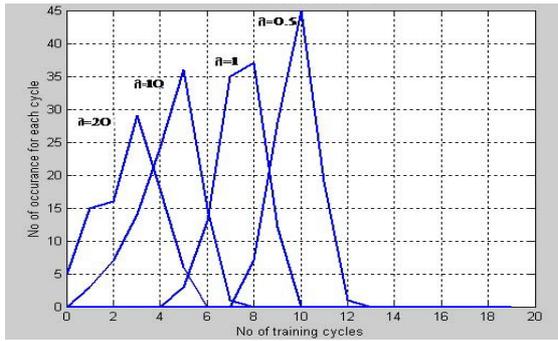
Fig. 5 Illustrates improvement of average response time (no. of training cycles) by increase of the gain factor values adapted from [34].
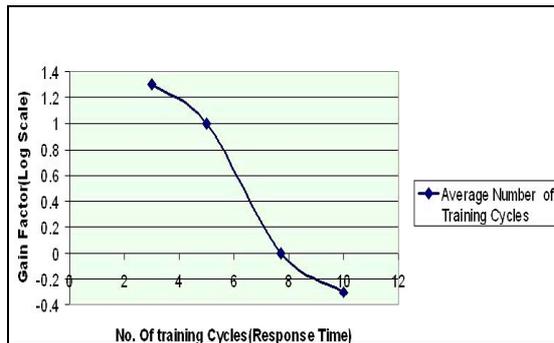

Fig. 6 Illustrates improvement of average response time (number of training cycles) by increase of average gain factor values (given in Log- scale description)

4.3 Improvement of Convergence Time By Learning Rate Increase [33]

At Fig.7 given in below simulation results illustrates measured values of convergence time considering two deferent learning rates (0, 1, and0.5). The statistical distributions in two cases are given at Fig.8.
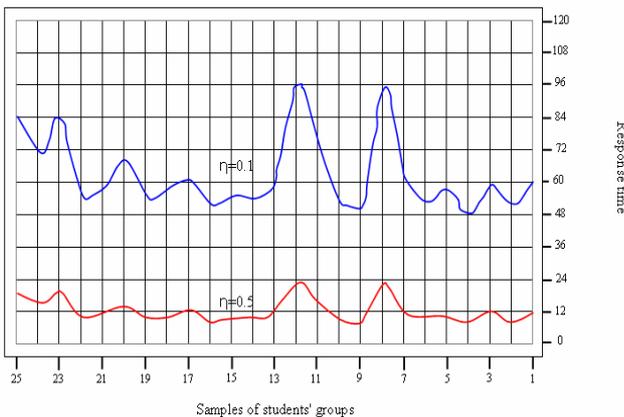

Fig. 7 Illustrates the effect of learning rate parameter on the learning response (convergence) time for two different values 0.1& 0.5 presented by upper and lower curves respectively, adapted from [24].
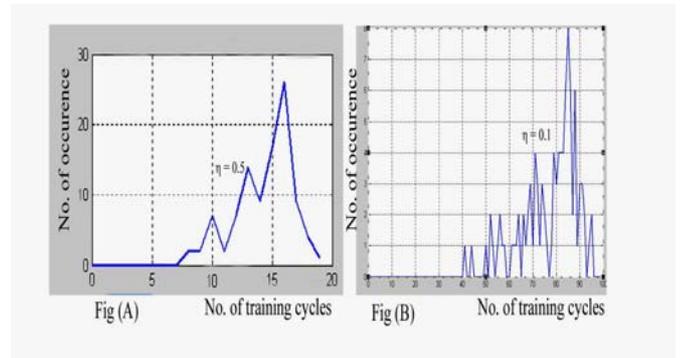

Fig. 8 Illustrates the statistical distribution for the relation between two values of learning rate parameter and learning response (convergence) time at Fig (A)&Fig(B) corresponding to two different values of learning rates 0.5& 0.1 shown at Fig.7 respectively.

4.4 Learning Rate Versus Learning Response Time

Simulation results for Learning Rate versus response time parameter are given in below at five illustrative figures (Fig.7 till Fig.9). All of these figures obtained after considering error correction learning paradigm (following equation (14) given in the above fifth section). The learning parameter associated with learning convergence time (response time) is given at Fig.9, considering 1000 students [2]. Its bell shape form seems similarly in agreement with Gaussian (Natural) distribution rather than other obtained results after only 100 virtual students shown in the above Fig. 7,Fig.8,and Fig.9. The statistical distribution of response time parameter is presented for four different learning rate values: (η =0.1, 0.2, 0.3, and 0.4).
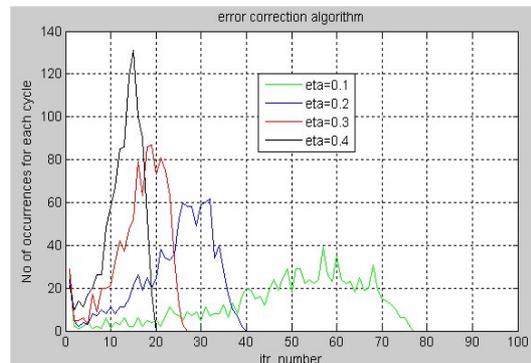

Fig. 7 Illustrates the statistical distribution of learning convergence time for different learning rate values eta, , adapted from [2]).

5. NUMBER OF CONTRIBUTING NEURONS' EFFECT ON E-LEARNING PERFORMANCE

The following simulation results are obtained after running of two computer programs designed by MATLAB VER.6. These results illustrated in below by two tables in addition to two graphical figures as follows.

Firstly, at Table 1, it is illustrated that by increase of number of neurons (# Neu.) contributing in e-learning process the convergence (response) time obtained is significantly decrease. However, e-learners who adopt self learning reach less convergence time rather than other depending upon his tutor (supervised learning). This table compares both e-learning phases given at [26], by two algorithms for error

correction (E.Corre.) and Hebbian learning, both are simulating dependant and self learning students respectively. Noting that running of computer program is carried out at learning rate = 0.1, and gain factor = 0.5 and training cycles. Table.2. Illustrates significant increase of e-learners achievement by increase of number of neurons (# Neu.) contributing in e-learning process the. However, e-learners who adopt self learning reach better achievement rather than other depending upon his tutor (supervised learning). This table compares both e-learning phases given at [26], by two algorithms for error correction (Error Corr.) and (Hebb rule). Both are simulating dependant and self learning phases respectively. These tabulated results are obtained for different Gain Factor values and fixed number of training cycles =500, learning rate value =0.05.

Table 1: Effect of increase of neurons' number on Learning Time Response (For error correction & Hebbian learning)

# Neu.	3	5	7	9	11	14
E.Corre.	79.7	61.8	36.9	19.8	14.8	7.31
Hebbian	56.5	36.7	19.5	10.7	6.72	3.89

Table 2: Effect of increase of neurons' number on Learning achievement (For error correction & Hebbian learning and different values of Gain Factor λ= 0.5, 1, 1.5)

# Neu.	Gain Factor λ =0.5		Gain Factor λ = 1		Gain Factor λ = 1.5	
	Hebb Rule	Error Corr.	Hebb Rule	Error Corr.	Hebb Rule	Error Corr.
2	18.2	19.2	35.5	35.9	50.3	49.3
3	25.7	25.8	48.5	47.8	63.4	62.8
4	30.7	31	56.6	56.1	74.5	71.5
5	36.8	36.7	62.5	62.9	79.9	78.5
6	43.5	43.7	73.1	72.1	87	86.7
7	50	49.7	79.7	77.8	92.1	90.9
8	55.3	53.9	84.2	83.4	94.5	93.3
9	63.3	62	90	87.9	96.6	95.9
10	65.6	64.8	91.3	89.3	97.4	96.8
11	70.9	69.6	93.6	92.4	98.3	97.8
12	76.1	74.6	95.9	94.9	98.8	98.5
13	77.9	76.7	96.5	95.3	98.8	98.7
14	79.2	77.8	97	96.2	98.9	98.8

Secondly, referring to Fig.10, and Fig.11 given in below, the obtained simulation results supports those illustrated in the above two tables (Table.1, and Table2). Interestingly, the changes of accuracy those measure learners' achievements are analogous to set of graphs shown at (APPENDIX I-Fig.1). Similarly, reaching minimum error by increase of number of neurons is analogous to increase of learning time shown at the same APPENDIX (Fig.2). Moreover, dynamics of synaptic connectivity due to increase of number of contributing neurons, is analogous to synergistic effect of intercommunications among number of agents (ants) at ACO [35],[36]. That is for reaching optimal solution of TSP cooperatively bases on behavioral learning performance , as shown at (APPENDIX I-Fig.3).
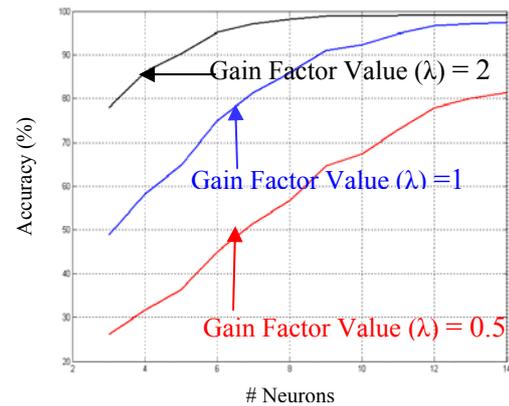

Fig. 10 Illustrate obtained learning achievement versus different gain factor values. (Considering #cycles = 300 and Learning rate = 0.3)
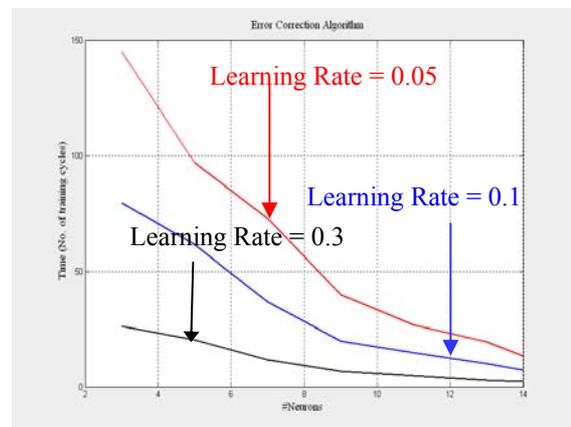

Fig. 11 illustrates the performance of error correction algorithm versus learning convergence time for different learning rate values.

6. CONCLUSIONS AND DISCUSSIONS

Through above adopted approach, obtained results are evaluated considering some other results for performance evaluation of some neural system models concerned with response (convergence) time of learning process. Conclusively, six interesting remarks related to enhancement of e-learning systems quality as follows:

1- Following previously suggested measuring approach of learning convergence/response time any e-learning system's quality could be quantitatively evaluated. So, experimental measurement of response time average values (quantified evaluation), provides educationalists with a fair and unbiased judgment for any e-learning system (considering a pre-assigned achievement level).

2- As consequence of above remark, relative quality comparison between two e-learning systems (on the bases of suggested metric measuring) is contributed by quantified performance evaluation.

3- Modification of learning systems performance obtained by increment of learning rate value, which is expressed by the ratio between achievement level (testing mark) and the response learning time. This implies that learning rate could be considered as a modifying parameter contributes to both

learning parameters (learning achievement level and learning convergence time response) [37], [38].

5- Simulation and modeling of complex educational issues such as deterioration of achievement levels due to: not good ordering of teaching curriculum simulated as input data vector to neural systems, in addition to not well prepared tutoring materials [16].

6- In future, more elaborate quantitative evaluation of interdisciplinary individual differences phenomena is expected .That is by incorporation of Nero-physiology, Psychology, and Cognitive sciences. That elaborate study urgently needed for modification of educational systems' processes [24], [39], [40]. It is carried out considering the effect of initial internal (intrinsic) brain status of learners as well as external environmental factors upon convergence of learning / training processes.

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APPENDIX I

MATHEMATICAL FORMULATION OF ANN DESIGN PARAMETERS

This appendix aims to formulate mathematically effective contributions of two specific ANN design parameters. So, it considers deferent values of gain factors, and learning rates presented by Greek letters (λ, η) respectively. Moreover, graphical presentations for suggested mathematical formulation contributed with different values of both parameters are shown at Fig.1, and Fig.2 given in below. Additionally, the effect of both design parameters is observed either implicitly or explicitly on dynamical synaptic plasticity illustrated at weigh dynamics equations [1]. Additionally, normalized behavior model considers the changes of communication levels (indicated by λ parameter). This parameter value causes changing of the speeds for reaching optimum solutions for Travelling Salesman Problem (TSP) using Ant colony System (ACS) [2],[3]. The following equation presents a set of curves changes in accordance with different gain factor values (λ).

$$y(n)= (1-\exp(-\lambda i(n-1)))/ (1+\exp(-\lambda i(n-1))) \qquad (1)$$

Where λi represents one of gain factors (slopes) of sigmoid function.

These curves represent a set of sigmoid functions to reach by time maximum achievement. Conversely , following formula where suggested (η_i). It presents a set of normalized decay (negative exponential curves) for different learning rate values given by as follows:
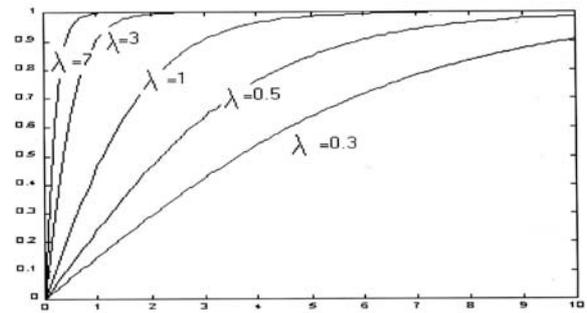
$$y(n)= \exp(-\eta_i(n-1)) \qquad (2)$$

Fig. 1 Graphical representation of learning performance of model with different gain factor values (λ) adapted from [2].

Where (n) is the number of training cycles. That set of curves is illustrated graphically at figure 8 given in blow. the examples given considering normalization of output response values.
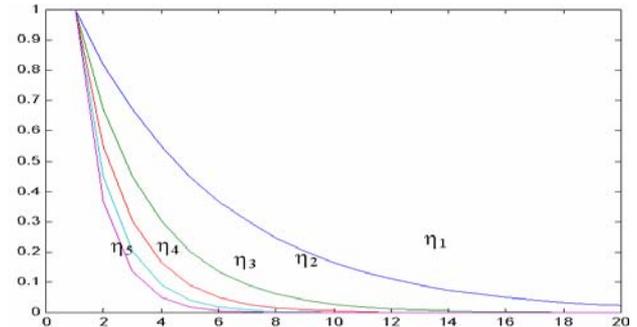

Fig. 2 Illustrates different learning performance curves for different learning rate values (η) , adapted from [1].
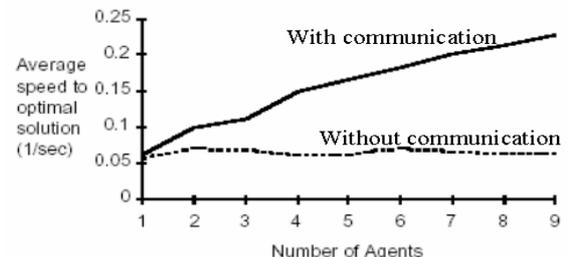

Fig.3 Illustrate performance of ACS with and without communication between ants, adapted from [3].

Interestingly, referring to above Fig.1, and Fig.2 both are analogous to Fig.10 and Fig.11 respectively . Also, it is noticed better synaptic connectivity dynamics resulting in improving of learning systems' performance due to increase of both values (λ , η). Moreover, dynamics of synaptic connectivity among neurons is analogous to synergistic effect observed by Ant colony intercommunications among number of agents (ants), for reaching TSP optimization as shown at Fig.3.

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