

Comparative Analogy of Neural Network Modeling Versus Ant Colony System (Algorithmic and Mathematical Approach)*

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Abstract— This piece of research addresses an interdisciplinary, challenging and interesting learning issue. More specifically, it deals with analytical and quantitative study comparing two suggested naturally inspired behavioral learning systems. In other words, this study presents an investigational comparison between two diverse realistic models of biological systems. Namely, these systems are associated with learning at mammalian (Pavlovian) and Ant Colony Systems. Introduced investigations have included behavioral responsive functions, for learning process contributed inside brain neural system (number of neurons), as well as Ant Colony Optimization ACO. Additionally, this work revealed an interesting analogy between both suggested systems considering adaptive mathematical learning equations and algorithms. Moreover, analogous results have been introduced for suggested system versus animal learning performance considering spikes (pulsed) neurons approach.

Keywords: *Artificial neural network modeling; Ant Colony System Traveling Salesman Problem; computational biology.*

1. INTRODUCTION

Herein an investigational approach is presented an analogy between two simulated naturally inspired systems originated from computational intelligence [1].

* This Paper belonged to the interdisciplinary research discipline (frame work), entitled: "Building up bridges for Natural Inspired Computational Models across behavioral brain functional phenomena; and open learning systems". That is belonged to previously disciplined research work by research team of Arab Open University (KSA Branch). For the more details, see the APPENDIX attached by this manuscript end.

In other words, it presents analogy between two naturally inspired computational examples belong to the field of reinforcement learning (RL). One example is characterized by methods of temporal differences (TD).

However, the other is classified to evolutionary algorithm (EA) approach [2]. Both have been are studied comparatively via their mutual (in-between) analogy. That's exemplified by adaptive equations of Pavlovian experimental learning process versus ant colony system (ACS); considering their computational biology performance.

More specifically, this analogy concerned with adaptive equations for weight dynamics laws at artificial natural network (ANNs) and pheromone updating rules at ACS.

Commonly, both examples appeared to obey original natural principles for biological information processing derived from rules for animal learning by interaction with environment.

Through simulation experimental work applied for solving of reconstruction problem during rat's movement inside figure 8 maze. It shows how pulsed neural system behaves during prediction of animal free movement, aiming to perform spikes' pattern recognition process. These spikes are recorded from animals' motor system at its hippocampus brain area, and supported the principal of learning by interaction with environment. By some details, this paper deals with the effect of neurons' number on learning time response for both ACS, and ANN^s (ecological and neural systems). That includes, comparison between adaptive dynamical equations for ant colony optimization, and Hebbian learning rule paradigm. All comparison elements are viewed as reinforcement learning

behavioral algorithm. That searches for space value function as temporal difference, [2].

The rest of this paper composed of six sections, other than introductory one. Its organization is given as follows. At the second section II., adaptive learning analogy is introduced. It considers Hebbian learning rule adopted for representation of adaptive process observed at Pavlov's experimental work versus ACS for optimized solution of Travelling Sales Man Problem (TSP). The neuronal population performance observed during animal's behavioral learning is presented by considering pulsed neural system at the third section [3][4]. Along with some other results taken into consideration for optimal solution of reconstruction problem carried out by a rat running on elevated figure 8 maze. This results supported by Least Mean Square (LMS) algorithm [5], applied for learning convergence to Cramer Rao's bound after Fisher information [4]. Furthermore, at the fourth section IV. , some obtained simulation results illustrate how the number of neurons may affect the time response of learning process performance are presented. The algorithmic analogy of ANN system versus ACO is introduced At the fifth section V. At the sixth section VI. Adaptive mathematical learning equations for both ANN and ACO systems are presented. Finally, at last seventh section VII. , some valuable and interesting conclusions and comments are given. An Appendix is attached by the end of this paper.

2. LEARNING ADAPTIVELY ANALOGY

By referring to ACO process, dynamical adaptation process is controlled by pheromone density on different pathways during ACS foraging. Therefore, reaching the end of learning iterative cyclic steps (through two forward and backward paths). The density of deposited pheromone converges to some steady state static distribution. That indicates the optimality obtained of chosen pathways [6][7].

At Figure 1, it is shown that foraging process is adaptively performed by ACS. That by existence of an obstacle (at D) through the pathway from nest to source and vice versa. Asymmetrical state given by different eccentricity across nest –food axis. The considered eccentricity is analogously represented by two factor values (δ & $1-\delta$) where ($0 \leq \delta < 1$). Accordingly, the increase of pheromone at one of pathways leading to be dominant rather than the other pathway following the two factor values (δ & $1-\delta$). This pheromone is observed as shown at figure2-D given in blow.

Analogously, by referring to [8][9] neural pathways for visual and audible neuronal signals have two complementing updating factors during training phase. Namely, when considering the value δ (this value is dynamically changes within range zero up to unity as shown in below). I.e. the two factors are time dependent following training cycles, and any of both is a complement of the other. Considering that δ is the factor for audible pathway, hence, during training phase this factor increases following reinforce learning paradigm. Consequently, complemented ($1-\delta$) as visual pathway factor decreases. So, it tends to have no contribution to stimulate motor neuron for salivation.

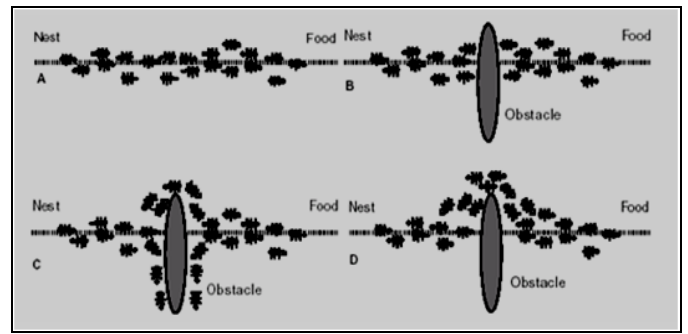


Fig.1: Illustrates the process of transportation of food (from food source) to food store (nest), adapted from [6].

I.e. by learning convergence, as the value of delta reaches unity, and audible signal comes so efficient as to fire motor output neuron. Consequently, salivation drops obtained resulting from stimulation by audible signal only. In other words, reinforcement learning attained by reaching the values zero and unity for visual and audible pathways factors respectively [8].

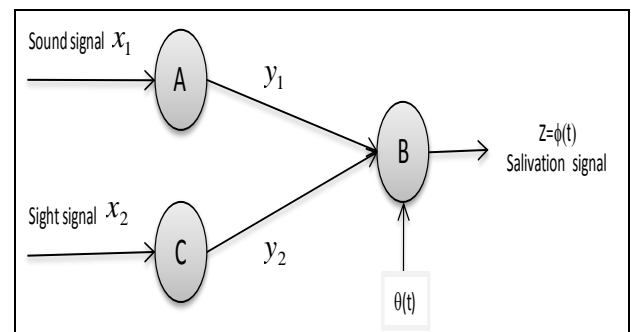


Fig. 2: The structure of the Hebbian learning rule model representing Pavlov's experimental work adapted from [9].

By some details, and referring to Figure 2 in the above, it represents the classical conditioning learning process where each of lettered circles A, B, and C represents a neuronal cell body[8]. The line connecting cell bodies are the axons terminating synaptic junctions. The signals released out from sound and sight sensory neurons A and C are represented by y_1 and y_2 respectively. The activation function of neurons A and C are considered as a fraction of signum function as follows :

Such that $0 \leq \delta < 1$

Where: δ is an implicit factor representing the interrelation between motivational and reinforcement learning. However this factor seems to be time dependent during training phases, herein it is considered as a constant for average signal decay through auditory and visual nervous pathways (1 and $1-\delta$) respectively. Noting that value of δ is increasingly changed by time leading to audible path to be dominant rather than the visual one.

$$\phi_A(\lambda) = \begin{cases} \delta & \lambda \geq 0 \\ -\delta & \lambda < 0 \end{cases} \quad \text{and} \quad \phi_c(\lambda) = \begin{cases} (1-\delta) & \lambda \geq 0 \\ -(1-\delta) & \lambda < 0 \end{cases}$$

3. NEURONAL POPULATION ACTIVITY

Referring to [10], and [4]; therein, the analogy is clear for two folds. Those folds are: learning performance, and dynamical adaptation equations. In details, according to Fisher's information [4], the performance of pulsed neural system is carried as exponential decrease bounded to minimum value that is namely, Cramer Rao's limit. So, that is similar to ACS, optimization processes following as LMS error algorithm when performing solution TSP. Also, the equations describing reconstruction problem solving, on Bayesian rule base, is analogous to probabilistic formula named as Pesdeuo-random proportional action choice rule. Both rules are applied following reinforcement learning paradigm[2]. Additionally, the algorithmic steps to reach solutions for both pulsed neural system and ACS, optimization seems well to be analogous to each other. Referring to [11] and [12], a pattern recognition problem is suggested as an example for reconstruction process. This example is given briefly as to reveal how the timing of spikes in a population of neurons can be used to reconstruct a physical variable is the reconstruction of the location of a rat in its environment from the place fields of neurons in the hippocampus of the rat. In the experiment reported here, the firing part-terns of 25 cells were simultaneously recorded from a freely moving rat [4]. The place cells were silent most of the time, and they fired maximally only when the animal's head was within restricted region in the environment called its place field [12]. The reconstruction problem was to determine the rat's position based on the spike firing times of the place cells.

Bayesian reconstruction was used to estimate the position of the rat in the figure-8 maze shown in figure 1. Assume that a population of N neurons encodes several variables ($x_1, x_2 \dots$), which will be written as vector x . From the number of spikes $n = (n_1, n_2, \dots, n_N)$ fired by the N neurons within a time interval τ , we want to estimate the value of x using the Bayes rule for conditional probability:

$$P(x | n) = P(n | x) P(x) / P(n) \quad (1)$$

Assuming independent Poisson spike statistics. The final formula reads

$$P(x | n) = k P(x) \left(\prod_{i=1}^N f_i(x)^{n_i} \right) \exp \left(-\tau \sum_{i=1}^N f_i(x) \right) \quad (2)$$

Where k is a normalization constant, $P(x)$ is the prior probability, and $f_i(x)$ is the measured tuning function, i.e. the average firing rate of neuron i for each variable value x . The most probable value of x can thus be obtained by finding the x that maximizes $P(x | n)$, namely,

$$\hat{x} = \arg \max_x P(x | n) \quad (3)$$

By sliding the time window forward, the entire time course of x can be reconstructed from the time varying-activity of the neural population. The effect of number of neurons at rat's brain hippocampus is similar to the consecutive iterative trials observed by Pavlov's experimental work result (given at Figure 4.)

4. NEURON'S NUMBER EFFECT ON LEARNING TIME RESPONSE

According to some obtained simulation results, it is shown how the number of neurons may affect the time response of learning process performance. Graphically, obtained results presented by changing number of neuronal cells (14, 11, 7, 5, and 3); brain based learning response during interaction of mammals with their environment [13]. The time response performance observed to be improved by increasing number of neurons (neuronal cells). That is shown at figures (5, 6, 7, 8, and 9) respectively; for fixed Learning rate = 0.1 and gain factor = 0.5.

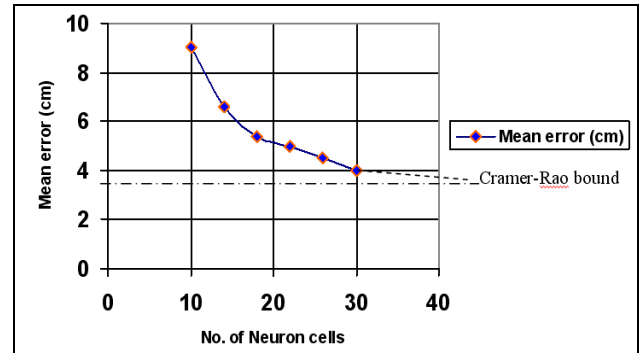


Fig. 3: The dashed line indicate the approach to Cramer-Rao bound based on Fisher information adapted from [4]

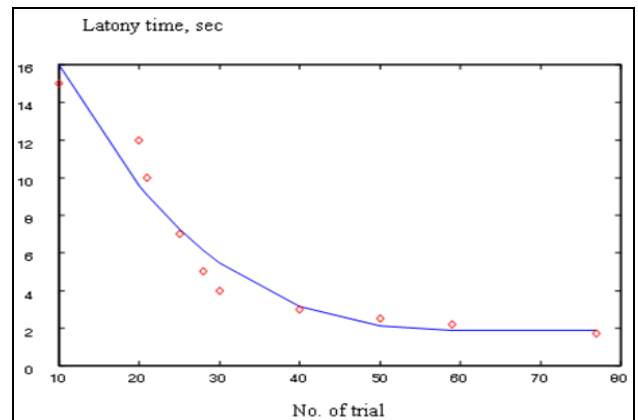
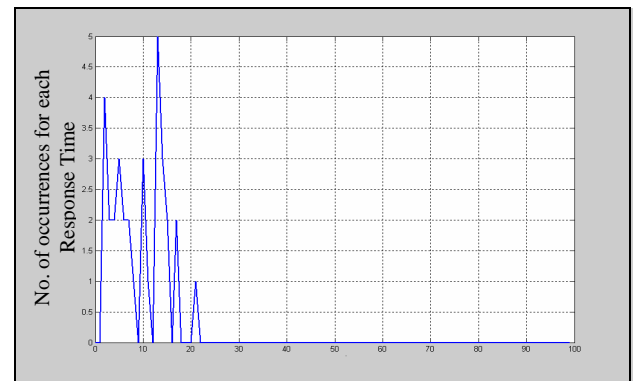
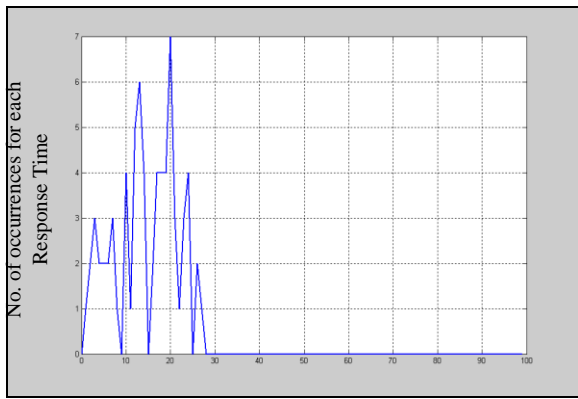


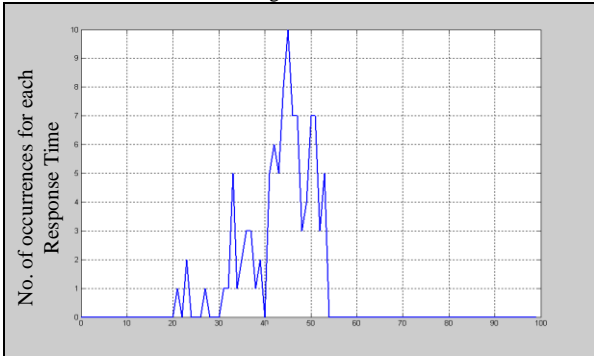
Fig. 4 Fitting curve of experimental Pavlovian results adapted from[8]



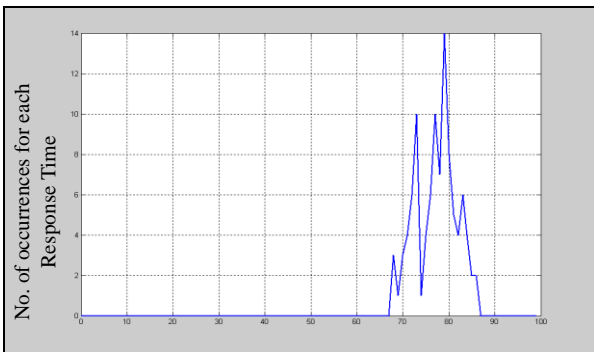
Time Response (No. of training cycles)
Fig.5.



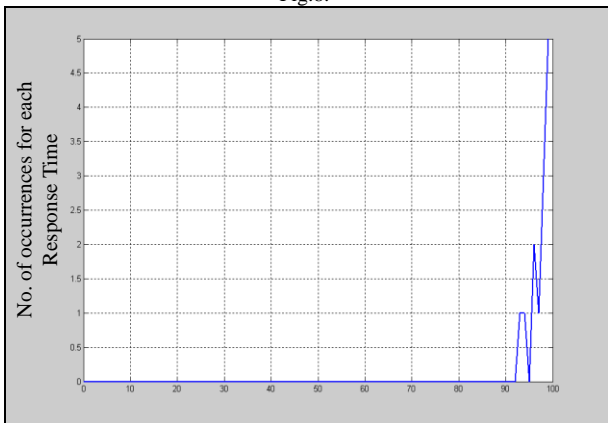
Time Response (No. of training cycles)
Fig.6.



Time Response (No. of training cycles)
Fig.7.



Time Response (No. of training cycles)
Fig.8.



Time Response (No. of training cycles)
Fig.9.

5. LEARNING ALGORITHMS ANALOGY

Figure 10 gives the algorithmic steps for solving basically the Travelling Sales Man (TSP) considering Figure 1. Interestingly, it clear that both algorithmic steps illustrated at Figure 10 and Figure 11 are well analogous to each other. Furthermore, the algorithmic steps shown at Figure 11 are describing behavioural training in Pavlov's iterative work processes based on neural network model presenting Hebbian learning (given at Figure 4) [8].

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. 10: illustrates ant colony algorithm in two loops with iterative learning cycles.

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 latency 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 latency time

A maximum salivation signal is obtained when threshold value reaches to zero // Until

End condition

Fig.11: illustrates training process in ANN models considering latency time phenomenon having two loops with iterative learning cycles.

6. MATHEMATICAL FORMULATION ANALOGY

This section 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 [14][15]. 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) [14][6]. The following equation presents a set of curves changes in accordance with different gain factor values (λ).

$$y(n) = (1 - \exp(-\lambda i(n-1))) / (1 + \exp(-\lambda i(n-1))) \quad (4)$$

Where λ_i 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:

$$y(n) = \exp(-\eta_i(n-1)) \quad (5)$$

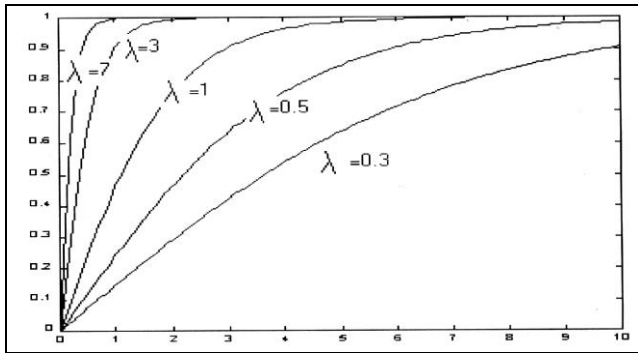


Fig. 12: Graphical representation of learning performance of model with different gain factor values (λ) adapted from [2].

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.

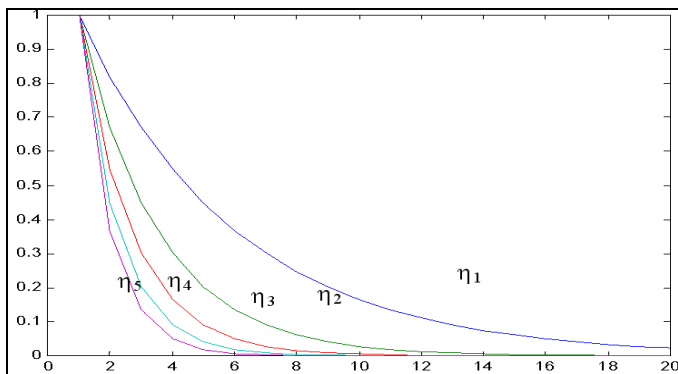


Fig. 13: Illustrates different learning performance curves for different learning rate values (η), adapted from [1].

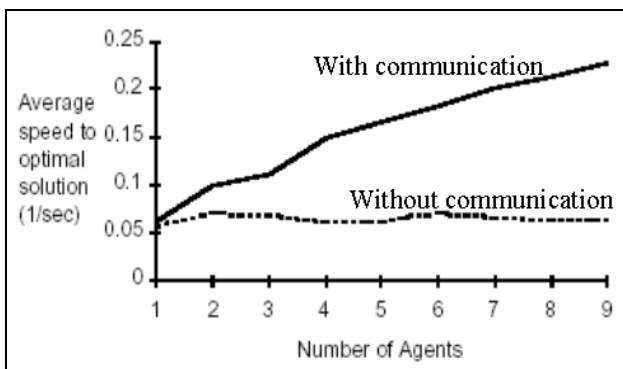


Fig 14: Illustrate performance of ACS with and without communication between ants, adapted from [3].

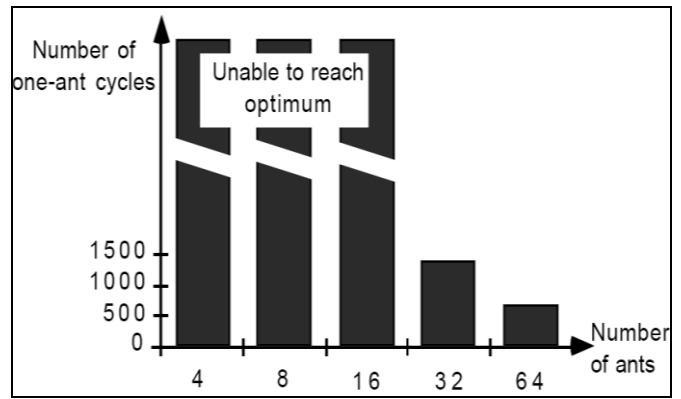


Fig.15: Number of cycles required to reach optimum rated to the total number of ants adapted from [9].

Interestingly, referring to above Fig.12, and Fig.13 both are analogous to Fig.14 and Fig.15 respectively. Similarly, the ants behavior given at figure 15 is analogous to the Pavlov's experimental results at figure 4. 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.14.

7. CONCLUSIONS AND DISCUSSIONS

According to above animal learning experiments (dogs, and rats), and their analysis and evaluation by Ann's modeling, all of them agree well as for ACS, optimization process. Also, the performance of both (ant and animals) is similar to that for latency time minimized by increasing of number of trials.

Referring to [3], therein, shown that both work for Thorndike and Pavlov are supporting each other for learning performance. So, it is obvious that both obeys generalize (LMS) for error minimization by learning convergence [5]. Also, that algorithm agrees with the behavior of brainier mouse behavior (that is genetically reformed) as given at [17][18].

Generally, the three introduced systems in this work (along its two parts) perform their function well similar to LMS error algorithm. By some details, artificial neural network models either performing computation on analogue signaling base or on pulsed spikes decoding criterion, they both leads to learning convergence following LMS error algorithm. Noting that, reconstruction method following Bayesian rule is bounded to Cramer Rao's limit. This limit is analogous to minimum response time in Pavlov experiment, and Thorndike work as well. Similarly, for ACS, optimization processes are following as LMS error algorithm when performing solution TSP. Additionally; adaptation equations for all of three systems are running in agreement with dynamic behavior of each other. Moreover, the learning algorithms for three systems are close to each other with similar iterative steps (either explicitly or implicitly).

Finally, it is worthy to note that the rate of increase of salivation drops is analogous to rate for reaching optimum

average speed in ACS optimization process. Similarly, this rate is also analogous to speed of cat getting out from cage in Thorndale's experiment. Moreover, the increase on number of artificial ants is analogous to number of trials in Pavlov's work.

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APPENDIX: Research Frame Work Suggested by Arab Open University (KSA)

Building up bridges for Natural Inspired Computational Models across behavioral brain functional phenomena; and open learning systems

The main topics of this presented frame work belong to some recently adopted interdisciplinary research direction. Namely , concerned with building up theoretical connections between neuroscience cognitive science, and swarm intelligence to enhance educational decisions and/or learning performance. In particular, such theories would be capable of evaluating learning performance tasks, in addition to complex educational decisions. So, that is performed by realistic dynamical modeling of some educational / learning phenomena associated with brain functions (Learning & memory) using Artificial Neural Networks. Briefly, these learning phenomena are learning creativity, individual differences, and different cognitive learning styles. By some details, the frame work timely planned as to be composed of three phases. These phases are motivated by dynamical learning mechanism and technologies and started by June 2007. Each of frame work phases, planned to elapse for (approximately) 10-12 months as follows:

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

Finally, it is worthy note that, above work currently started by A.O.U. research team. It is planned to elapse for (30 up to 36), months. Until now, that work results in a set of interdisciplinary recently published papers interacting Neurobiology & AI & experimental Psycho-learning, and swarm intelligence as follows:

- 1- "Towards Evaluation of Phonics Method for Teaching of Reading Using Artificial Neural Networks (A

- Cognitive Modeling Approach)", published at IEEE Symposium on Signal Processing and Information Technology Seventh Symposium held in Egypt-Cairo during 15-18 December 2007.
- 2- "On Quantifying Learning Creativity Using Artificial Neural Networks (A Neuro-physiological Cognitive Approach)", published at National Conference on Applied Cognitive Psychology held in India, Calcutta, 29 –30 November, 2007.
 - 3- "On Analysis of Quantifying Learning Creativity Phenomenon Using Artificial Neural Networks' modeling ", published at January 2008 issue of Journal of Al Azhar University Engineering Sector JAUES.
 - 4- "On Learning Performance analogy between Some Psycho-Learning Experimental Work and Ant Colony System Optimization", published at IEMS 2008-International Conference on Industry, Engineering, and Management Systems Cocoa Beach, Florida March 10-12, 2008.
 - 5- "On Optimal Selection of Software Learning Packages Using Artificial Neural Networks' Modeling (Educational Simulation Approach)", published at IEMS 2008-International Conference on Industry, Engineering, and Management Systems Cocoa Beach, Florida March 10-12, 2008.
 - 6- "On Analysis of Individual Differences Phenomenon by Using Artificial Neural Networks ", to be published at The International Conference on Modeling & Simulation AMSE08 to be held during the period from Apr.8th to Apr. 12th, 2008 Egypt – Port Said - Sadat Academy for Management Sciences(Port Said Branch).
 - 7- "On Comparison Between Swarm Intelligence Optimization and Behavioral Learning Concepts Using Artificial Neural Networks (An over view)", to be published at the 12th World Multi-Conference on Systemics, Cybernetics and Informatics: WMSCI 2008 The 14th International Conference on Information Systems Analysis and Synthesis: ISAS 2008 June 29th - July 2nd, 2008 – Orlando, Florida, USA.
 - 8- "On Artificial Neural Network Application for Modeling of Teaching Reading Using Phonics Methodology (Mathematical Approach)"to be published at the 6th International Conference on Electrical Engineering, ICEENG 2008, M.T.C., Cairo, Egypt.