On Analysis and Evaluation of Learning Creativity Quantification via Naturally Neural Networks' Simulation and Realistic Modeling of Swarm Intelligence

Hassan M. H. Mustafa[1],and Fadhel Ben Tourkia[2]

***Abstract*- This piece of research addresses a systematic quantified investigation of a challenging and interesting educational issue concerned with environmental learning creativity phenomenon. Herein, that presented creativity issue considered the interactive behavioral learning of human and non-human creatures.**

At one hand, for long time ago and till recently, educationalist and psychologists have been cooperatively interested in systematic searching for the interdisciplinary analysis, evaluation and improvement of students' academic achievement in classrooms. Therefore, a novel approach associated with realistic Artificial Neural Networks (ANNs) modeling and simulation of quantified learning creativity has been adopted .

At the other hand, by referring to the Swarm intelligence as a relatively new discipline that deals with interesting aspects of self-organizing social insect behavioral processes in both natural and artificial systems. A specific attention is given to the ecological behavioral learning of swarm intelligence agents (Ants), during performing foraging process. Finally, the announced simulation and modeling results seemed to be valuable and promising for the future more elaborate and systematic research work investigating. Comparative analogous study of learning creativity phenomenon considering natural environments associated to modeling of both Neural Networks' leaning, Swarm Intelligence Modeling.

***Index Terms*— Artificial Neural Network Modeling;; Ant Colony System Optimization; Swarm Intelligence, Travelling Salesman Problem; Computational Intelligence , Learning Creativity.**

I. INTRODUCTION

It is announced (in U.S.A.) that last decade (1990-2000) named as Decade of the brain [1]. Accordingly, neural network theorists as well as neurobiologists and educationalists have focused their attention on making interdisciplinary contributions to investigate essential brain functions (learning and memory). Recently, Artificial Neural Networks (ANN^{s}) combined with neuroscience considered as an adopted interdisciplinary research direction relevant for analysis and evaluation of quantified learning creativity. Additionally, it is observable in the educational field practice, that learning process performed by human brain is affected with the simple neuronal cell performance mechanism. That is in accordance with the extremely composite biological structure of Human brain resulting in everyday behavioral brain functions.[2]. In general, learning creativity is an interesting phenomenon considered under investigational work performed by diverse interdisciplinary researchers at the fields of education, cognitive science, and psychology. Accordingly, the research work which adopts quantitative analysis of learning creativity phenomenon is a rather interesting, critical, and challenging issue [3][4].In more details, in our classrooms, instructors mostly observe -during their interactive tutoring/learning sessions- that some of individual learners were more creative than there other colleagues. That is due to their distinct observable learning response, while performing assessment of learning process academic achievement [5][6][7]. Herein, suggested ANN model considers the dynamics of synaptic connectivity via two neuronal design factors. Namely, gain factor (slope) of neuronal activation function (sigmoid) as to measure time for learning convergence. Additionally, the model considers statistical study for the effect of learning rate factor (value) on learning time responses. Also, it gives an attention for supervised learning paradigms (error correction learning), rather than unsupervised one [8]. Additionally, by considering the published work of Perkins [9], quantification of learning creativity phenomenon is a very interesting and challenging educational issue, that associated as coincident set with intelligence. This piece of research deals with an interdisciplinary challenging problem associated with two emerging fields namely: nature inspired computing (NIC) and computational intelligence (CI) [10]. Therefore, this article presents the conceptual analysis and evaluation of quantified learning creativity phenomenon via simulation and modeling of two diverse natural biological systems [11]. More precisely, it considers diverse aspects of measurable behavioral learning performance of both biological systems. Consequently, this paper introduces comparative analogy between two distinct biological behavioral systems considering quantification of learning creativity [12].

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Referring to, the definition of Swarm intelligence which considered as a relatively new discipline that deals with the study of self-organizing (autonomous) processes both in natural and artificial systems as well. Researchers in ethological, and animal behavior have proposed many models to explain interesting aspects of social insect behavior such as self-organization and shape-formation[13].Accordingly, the presented study observed during human interactive tutoring/learning processes with natural environment. Versus ecological behavioral learning of swarm intelligence agents (Ants), while performing foraging process [14][15]. Systematic investigational study of quantified human learning creativity phenomenon is an interdisciplinary, challenging, and interesting educational issue. At educational field practice (classrooms), while face to face tutoring sessions are performed, learning creativity phenomenon is detectable via bidirectional feedback between teacher and pupil. In short, this research work adopts comparative study of simulation and modeling for learning creativity issue considering two diverse disciplinary approaches namely: swarm intelligence SI, and neural networks. The rest of this paper is organized as follows. At the next second sections, revising some of brain aspects which concerned with ANN modeling and ACS. Revising of some concepts of biological and artificial Neural Networks are introduced at the third section. At the fourth section, a brief revising of the analogy of ANN learning versus swarm intelligence associated to ACS is presented. Some of obtained interesting simulation results are given at the fifth section. At the sixth, some of conclusive remarks and future work are introduced at the seventh section. Finally, by the end of this manuscript three appendices are attached. The two Appendix I and Appendix III, introduce two lists of simulation programs. Some of obtained results after running of the program listed at Appendix II, are presented.

II. REVISING SOME BRAIN ASPECTS OF HUMAN AND NON-HUMAN CREATURES

Referring to the observed findings and facts about social insects' learning {such as Honeybees and Ant Colony Systems (ACS)}, relation among the number of neurons in the two biologically systems' models: human & nonhuman creatures is briefly revised as follows. For examples, the very simple creatures' brains find even a small number of neurons' connectivity performs useful complex behavioral function. Honeybees find it economic to support brains comprising around 850,000 neurons, which give them exceptional navigational capabilities while travelling several miles from their hive. Interestingly, experts estimate that an ant brain contains about 250,000 brain neuronal cells [16]. That number pales in comparison to the human brain, which is believed to contain over 86 billion neurons. However, for the ant, its brain is quite powerful. Humans have evolved to carry brains comprising 1011neurons or so and use these to support exceptional motor control and complex societal interactions. Accordingly, any human brain has about 10,000 million so a colony of 40,000 ants has collectively the same size brain as a human.[17]. More specifically, ACS of Temnothorax albipennis (formerly Leptothorax albipennis) ; its individual agents (ants) adopt an intelligent teaching technique known as tandem running . Briefly, 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; specifically, that ant colony system perform a creative communication technique which involves teaching by interactive feedback between two ants controlling trade-off between speed and accuracy[14]. ACS model used combinatorial optimization, for solving (TSP) by analysis of brining food from different food sources to store (in cycles) at ants' nest. On the other hand, at ecological and educational fields, biological observations for either human or non human creatures' behaviors resulted in detection of learning creativity phenomenon. By adopting Artificial Neural Network discipline; modeling of quantified human learning creativity phenomenon has been realistically achieved.

Interestingly, the interactive bidirectional phenomenon between teacher/pupil, it is worthy to refer what has been announced by Professor Franks [18] ,who said: "We also believe that true teaching always involves feedback in both directions between the teacher and the pupil. In other words, the teacher provides information or guidance for the pupil at a rate suited to the pupil's abilities, and the pupil signals to the teacher when parts of the 'lesson' have been assimilated and that the lesson may continue". Accordingly, supervised learning paradigm related to ANN, is analogously relevant to represent the interactive relation between leader and follower in ants during Tandem learning. Moreover, the findings of this paper illustrated the analogy between the number of neurons in artificial neural networks' system versus the number of agents (ants) in ACS. Furthermore, obtained realistic simulation and modeling results have announced that learning performance curves of either models behave in close similarity to each other. That while considering various gain factor values for ANN and the intercommunication among ants for ACS [19].

Moreover, the optimal selectivity for both design parameters values of ANN models namely : gain factor, and learning rate parameters. In addition to the choice of hidden neurons' number are relevantly considered for enhancement of quantified learning creativity virtually [20]. Interstingly, presented results herein , for both swarm intelligence and neural networks models seemed to be well promising for future more elaborate, systematic, and innovative research in evaluation of human learning creativity phenomenon regarding (NIC) and (CI) [10].

III. REVISING OF NEURAL NETWORKS CONCEPTS

On one hand, the biological neural networks are made up of real biological neurons that are physically connected or functionally-related in the human nervous system and especially in the human brain.[21]. Artificial neural networks (ANN or simply NN) on the other hand, are made up of artificial neurons interconnected with each other to form a programming structure that mimics the behavior and neural processing (organization and learning) of biological neurons.

Human brain can perform tasks much faster than the fastest existing computer thanks to its special ability in massive parallel data processing. NNs try to mimic such a remarkable behavior for solving narrowly defined problems i.e., problems with an associative or cognitive tinge [22]. To this effect, NNs have been extensively and successfully applied to pattern (speech/image) recognition, time-series prediction and modeling, function approximation, classification, adaptive control and other areas. Referring to the above stated NN definition, it consists of a pool of simple processing units, the ‘neurons’. Within NNs three types of neurons are distinguished at (Fig.1). Obviously, any one of these nodes represents / simulates a single biological neuron, which illustrated schematically at (Fig.1). The adopted neural model for simulation of quantified learning creativity follows the commonest type of ANN. That is a feed forward model consisted of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. (See Figure 1).: input neurons (nodes, which receive data from outside the NN and are organized in the so called input layer, output neurons (nodes), which send data out of the NN called the output layer, and hidden neurons (nodes), whose input and output signals remain within the NN and form the so called hidden layer (or layers). The adopted neural model for simulation of reading brain performance evaluation is similarly following the most commonly known structural type of ANN. By referring to (Fig.1), it is noticed that: nine that depicted circles (4-3-2) are representing three distinct groups, or layers of biological neurons. For the four nodes represent Input layer, three nodes represent Hidden layer, and the Output two layer nodes (neurons). That is a structure of the Feed Forward Artificial Neural Network (FFANN) model consisted of three layers comprise nine nodes : an "**input**" layer of four nodes which denoted by (I1, I2, I3, and I4) is connected to a "**hidden**" layer of three nodes, which is connected to an **"output**" layer of two nodes that denoted by (O1, and O2).

Generally, the activity function of that (FFANN) structure is briefly given as follows:

a) The activity of the input comprises four nodes, represents the raw information that is fed into the network.

b) The activity for each node of the hidden layer is determined by the activities provided by the four input layer's nodes and the synaptic weights' connections between the input nodes and the hidden layer's nodes.

c) The behavioral activity of the output nodes depends on the activity of the hidden nodes and the weights between the hidden and output nodes.

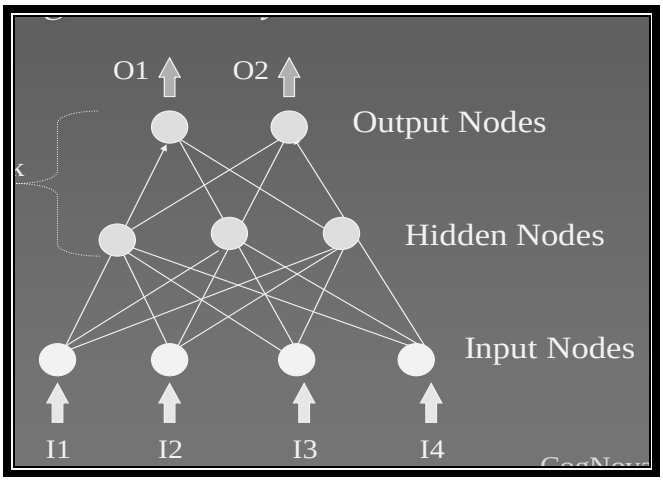

Fig. 1. A simplified schematic diagram for a (FFANN) model {adapted from, [23] }.

Referring to Fig.2, a simplified macro-level flowchart for simulation program is introduced. It describes briefly the algorithmic steps for a suggested realistic simulation program of adopted Artificial Neural Networks’ model taking into account the different number of neurons.(# neurons).

After running of that program, the set of graphs depicted at Fig.9. is obtained.

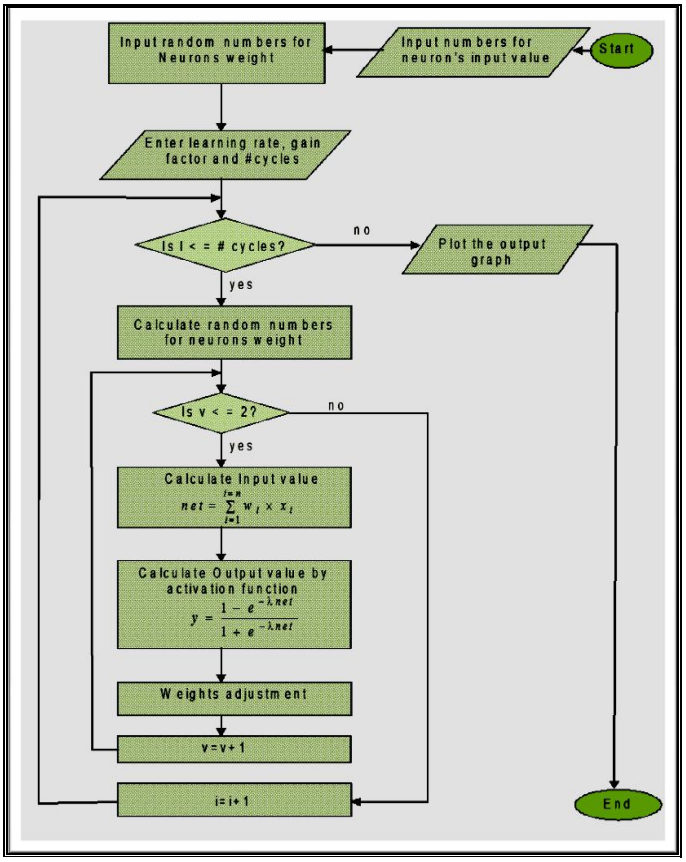

Fig.2. A simplified macro level flowchart describing algorithmic steps (for various numbers of neurons) using Artificial Neural Networks modeling.

IV. ANALOGY OF (SI) ACS VERSUS ANN LEARNING CREATIVITY [24][25][26]

A. Revising Swarm Intelligence of ACS

On the other hand, by referring to Fig. 3, ants are moving on a straight line that connects a food source to their nest. It is well known that the primary means for ants to form and maintain the line is a pheromone trail. Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone(Fig.3 A). This elementary behaviour of real ants can be used to explain how they can find the shortest path that reconnects a broken line after the sudden appearance of an unexpected obstacle has interrupted the initial path (Fig.3 B). In fact, once the obstacle has appeared, those ants which are just in front of the obstacle cannot continue to follow the pheromone trail and therefore they have to choose between turning right or left. In this situation we can expect half the ants to choose to turn right and the other half to turn left. A very similar situation can be found on the other side of the obstacle (Fig.3 C). It is interesting to note that those ants which choose, by chance, the shorter path around the obstacle will more rapidly reconstitute the interrupted pheromone trail compared to those which choose the longer path. Thus, the shorter path will receive a greater amount of pheromone per time unit and in turn a larger number of ants will choose the shorter path. Due to this positive feedback (autocatalytic) process, all the ants will rapidly choose the shorter path (Fig.3 D). Referring to more recent work,[27][28] an interesting view distributed biological system ACS is presented. Therein, the ant Temnothorax albipennis uses a learning paradigm (technique) known as tandem running to lead another ant from the nest to food with signals between the two ants controlling both the speed and course of the run. That learning paradigm involves bidirectional feedback between teacher and pupil and considered as supervised learning , [23]. Interestingly, adopted animal learning principles herein, are recently applied for evaluation of some human educational issues[29][30].

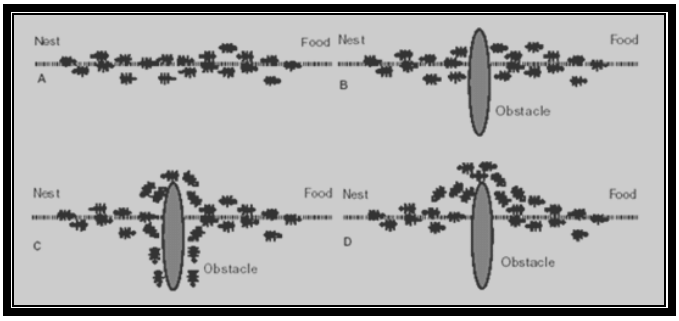

Fig. 3. Illustrates the transportation process of food back and fro, (from food source) to food store (nest site) .{ adapted from [25]}

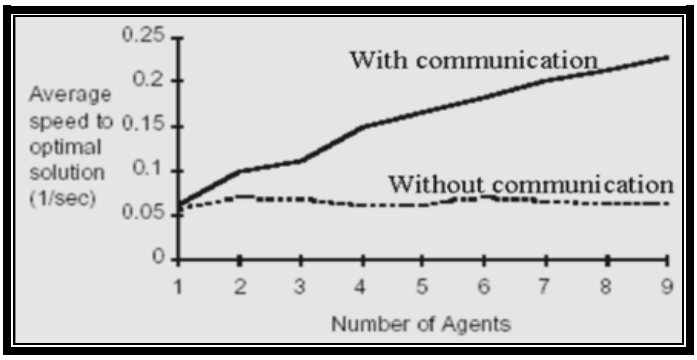

Fig. 4. Illustrates performance of ACS with and without intercommunication between ants {adapted from [25]}

B. Tandem running for a pair of ants

Tandem running technique involves an interactive bidirectional feedback between teacher and pupil corresponding to leader and follower ants respectively. Furthermore, in this figure, depicted block named as (Follower/Leader Ant Colony Model) suggests that tandem follows after learning their lessons so well, that they can become tandem leaders. Tandem leaders have experience of the food source, whilst followers are naïve of its location. The leader proceeds towards the food source (red path) so long as the follower (blue path) maintains regular antennal contact with the leader's legs or abdomen. Progress of the tandem pair is slowed by frequent periods when the leader remains still whilst the follower performs a looped circuit, possibly to memorize landmarks along the path (points 1 and 3) [26][31].

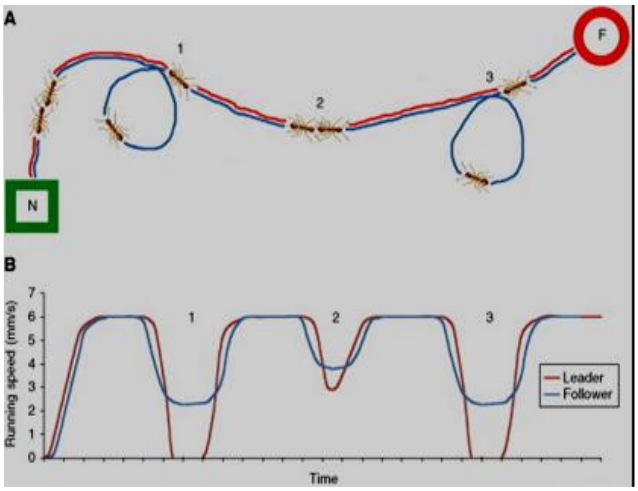

Fig. 5. A Schematic view of path taken by a tandem-running pair of Temnothorax albipennis ants from their nest (N) to a food source (F). (B)
Running speed of leader (red line) and follower (blue line) during the same tandem-run.

Once this exploratory circuit is completed, and the follower re-establishes antennal contact, the leader continues onwards towards the food. If contact between follower and leader becomes less frequent during a tandem-run, the leader will slow down to allow the follower to catch up (point 2). Interestingly, Tandem leaders pay a cost because they would normally have reached the food around four times faster if not hampered by a follower. But

the benefit is that the follower learns where the food is much quicker than it would have done independently. Tandem followers learn their lessons so well that they often become tandem leaders and in this way time-saving information flows through the ant colony. Referring to Fig.5 in below , it illustrates the path taken by tandem running pair of Temnothorax albipennis ants from their nest (Green Square) to food source (Red circle). The leader proceeds towards the food source (red path) so long as the follower (blue path) maintains regular antennal contact with the leader"s legs or abdomen [31].

C. Learning Principles and Algorithms of NN and ACS

The structure of the model given in Fig.8, is following the Hebbian learning rule in its simplified form [32]. This figure represents the classical conditioning learning process where each of lettered circles A, B, and C represents a neuron cell body. The line connecting cell bodies are the axons that terminate synaptic junctions. The signals released out from sound and sight sensory neurons A and C are represented by y1 and y2 respectively. The output of Hebbian structure after Pavlov's conditioning experimental process, is given by the function: Z = (ϕi). The obtained measurements' values are shown at Fig. 6. The two algorithmic steps of Pavlov's learning and ACS while solving TSP are given at Fig.7 A, and Fig.7 B, respectively.

s

Initialize

Loop /* at this level each loop is called an iteration that completed by the end of learning process*/

Each pairing stimulus is positioned on a starting latony time cycle
Loop /* at this level each loop is called a step which completed by developing some output by the motor neuron */

Each weight is changed dynamically according to Hebbian learning law

Until developing output signal corresponding to any arbitrary latony time
A maximum salivation signal is obtained when threshold value reaches to zero // Until

End_condition

Fig.7 A. Illustrates training process in ANN models considering latency time phenomenon having two loops with iterative learning cycles.

Initialize
Loop /* at this level each loop is called an iteration */
Each ant is positioned on a starting node
Loop /* at this level each loop is called a step */
Each ant applies a state transition rule to incrementally build a solution and a local pheromone updating rule until all ants have built a complete solution
A global pheromone updating rule is applied // until

End_condition

Fig. 7 B. Illustrates briefly the algorithmic steps of (ACS) presented in two loops with iterative learning cycles:

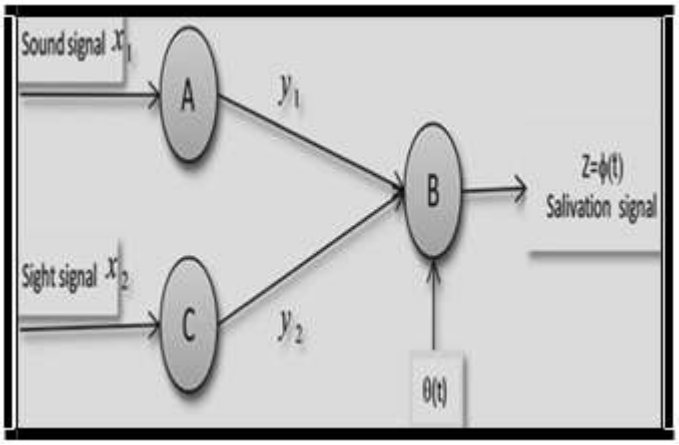

Fig.6 The structure of the Hebbian learning rule model representing Pavlov"s psycho-experimental work form {adapted from [33]}.

When the number of training cycles increases virtually to an infinite value, the number of salivation drops obviously reach a saturation value, additionally the pairing stimulus develops the learning process turned in accordance with Hebbian learning rule [32][33].

Cooperation among ant agents results in observable learning creativity via swarm intelligence of Ant Colony System. That is while these agents were performing the optimal solution of any Travelling Sales-man Problem (TSP) derived from Fig.3. which adapted from [25]. It is noticed by referring to {Fig. 3, and Fig.4}, that various intercommunication levels among ant agents, develop different outputs average speed to reach an optimum solution of a TSP. The changes of various intercommunication levels are seemed in well analogy to different gain factor values denoted by (λ) in an odd sigmoid function given at equation (1). However in case of different values of λ other than zero implicitly means that output signal is developed by neuron motors. Furthermore, by increasing of number of neurons which analogous to number of ant agents results in better learning performance for reaching accurate solution as graphically illustrated for fixed gain factor (λ) [26][34].

V. SIMULATION RESULTS

The difference in responsive speed to reach solution of TSP is analogous to the various intercommunication levels among artificial ants (agents), as shown in Fig.8. In other words, it is noticed that different intercommunication levels among the ant (agents) model develops different speed values to reach an optimal solution of TSP, considering variable number of agents (ants).

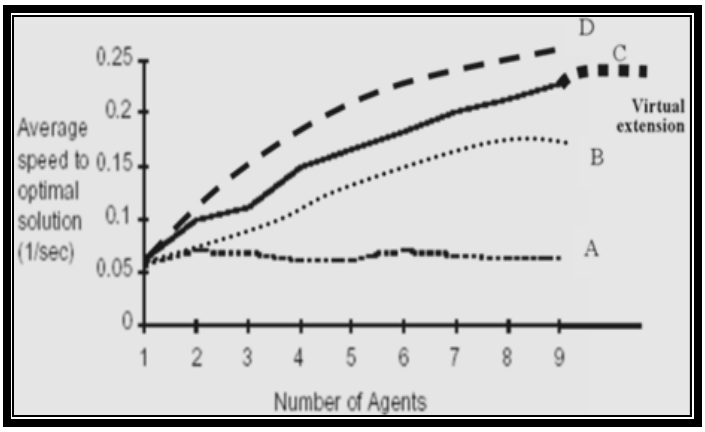

Fig. 8 Communication determines a synergistic effect with different communication levels among agents leads to different values of average speed. The source is : "On Comparative Analogy between Ant Colony Systems and Neural Networks Considering Behavioral Learning Performance" Journal of Computer Sciences and Applications, 2015, Vol. 3, No. 3, 79-89 Available online at http://pubs.sciepub.com/jcsa/3/3/4 © Science and Education Publishing DOI:10.12691/jcsa-3-3-4.

Consequently as this set of graphs reaches different normalized optimum speed to get TSP solution (either virtually or actually) the solution is obtained by different number of ants, so this set could be mathematically formulated by following formula:

$$f(n) = \alpha\left(\frac{1-e^{-\lambda n}}{1+e^{-\lambda n}}\right) \quad (1)$$

Where α……. is an amplification factors representing asymptotic value for maximum average speed to get optimized solutions and λ in the gain factor changing in accordance with communication between ants. Referring to the figure -- in below, the relation between number of neurons and the obtained achievement is given considering three different gain factor values (0.5 , 1 ,and 2).

Referring to Fig.9, it illustrates obtained neural modeling results which declares an interesting qualitative comparative analogy between performance evaluation of behavioral ANNs modeling; versus smart optimization performance of Ant Colony System as presented at Figures (4&8)..More precisely, the gain factor values given at Fig.9 are analogous with the intercommunication level values inside the ACS given at Fig.4, and Fig.8.

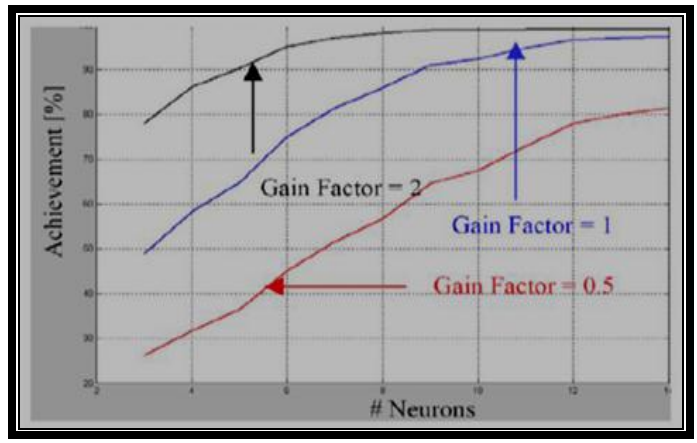

Fig.9 Illustrate students' learning achievement for different gain factors and intrinsically various number of neurons which measured for constant learning rate value (η) = 0.3. The source :."On Quantifying of Learning Creativity Through Simulation and Modeling of Swarm Intelligence and Neural Networks" 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.

However by this mathematical formulation of that model normalized behavior it is shown that by changing of communication levels (represented by λ) that causes changing of the speeds for reaching optimum solutions. In given Fig. 10. in blow, it is illustrated that normalized model behavior according to following equation.

$$y(n)= (1-\exp(-\lambda i(n-1)))/ (1+\exp(-\lambda i(n-1))) \quad (2)$$

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

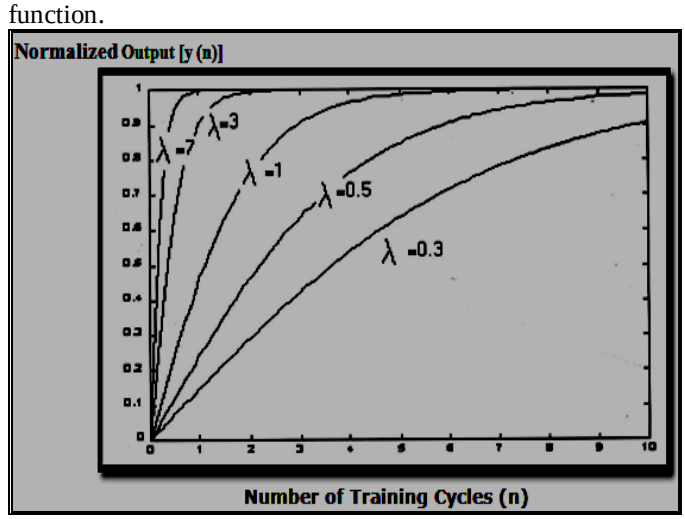

Fig.10 Graphical representation of learning performance of model with different gain factor values (λ). The source :."On Quantifying of Learning Creativity Through Simulation and Modeling of Swarm Intelligence and Neural Networks" to be published at IEEE EDUCON 2011, on Education Engineering – Learning Environments and Ecosystems in Engineering Education , held on April 4 - 6, 2011, Amman, Jordan.

VI. CONCLUSIONS & FUTURE WORK

This piece of research comes to four interesting conclusive remarks presented as follows:

- The number of trials during Hebbian coincidence learning are in good resemblance with number of agents (ants) and the number of neurons as stored experience due to interaction with environment [35].(See Fig.8, and Fig.9)
- The existence of an obstacle at some point of ants' pathway (Fig.3), is analogous to noisy applied when training some neural model. Due to the asymmetry of obstacles' shape, the time needed to find the shorter pathway (Solution of TSP)is directly proportional to the discovered minimum path.
- The stored experience during Hebbian process and computational intelligence of ACS are both analogues to the needed CPU time in order to develop minimum error for reaching optimum learning output (solution).
- Considering interestingly revealed findings based on the resemblance of quantified learning creativity phenomenon associated with both (human and non-human) creatures' aspects. The presented analysis and evaluation herein may shed light on promising future extension enhancement of learning performance quality.

Finally, as a consequence of the given four conclusive remarks in the above, it is highly recommend to implement realistically modeled ANNs, and ACS for analysis and evaluation of more complex educational phenomena's issues. That are concerned with cognitive leaning styles of human and non human creatures. Such as: early discovery of learning creativity, quality assurance of learning performance, evaluation of students' diversity a learning styles, cooperative learning modeling , Learning under noisy data environment, learning disabilities,……etc.[5][6][30][36][37].

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APPENDIX I

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

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

APPENDIX II

The two samples of obtained results are shown at Fig. 4, and Fig.5 were obtained after running of the simulation program listed at APPENDIX I. Both figures were concerned with the improvement of response time learning parameter (number of training cycles). That improvement observed by the increase of gain factor (from 0.5 to 1).

Referring to both figures (Fig.4 &Fig.5), the number of training cycles decreased on the approximate average, (from 80 to 30) cycles. That result indicates gain factor effect on improving the value of time response measured after learning process convergence, [5][8].

Considering the second learning rate parameter the improvement of that parameter clearly observed comparing figures 6 and 7 given in the below In more details, as the gain factor have fixed value(0.5), learning rate parameter increased from its value 0.2(at figure 6) to the value 0.6 (at figure 7),the average(normalized) number of training cycles decreased on the approximate average, (from 38 to 12)cycles.

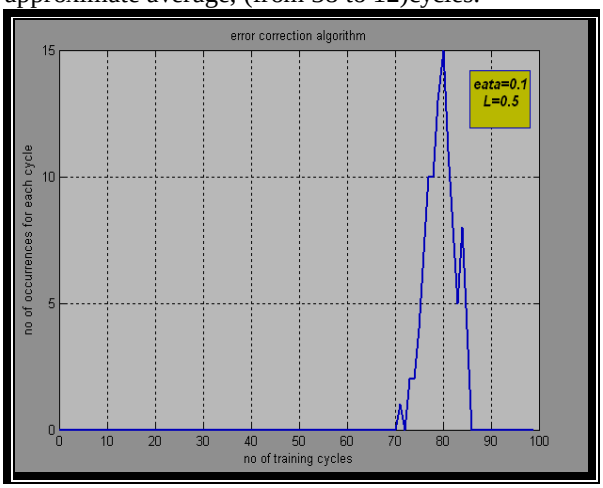

Fig.4. Illustrates the statistical distribution of learning convergence time for learning rate values =0.1, gain factor =0.5.

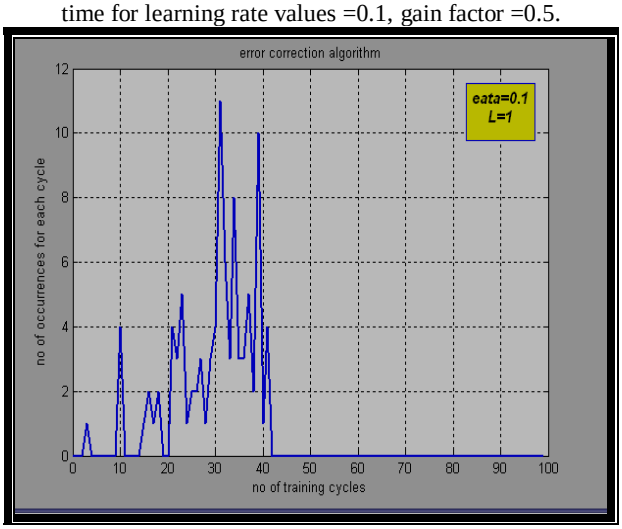

Fig.5.Illustrates the statistical distribution of learning convergence time for learning rate values =0.1,gain factor =1.

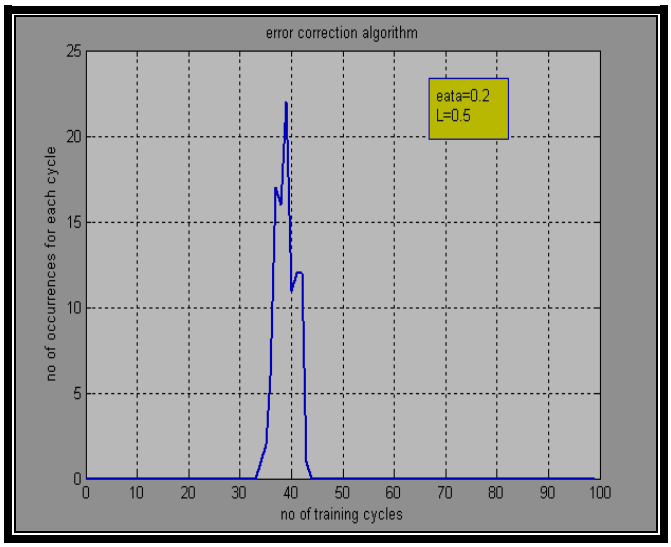

Fig.6 Illustrates the statistical distribution of learning convergence time for learning rate values =0.2,gain factor =0.5.

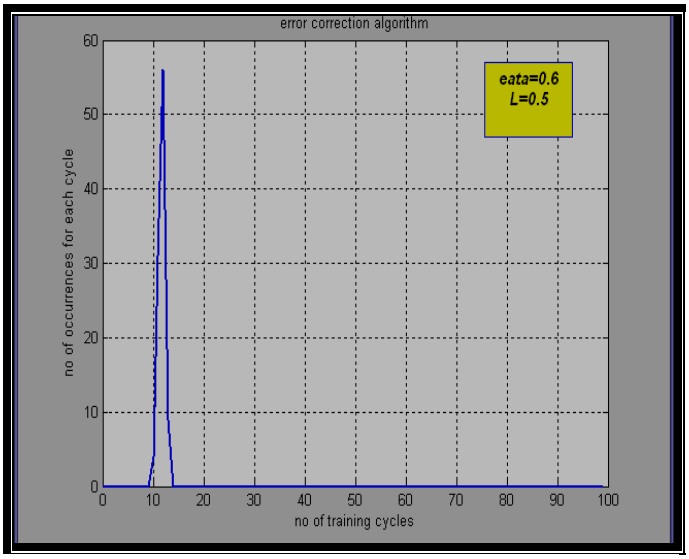

Fig.7. Illustrates the statistical distribution of learning convergence time for learning rate value =0.6, gain factor =0.5.

APPENDIX III

ERROR CORRECTION LEARNING ALGORITHM
For Changed Learning Rate Values eta [η=(0.1,0.2,0.3,0.4)]

```
w=rand(1000,1000);
x1=0.8; x2=0.7;x3=0.6; l=1; eta=0.4;

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

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

end

for i=1:100
    nog(i)=0;
    for x=1:1000
       if no(x)==i
        nog(i)=nog(i)+1;
       end
    end
end

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