



On analysis and evaluation of natural inspired computational models for open learning systems

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ABSTRACT

Nature Inspired Computation defined as a computational intelligence paradigm inspired from natural biological systems (such as human brain and neural systems, Genetic Algorithms; Bees and Ants Colonies Optimization, etc.....). Recently, this paradigm has been successfully applied for solving computational optimization problems, in many fields (such as, machine learning, and engineering design, etc.....). Moreover, by considering its unique computational intelligence characters of self-adaptive, self-organizing and self-learning. It is relevant to adopt its application for modeling and performance evaluation of educational Systems. Herein, the presented work motivated by recent research publications inspired by two interdisciplinary computational intelligence Models. Both have been characterized by challenged bridging of two Natural inspired Models across an interesting practical educational issue. More specifically, this piece of research concerned with the theoretical analysis and evaluation of constructive bridges of Artificial Neural Networks (ANN^s) & Ant Colony Systems (ACS) across Open Learning Systems. Noting that motivating research publications include the following two topics:

- 1-Assessment of students' adaptability using ANN^s models (Cognitive Styles Approach).
- 2-Modeling of Cooperative e-Learning Performance (ACS Approach).

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1. Introduction

The field of the learning sciences is represented by a growing community internationally. Many experts now recognize that conventional ways of conceiving knowledge, educational systems and technology-mediated learning are facing increasing challenging issues in this time of rapid technological and social changes. Furthermore, due to recently excessive progress in information and computer technologies applied at the field of the learning sciences, some complex interdisciplinary educational issues arise in practice. More recently, the adopted educational issue at this work has been presented as a special tutorial session [1].

Herein, this piece of research presents specifically an overview of two recently published work inspired by computational intelligence models. Both have been characterized by challenged bridging of two Natural inspired Models {Artificial Neural Networks (ANN^s) & Ant Colony Systems (ACS)} across an interesting practical educational issue (Open Learning) [2][3]. Accordingly, this paper is organized by dividing into two main parts as follows. The first part, concerned with application of ANN^s models for assessment of students' adaptability considering their individual diverse Cognitive Styles. Additionally, the second part presents mathematical modelling of ACS optimization for evaluation of Cooperative e-Learning (equivalently Open Learning) performance during face to face tutoring sessions. For more details about the organization of both paper's main parts, the following next section is specifically dedicated. It is worthy to note that work presents an open interdisciplinary research approach to model and evaluate realistically observations concerned with open learning phenomenon. Finally, some valuable conclusive remarks and

suggestions for future research work have been presented at the end of this paper.

Paper Organization

In brief, this paper is divided into two main parts. Their organizations are introduced as follows:

1. The first part

A brief summary of this part is given at the paper's 3rd section. At the 4th section, a general adaptability model in e-learning system is presented. A description of Neural Network Model for Adaptability is given at the fifth section. At the 6th section, after running of adaptability simulation programs, assessments of obtained results are shown in details.

2- The second part

At the paper's 7th section, a brief summary of the second part is presented. Performance of one type of Ant Colony System (that formerly called *Leptothorax albipennis*) is given at the 8th section. That's based on learning / teaching technique known as tandem running. At the 9th section, mathematical formulation of cooperative learning performance considering the (Follower/Leader) as teacher and pupil guided-error correction algorithm is introduced, in addition to its association to both supervised and unsupervised ANN^s learning paradigms.

Finally, at the last 10th section some valuable conclusive remarks and suggestions for future research work have been presented.

Summary (Part I)

This part of research work adopts an innovative trend concerned with assessment of learners' adaptability at Open Learning Systems (OLS). Courses presented via OLS are a new revolutionary approach of providing educational process. Even traditional institutions are increasingly incorporating the Internet e-learning online interaction means and software tools into their

programs [4]. Consequently, assessment of learners' adaptability in e-learning systems is an interdisciplinary recent issue motivated by researchers at the fields of education, cognitive science, and psychology. So, it is a rather critical and challenging issue concerned with realistic behavioral brain modeling. Also, it is associated with learners' ability to match their learning styles with instructor's teaching style and/or e-courses material. This part adopts an investigational approach dealing with e-learning systems' adaptability considering learners' cognitive styles. So, by using ANN^S modeling, a novel realistic simulation is presented herein for learning adaptability phenomena taking into consideration learners' diverse performance with different cognitive styles. At educational field practice, both learners' styles are called as Field Dependant (FD), and Field Independent (FI) cognitive styles [5][6]. Briefly, adopted approach herein, is a mapping of interactive e-learners' cognitive styles with adaptable e-learning systems into realistic domain to ANN modeling. Conclusively, investigational objectives of this work are fulfilled using two different learning paradigms inspired from ANN models to simulate relevantly learners' cognitive types [5]. In more details, the FD cognitive style is simulated as error back propagation learning rule as one type of supervised learning paradigm[7]. However, to simulate other FI cognitive style, Hebbian learning rule is adopted as one of unsupervised learning paradigms [7]. Interestingly, obtained results shown to be agree well with results obtained by practical educational experimental work [8].

Finally, it is worthy to note that presented approach opens more elaborate interdisciplinary research area for realistic evaluation of observed educational phenomena. That's concerned with adaptation of educational systems considering individual deference of learners' cognitive styles, as well as their cooperative learning performance.

General Adaptability Model

In general, the adaptation in systems is classified as either adaptable systems or adaptive systems [9]. Adaptable systems allow the user to change certain parameters and adapt the systems' behavior accordingly. On contradictory, adaptive systems adapt to the users automatically based on the system's assumptions about the users' needs [10]. Herein, assessment of adaptable e-learning systems is considered. Such systems facilitate learners to change their own specific parameters individually. These changes needed to be adaptable with instructional teaching styles (system inputs). Practically, at educational field, adaptable instructional methodologies are varying much. Such methodologies' variations range from either oral lectures presentation, demonstrations, focusing on principles or emphasizing on memory [11]. Herein, all of instructional methodologies assumed to be virtually in correspondence with various values of learning rate factor. Matching between instructional teaching styles and learners' preferred learning style increased comfort level and willingness to learn, which provides practice and feedback in ways of thinking and solving problems [11]. In most of OLS, all learners are capable to control accessing of some E-course materials in accordance with their own learning objective(s). In other words, such controlled accessibility is attained through fixable navigation via e-learning system's materials available to all of e-learners (students). Generally, individual learners adopt preferable learning strategy. An individual's collective strategies for learning are his or her "learning style." A learning style includes strategies for cognitive (mental), affective (emotional),

social (interpersonal and cultural), and physiological (physical) components of learning [12].

This piece of research concerned mainly with two e-learners' diverse cognitive styles, while interacting with their tutors besides e-course learning materials. By more details, in practical educational field; performing of learning process essentially supported by two e-learners' multimedia brain functions. Both functions are required to perform efficiently learning/teaching interactive process as follows. Firstly, pattern classification function for e-course material given through (visual / audible) interactive signals. Referring to ANN^S point of view, that function originated for signals' perception, essentially needs supervisor's (tutor's) intervention (face to face interactive tutoring) to converge learning process [13]. Secondly, associative memory function which is originally based on classical conditioning motivated by Hebbian learning rule. It belongs to the principle of learning without a teacher (unsupervised) [7].

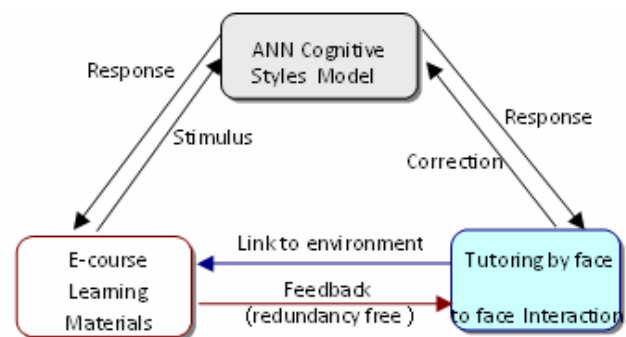


Figure 1: A general adaptability model for e-learning system with diverse cognitive learners' styles

In other words, from educational point of view, e-learning processes could be performed well either via interaction with a teacher (face to face learning) or by applying computer aided learning (interactive visual/audible) software [13][14][15].

At Figure 1, a qualified teaching/learning adaptability model is illustrated to perform realistic simulation of above mentioned adaptable brain functions, (referred to next section). Inputs to neural network cognitive style model are provided by environmental stimuli (supervised E-course learning material). The correction signal for the case of learning with a teacher is given by responses outputs of the model will be evaluated by either the environmental conditions (unsupervised learning) or by the teacher. Finally, the teacher plays a role in improving the input data (stimulating the learning) by reducing noise and redundancy of the model input. That is according to the teacher's experience, he provides the model with clear data with maximum signal to noise ratio. However, that is not our case which is based upon unsupervised Hebbian self-organized (autonomous) learning.

Neural Network Model of Adaptability

Diverse cognitive styles are classified into either field dependent (FD) or field independent (FI) cognitive style [5]. The shown model at Figure2 presents adaptability of FD cognitive style is considered. Error correction learning rule is adopted to simulate learner's adaptability towards coincidence with instructional environment. In other words, this coincidence state implies the occurrence of matching between students' learning style preferences and the instructor's teaching style. Furthermore, presented ANN model in below gives attention to simulate of student's personality indicator that influences his/her

way of adaptable learning after Myers-Briggs Type Indicator (MBTI) [16]. This MBTI based on Jung's theory of psychological types [18].

It has been recently adopted for learning style analysis and evaluation in engineering education [18]. Therein, based on (MBTI), simulation of students' individual characteristics are given by (extroversion/introversion). An extrovert attitude represents interaction with learning environment is relevantly simulated by learning rate. Whereas learner's introvert's preferred focus is on his/her own thoughts and ideas (Intrinsic neuronal weight parameters).

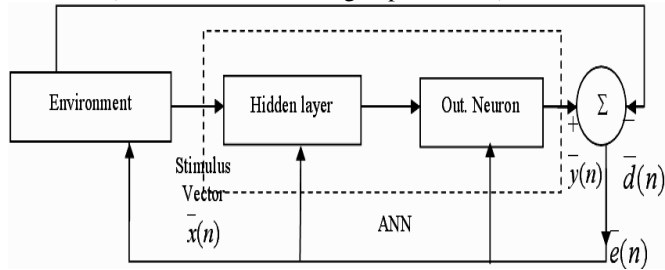


Figure 2: Block diagram of adaptability Model for FD cognitive style.

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

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

Where

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

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

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

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

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

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

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

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

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

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

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

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

Where X is input vector, W is the adaptable weight vector, φ is an odd sigmoid (activation) function characterized by λ as gain factor and Y as its output, e_k is the error value, and d_k is the

desired output. Noting that $\Delta W_{kj}(n)$ is the dynamical change of adaptable weight vector value connecting the k^{th} and j^{th} neurons. Equations (2,3,4,and 5) are commonly applied for both FD and FI cognitive styles.

Simulation Results

The obtained simulation results are depicted as four sets of graphs shown in below , at the four Figures (3, 4 , 5 , and 6) described as follows:

1- The two sets of graphs shown in Figure 3 and Figure 4 are following the above two equations (6),(7) respectively. Both represent graphical simulation results obtained after running a computer program model. Noting that learning environment is considered as input vector having the same dimension as learners' self-intrinsic weight vector. Furthermore, it represents one of the teaching methodologies (corresponding to learning rate value). That is selected to measure behaviors of FD, and FI learners' cognitive styles. Additionally, both sets of obtained graphical results(at Figure. 3 and Figure. 4) simulate realistically students' behavioral learning by increasing number of neurons(dimension of weight vector) contributing to adaptability dynamics. These results presented for both cognitive style FD, and FI are corresponding to error correction and Hebbian learning paradigms, respectively.

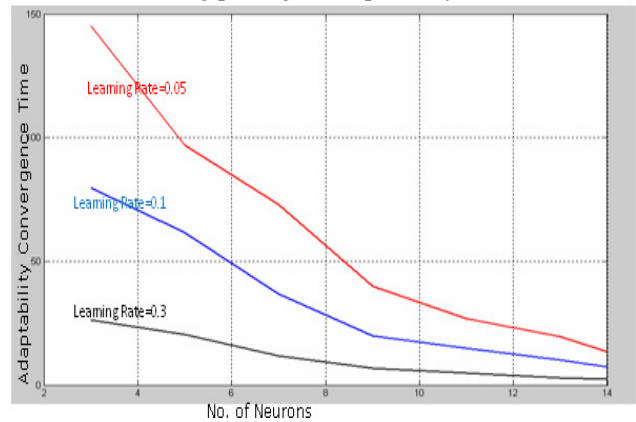


Figure 3: Adaptability convergence time considering FD learners' cognitive style for three different teaching methodologies corresponding to three learning rates

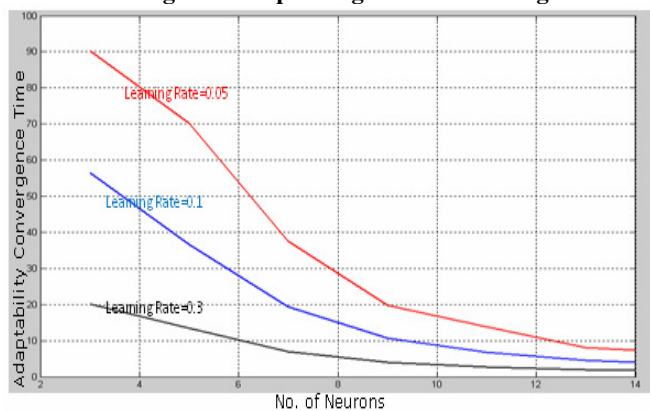


Figure 4: Adaptability convergence time considering FI learners' cognitive style for three different teaching methodologies corresponding to three learning rates.

2- By referring to the set of graphs shown at Figure 5 & Figure 6, some interesting interpretations concerned with quantifying learning adaptability are investigated. The nearness of learners' styles towards the instructor's style vector measured on the abscissa (with 90 %). However on the ordinate axis, it is

shown frequency of occurrence (probability) for various matching values.

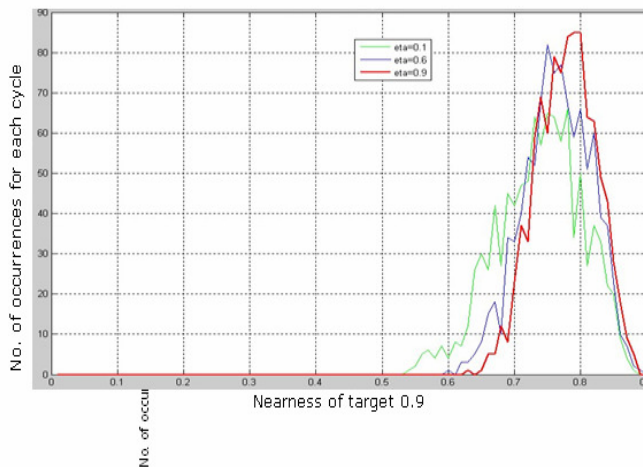


Figure 5: Statistical distribution of adaptability matching individual learners' differences with FD cognitive style after running of computer program

Briefly, referring to Figure 5, value by improvement of learning rate factor -for FD cognitive styles- results in very slightly increase in average matching value which measures quantitatively learning adaptability. Conversely, referring to Figure 6, improvement of learning rate factor -for FI cognitive styles- results in well observed increase in average measured adaptability matching values.

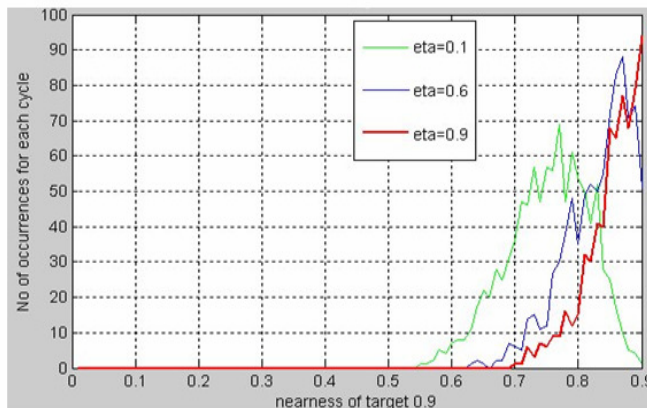


Figure 6: Statistical distribution of adaptability matching individual learners' differences with FI cognitive style after running of computer program

Summary (PartII)

In face to face tutoring , the phase of interactive cooperative learning is an essential paradigm aiming to improve any of Open Learning Systems' performance. In some details, it has been recently, declared that cooperative interactive learning among studying agents fellows (learners), contributes about one fourth of learning achievement (output) attained at face to face tutoring sessions [13]. The presented work develops educationalists' special attention towards addressing of learning convergence speed considering metric time measurement (as one of main learning parameters). Referring to realistic Ant Colony System (ACS) approach, that time measurement equivalently considered as natural analogy to learning response time. That's in fulfillment of a pre-assigned learning output level observed practically -at educational field- to be attained after time period defined as learning response time. Herein, cooperative

interaction among e-learning agents (students) adopted for realistic analogical modeling in accordance with ACS agents (ants) behavior. Consequently, by referring to cooperative tutoring sessions and on the bases optimal solution of Traveling Sales-man Problem (TSP) reached by (ACS), cooperative learning process is mathematically modeled. It is noticed that optimal solution of TSP obtained-by some speed- with dependence upon different values of inter-communication levels among ACS agents (ants) . So, consecutive steps performed by Open Learning Systems analogously accumulate cooperative learning function as that happens at ACS with and without communication[19-21]. Adopted mathematical model herein is well supported by some recently published papers. Such as that deals with Biological Information Processing Mechanism in Neural and Non-Neural Bio-Systems [22]. And others associated with comparative study of behavioral learning in human versus some non-human creatures[22-26]. Moreover, presented model inspired by interesting analogy shown between cooperative ACS performance(ants), and cooperative behavioral learning among number of place field neuronal cells(at hippocampus rat's brain area), for solving reconstruction problem [26-29]. This rat's behavioral learning model illustrated the effect of increasing number of neuronal cells upon better performance in reaching more accurate result when solving pattern recognition problem. In other words, results for interesting comparative analogy between two distinct types of computational intelligence agents illustrated the effect of increasing number of agents (either neuronal cells or ants), on cooperative learning performance. Finally, suggested mathematical model proved to perform realistically natural as that expected for mutual cooperative learning interaction among learning agents. Objectively, presented comparative study may results in optimal improvement of Open Learning performance.

Leptothorax Albipennis Performance

A specific type of ant colony systems formerly called *Leptothorax albipennis* performs a paradigmatic decentralized decision-making based on learning/teaching technique known as tandem running. Briefly, this type of ACS adopts (tandem running technique) and performs its behavioral learning function sequentially (in stepwise) as follows. In case of one ant running to lead another ant moving from the nest to food, both leader and follower (teacher and pupil) are acutely adaptive sensitively to the progress of their partner. To the best of our knowledge; agents of *Leptothorax albipennis* ACS perform a creative inter-communication technique among ants. That's involves teaching by interactive feedback between two ants controlling trade-off between speed and accuracy [24][26][30]. Its individual agents (ants) adopt tandem running which is an intelligent behavioral teaching technique [30]. Colonies of that ant type have been shown flexibly to compromise accuracy for speed. Briefly, in case of one ant running to lead another ant moving from the nest to food, both leader and follower are analogous to teacher and pupil. Both are acutely sensitively adaptive to progressing of their partner. This learning technique involves teaching by interactive feedback between two ants controlling trade-off between speed and accuracy[31].

Tandem running technique

Referring to Figure 7, it illustrates schematically the learning paradigm inspires from tandem running technique. This technique involves interactive bidirectional feedback between teacher and pupil corresponding to leader and follower ants respectively. Furthermore, at this figure, depicted block named

as (Follower/Leader) suggests that tandem followers after learning their lessons so well, that they often become tandem leaders [30][31].

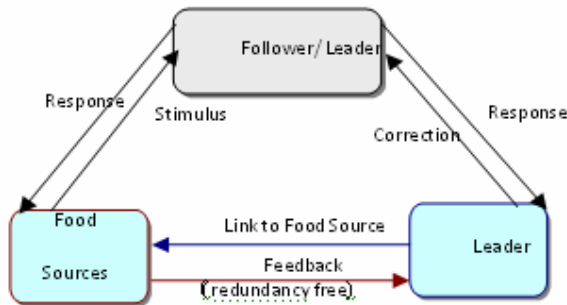


Figure 7: Illustrates a schematic diagram for tandem running technique involves bidirectional feedback.

In cooperative learning context, the above type of ACS behavioral learning performance [31][32] is analogous to what could be observed in classrooms; if one agent (student) behaves independently upon other agents' achievements [33]. So, it described as teacher-centered providing Individual learning which implies that leader ant (teacher) can transfer knowledge and cognitive skill to the learner (another ant) [33][34]. Accordingly, via that teacher-centered type of learning the teacher provides the major source of information, and feedback [22]. Conclusively, ANN models based on supervised learning paradigm are relevant for realistic simulation of cooperative teacher-centered learning performance [20][21].

Performance of ACS optimization

Following ANT-density algorithm, the Ant Colony of type (Leptothorax albipennis), is capable of solving TSP optimally. That solution is given by simulation results shown therein, at [35]. Therein, it is shown that efficiency per ant (required to reach optimal TSP solution), is well improved as number of ants increase. Furthermore, it could be observed that number of trials increase at Thorndike's psycho-learning experimental model, is analogous to number of ants at ANT-density algorithm [26]. Finally, the presented model seems to take into account the mixed learning paradigms in accordance with the performed functions either at the level of Follower/Leader or at the global ACS agents to perform main objective foraging function. At the bidirectional feedback between teacher and pupil respectively corresponding to leader and follower ants, error correction (supervised) learning with a teacher (at ANN^s paradigm) is considered [7][35][36]. However, learning by interaction with environmental conditions is considered for performing main ACS foraging function[35][37].

Mathematical Formulation Of Cooperative Learning Performance

The following two subsections (A&B) illustrate conclusively the mathematical formulation of cooperative learning performance. That's by referring to ANN models' analogy, considering both supervised and unsupervised learning paradigms. By some details, presented Figure 6. illustrates set of performance curves of ANN model after running program (unsupervised learning). However, Figure 9 presents set of curves after running program (supervised learning). Both figure considered for different number of agents (neurons), different gain factor values, and different learning rate values. The mathematical formulation given by equations (8)&(9) are described generally by set of curves given at Figure 9 and Figure 12, respectively. Conclusively, presented mathematical

formulation model proved to perform as realistically natural as expected performance for mutual cooperative learning among interactive learning agents (either neuronal cells or ants).

A. Generalized Model Of Learning Performance Curves (Learning Achievement Measurement)

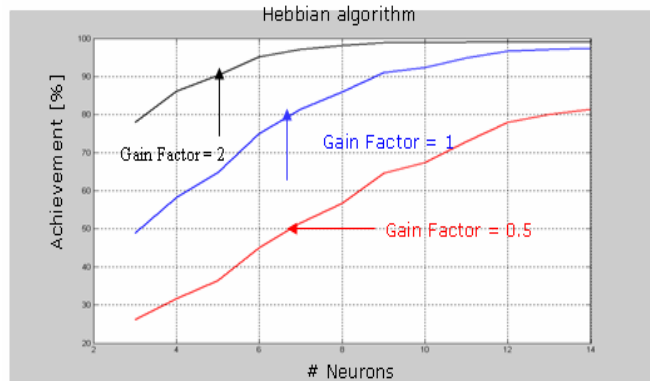


Figure 8: Learning performance to get accurate solution with different gain factors 0.05, 1, and 2, while #cycles = 300 and Learning Rate = 0.3

Referring to the normalized behavioral model of ACS (Optimization Algorithm), adopted for solving TSP [23]. Therein, considered changes of communication levels (indicated by λ parameter). The value of this parameter causes directly the speed changes for reaching optimal solutions following the mathematical formula:

$$y(n) = (1 - \exp(-\lambda_i(n-1))) / (1 + \exp(-\lambda_i(n-1))) \tag{8}$$

where λ_i represents one of gain factors (slopes) for sigmoid function.

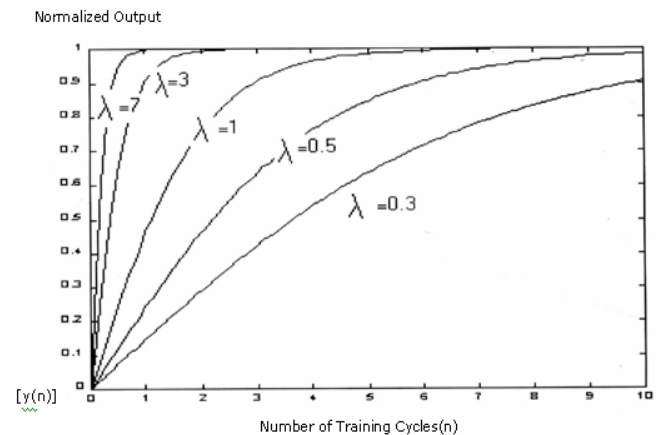


Figure 9: Graphical representation of learning performance of model with different gain factor values (λ) adapted from[23].

B. Generalized Model Of Learning Performance Curves (Error-rate measurement)

In agreement with all of the set of curves shown at three figures (10,11, and 12), they are all with close similarity to exponentially decayed performance curves. A normalized abstract set of decayed exponential curves are given at Figure 12. That's following the mathematical formula where suggested (η_i) to be defined as a value learning rate factor. The set of various learning rate factor values are denoted by (η_i). These factor values are mathematically presented after normalization of different learning performance curves (at Figure 10) as follows:

$$y(n) = \exp(-\eta_i(n-1)) \tag{9}$$

where (n) is the number of training cycles.

Referring to Figures (10 & 11), the effect of gain factor as well as learning rate changes on cooperative learning performance is introduced graphically. It is very interesting to note that analysis of introduced effect is supported well by the exponentially decayed graphs described by equation (9) and illustrated by set of curves at Figure 12.

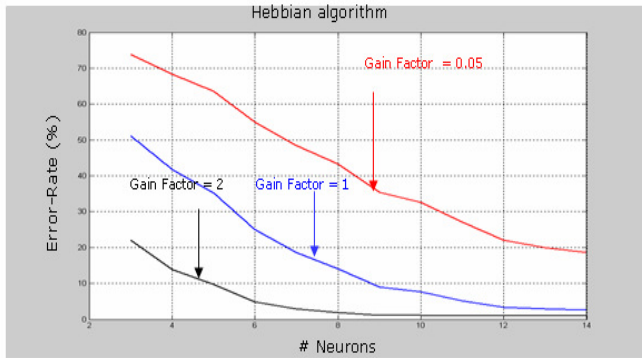


Figure 10: Hebbian learning performance error-rate with different gain factors : 0.05, 1, and 2, while #cycles = 300 and Learning Rate = 0.3.

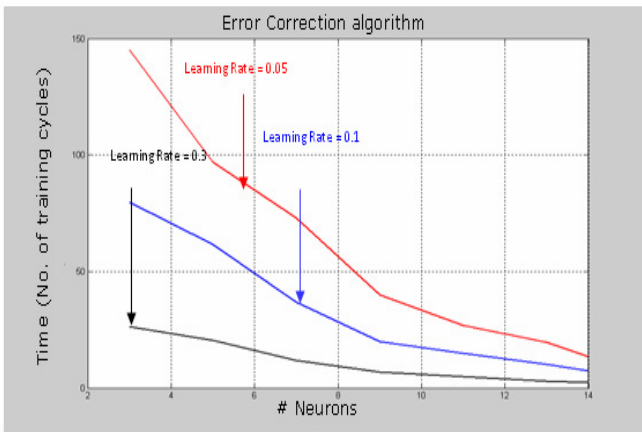


Figure 11: Error correction performance based on time response parameter with considering three different learning rates: 0.05, 0.1, and 0.3 for gain factor = 0.5, while #cycles = 300.

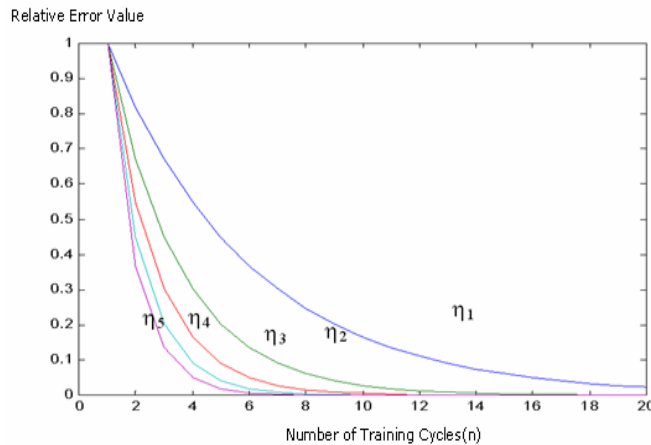


Figure 12: Different learning performance curves for different learning rate factor values (η_i) adapted from [38]

Conclusions and Discussions

Six interesting and valuable conclusive remarks are given as follows:

1-Analysis and evaluation of adaptability in e-learning systems is an interesting interdisciplinary issue motivated at the fields of education, cognitive science, and psychology. It is a rather critical and challenging concerned mainly with e-learners' brain function resulting in ability to match their preference learning styles with instructor's teaching styles (e-courses material).

2-An extension of presented work, more elaborate assessment is urgently needed for learning adaptability as well as adaptivity phenomena at OLS. That mainly aims is that to investigate mystery of brain adaptation observed at educational field. Which possibly carried out by considering the effect of either dynamical changing of learners' internal weights of brain status via ANN modeling (self-intrinsic gain factor of Sigmoid function), or external learning environment (instructor's teaching style) via different learning rate values.

3-Future research work has to consider other observed learning phenomena. Such phenomena would have subjected to investigational analysis and evaluations. One of very recently considered learning phenomenon which based on cognitive psychology and neuroscience That's considerate computing applied to modify learning systems. These systems have to monitor interruption phenomena carried out by students following computer screen (VDU) activities [39].

4-The existence of an obstacle at some point of ants' pathway is analogous to noisy data applied when training some artificial neural model[39]. In accordance with the asymmetry degree of obstacles' shape, signal to noise ratio is inversely proportional. Consequently, the time needed to find the shorter pathway (analogous to cooperative learning convergence) is directly proportional to degree of obstacle asymmetry [40][41].

5-The stored experience during Hebbian learning process, and computational intelligence of ACS are both analogues to the needed CPU time in order to develop minimum error for reaching optimum learning achievement[22][42][43].

6- Generally, realistic simulation of learning processes th based on brain performance have been presented recently via mental stimulation of brains' synapses and neurons [44].

6-Finally, presented analysis and evaluation herein -based on suggested mathematical modelling- may shed light on promising enhancement of cooperative learning performance. That's by considering obtained interesting resemblance of cooperative learning phenomenon (foraging process), with unsupervised (Hebbian) learning rule, (presented by equation (7)). However, supervised ANN learning model simulates realistically the (Follower/Leader) performance considered as teacher and pupil guided-error correction algorithm (presented by equation(6)).

Reference

[1] Mustafa, H.M, " A tutorial Lecture On: Building Up Bridges For Natural Inspired Computational Models Across Behavioral Brain Functional Phenomena ; And Open Learning Systems" Presented at the International Conference on Digital Information and Communication Technology and its Applications [DICTAP2011] held on June 21-23, 2011, University of Bourgogne, Dejon France.
 [2] Mustafa, H.M, et. al. "On Quantifying of Learning Creativity Through Simulation and Modeling of Swarm Intelligence and Neural Networks" to be published at IEEE EDUCON 2011, on Education Engineering – Learning

Environments and Ecosystems in Engineering Education , held on April 4 - 6, 2011, Amman, Jordan.

- [3] Mustafa, H.M, et. al. "On Mathematical Modeling of Cooperative E-Learning Performance During Face to Face Tutoring Sessions (Ant Colony System Approach)" to be published at IEEE EDUCON 2011, on Education Engineering – Learning Environments and Ecosystems in Engineering Education , held on April 4 - 6, 2011, Amman, Jordan.
- [4] Khodamoradi, S., and Abedi, M. "Online Classes VS Traditional Classes: Comparison between the Two Methods". *Journal of American Science* 2011;7(4):307-314]. (ISSN: 1545-1003). <http://www.americanscience.org>.
- [5] H.M. Hassan "Statistical Analysis of Individual Differences in Learning/Teaching Phenomenon Using Artificial Neural Networks Modeling." (With a Case Study(Published at ICCS 2005(14-15 Dec.2005).
- [6] Best, J. *Cognitive Psychology*, No Y.: West Publishing, 1986.
- [7] Haykin S., *Neural Networks*, Englewood Cliffs, NJ: Prentice-Hall, 1999, pp. 50-60.
- [8] Yosry El-Gamal & Abdel Hamid El-Maghrabi: *Learner Control in Computer Assisted Instruction*, The First International Conference on Computer and Advanced Technologies in Education, Cairo, March 1996
- [9] Oppermann, R. (1994). Introduction. In R. Oppermann (Ed.), *Adaptive User Support*. Hillsdale, New Jersey, Lawrence Erlbaum Associates, pp. 1-13.
- [10] Oppermann, R., Rashev, R., and Kinshuk. (1997). *Adaptability and Adaptivity in Learning Systems*. In A. Behrooz (Ed.), *Proceedings of the International Conference on Knowledge Transfer*. London, Pace, Vol. 2, pp. 173-179.
- [11] Sabine Graf, "Adaptivity in Learning Management Systems Focusing on Learning Styles" PhD Thesis , Submitted to the Vienna University of Technology Faculty of Informatics by Vienna, December 2007.
- [12] Keefe, J.W. (1987) *Learning style theory and practice*. Reston, VA: National Association of Secondary School Principals.
- [13] H. Al-Ajrourh, " Associate Manual for Learners' Support in Face to Face Tuition" Arab Open University (KSA),May 2004 .
- [14] Mustafa H.M., Ayoub Al-Hamadi, "On Teaching Quality Improvement of A Mathematical Topic Using Artificial Neural Networks Modeling" (With A Case Study)",to be published at 10th (Anniversary!) International Conference Models in Developing Mathematics Education” held in Dresden, Saxony, Germany on September 11-17, 2009.
- [15] Mustafa , H.M. , Al-Hamadi ,A., and Kortam , M. H.(2010) "On Assessment of Teaching A Mathematical Topic Using Neural Networks Models (with a case study) ", to be published at conference proceeding of Technology and its Integration into Mathematics Education Time 2010 , held in Malaga , Spain , on July 6th-10th, 2010. Furthermore this work is recently published at the *Journal of COMPUTER SCIENCE AND APPLICATION*, VOL. 1, NO. 2, FEBRUARY, 2012, pp. 12-19.
- [16] Myers, I. B., and McCaulley, M. H. (1998). *Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator*. Consulting Psychologists Press, PaloAlto, CA.
- [17] Jung, C. (1923). *Psychological Types*. Pantheon Books, London.
- [18] H.M. Mustafa , T. F. Al-Somani , A.A. Khedr "On Analysis and Evaluation of Students' Grade Point Average in Engineering Education Considering a specified Learning Style Model Using Neural Networks (with a case study)" published at the proceeding of the International conference on Interactive Computer aided Learning ICL 2010 held in Hasselt, Belgium , on September 15 – 17, 2010. (<http://www.icl-conference.org>)
- [19] Marco Dorigo , and Luca Maria Gambardella "Ant Colony System:A Cooperative Learning Approach to the Traveling Salesman Problem" published at the IEEE Transactions on Evolutionary Computation, Vol.1, No.1, 1997.
- [20] Dorigo, M. et al., *Ant colonies for the traveling salesman problem*, A set of papers at a web site: <http://www.iritia.ulb.ac.be/dorigo/aco/aco.html> ,1997.
- [21] Eric Bonabeau, and Guy Theraulaz, "Swarm Smarts" *Majallat Aloloom*, May 2001, vol 17, No 5, pp 4-12.
- [22] H.M. Hassan "On Principles of Biological Information Processing Concerned with Learning Convergence Mechanism in Neural and Non-Neural Bio-Systems." Published at IEEE conference, CIMCA 2005 , 28-30 Nov.2005 , Vienna, Austria.
- [23] H. M. Hassan "On Learning Performance Evaluation for Some Psycho-Learning Experimental Work versus an Optimal Swarm Intelligent System." Published at IEEE Symposium on Signal Processing and Information Technology ISSPIT, on 18-20 Dec.2005.Athens , Greece.
- [24] H.M.Hassan,"A Comparative Analogy Between Swarm Smarts Intelligence and Neural Network Systems.", published at WSSEC08 conference held on 18-22 August 2008, Derry, Northern Ireland.
- [25] H.M.Hassan,"On Analysis of Quantifying Learning Creativity Phenomenon Considering Brain Synaptic Plasticity", published at WSSEC08 conference held on 18-22 August 2008, Derry, Northern Ireland.
- [26] H.M.Hassan,"A Comparative Analogy of Quantified Learning Creativity in Humans Versus Behavioral Learning Performance in Animals: Cats, Dogs, Ants, and Rats.(A Conceptual Overview), published at WSSEC08 conference held on 18-22 August 2008, Derry, Northern Ireland.
- [27] Sejnowski, T.J: "Neural pulse coding" foreword article for (Pulsed neural networks), MIT press, 1999, pp 13-23,1999.
- [28] Zhang et al. Interpreting neuronal population activity by reconstruction." *Journal of Neurophysiology*, 79:1017-44, 1998.
- [29] Wilson, M. A. and McNaughton, B. L., 1993: Dynamics of the hippocampal ensemble code for space. *Science*, 261: 1055-8.
- [30] Recharadson T.,Franks N.R. "Teaching in tandem-running ants", *Nature*, Jan 2006,12;439(7073):153.
- [31] Marshall JA, Dornhaus A, Franks NR, Kovacs T."Noise, cost and speed-accuracy trade-offs: decision-making in a decentralized system" *J R Soc Interface*. Royal Society Publishing ,2006 Apr 22;3(7):243-54.
- [32] Simon Garnier, Jacques Gautrais, and Guy Theraulaz" The biological principles of swarm intelligence "Swarm Intelligence *Journal* Volume 1, Number 1 / June, 2007 pp.3-31
- [33] Johnson D, Johnson R. (1991) *Learning Together and Alone* ed3.;Allyn & Bacon, Sydney , pp.2.
- [34] PLSB, Professional Learning Services Branch, 1999, *Five Basic Elements of Cooperative Learning* [Online access14/6/02] URL: <http://web.ec.tased.edu.au/las/sose/fiveelem.htm>
- [35] Alberto C., et al., 1991: *Distributed optimization by ant colonies*. Proceeding of ECAL91, Elsevier Publishing , pp 134-142.
- [36] Salomon, g. Perkins, D. Theroux, P, 2001 *Comparing Traditional Teaching and Student Centered, Collaborative*

- Learning Online, accessed 14/6/02]URL: <http://shaw.ca/priscillatheroux/collaborative.html>
- [37] Fukaya, M., et al., 1988: Two level Neural Networks: Learning by Interaction with Environment, 1st ICNN, San Diego.
- [38] Hassan H. and Watany M., "on comparative evaluation and analogy for Pavlovian and Thordikian psycho-learning experimental processes using bioinformatics modeling", AUEJ, 6, 3, 424-432, July, 2003.
- [39] Wayt G. Considerate Computing. Majallat Al-oloom, Vol. 21, No. 5/6. pp 64-71, May/June-2005.
- [40] Ghonaimy M.A., Al – Bassiouni, A.M., and Hassan, H.M "Leaning Of Neural Networks Using Noisy Data". Published at the Second International Conference on Artificial Intelligence Applications, AUC , Cairo, Egypt, Jan 22-24, 1994. PP. 387-399.
- [41] Ghonaimy M.A., Al – Bassiouni, A.M., and Hassan H.M "Learning Ability in Neural Network Model".Published at the Second International Conference on Artificial Intelligence Applications, AUC, Cairo, Egypt, Jan. 22-24, 1994, PP-400-413.
- [42] H.M.Hassan, Ayoub Al-Hamadi , and Saleh Al-Saleem "Towards Evaluation of Phonics Method for Teaching of Reading Using Artificial Neural Networks (A Cognitive Modelling Approach)", Published at IEEE Symposium on Signal Processing and Information Technology ISSPIT 2007 , Cairo-Egypt.
- [43] H.M.Hassan, "On Simulation of E-learning Convergence Time Using Artificial Neural Networks", Published at the 7th International Conference on Education and Information Systems, Technologies and Applications (EISTA) to held in Orlando, USA, on July 10-13, 2009.
- [44] H.M. Mustafa "On Performance Evaluation of Brain Based Learning Processes Using Neural Networks" Published at The Seventeenth IEEE Symposium on Computers and Communication (ISCC '12) July 1 - 4, 2012, Cappadocia, Turkey.