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On Analytical Comparative Study for Performance Evaluation of Three Psycho-Learning Experimental Results versus Searching for Optimal Algorithmic Solution of Travelling Sales' Man Problem Using Smart Ant Colony System

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ABSTRACT: *This research work introduces an interesting comparative analytical study associated with performance evaluation of two diverse intelligent learning paradigms. Both paradigms are described in brief as follows. Firstly, the paradigm concerned with practically obtained psycho-learning experimental results after Pavlov's and Thorndike's work. In addition to the obtained experimental results while performing optimal solution of reconstruction problem by a mouse's movement inside a figure of eight (8) maze. Secondly, considering the paradigm associated with observed application results of a bio-Inspired clever algorithm after searching for an optimal solution of Traveling Sales-man Problem (TSP). The adopted bio-inspired clever algorithm originally based on observed Ant Colony System (ACS) performance. The comparative study for both paradigms' results in agreement of their performances with a learning process convergence which based on Least Mean Square (LMS) error. That's derived after training of an Artificial Neural Network (ANN) model namely Single Layer Perceptron .By the end of this manuscript, more performance analysis of two types of learning models have been introduced in comparative with the previously suggested two paradigms. Namely, these two models are related to parallel genetic algorithmic programming, and modified Hebbian learning (Oja's rule).*

Keywords: *Artificial neural network modeling, Animal learning, swarm Intelligence, ant colony system, traveling salesman problem and clever algorithm*.

I. INTRODUCTION

This paper concerned mainly with four computationally intelligent learning models. They classified into two diverse (distinct) learning paradigms. In other words, both of them are related tightly to natural biological Neural and Non-Neural Systems given in details respectively as follows [1][2][3].

Firstly, the neural system which considers the performance of three types of animals' (non-human creatures) models [4][5][6]. Which are all originated from behavioral learning phenomenon observed by three models' types of psycho-learning experimental processes [7][8][9][10][11][12]. By more details, the three introduced animal's models are inspired by creatures' intelligent learning performance observed in nature. Two of these models are based on Pavlov's and Thorndike's psycho-learning experimental performance results respectively [10][11]. Pavlov's dog learns how to associate between two sensory inputs stimuli (audible, and visual signals).Thorndike's cat psycho-learning behaves so that it could get out from a cage (after its' multiple trails to fulfill cage opening) aiming to obtain food (outside the cage). The third learning model considers a mouse's activity trials for solving a reconstruction problem through its movement inside figure (8) maze [12]. Additionally, other non-neural system learning paradigm) is associated with observed simulation results after running of a bio-Inspired clever algorithm, that aims to reach optimal solution of Traveling Sales-man Problem (TSP). It is motivated by the optimized performance of Ant Colony System (ACS) model [13]. The introduced model simulates ants (as one of swarm intelligent systems) adopted for solving TSP problem optimally. That model considers foraging behavior by bringing food from different food sources to store (in cycles) at ant's nest [13][14][15].

Moreover, by the end of this manuscript, two other learning models have been presented. They are parallel genetic algorithmic programming, and modified Hebbian learning paradigm (Oja's rule) [16][17][18].This work presents comparative analytical study for some behavioral learning processes, referring to practical psycho-experimental results. That are derived from adaptive behavior reinforcement learning [1][2] and combinatorial optimization observed for two types of natural bio-systems. Namely such experimental work based firstly on original animal learning carried out by Pavlov's and Thorndike's work [3][4], (about one century ago). Secondly, concerned with an example of swarm intelligent system. That is artificial ant colonies solving the traveling salesman problem. Behavioral learning processes for both are simulated by artificial neural network and artificial ant modeling respectively [5].

However, commonly, both systems observed to obey learning paradigm originated from principles of learning without a teacher. Thorndike's cat behavioral learning observed to converge for optimization, through sequential trial and error steps [6], (without any supervision). The convergence process obeys exponential decay function till reaching minimum error. Thus, cat's stored experience subjected to sequence improvement, as number of trials increases. Similarly, for Pavlov's dog modifies its behavioral learning process as to associate (paired stimuli) during minimum response time. For each model, this experience is modified continuously following dynamical synaptic adaptation (internal weights dynamics), resulting in better learning performance. It is worthy to note that response speed in Thorndike's experimental work, learning performance curves (for different individuals), agree well with a set of odd sigmoid functions. Similarly, this set obeys performance speed curves (for different communication levels) concerned with (ACS) optimization processes while solving (TSP).

Learning time response performance of original Thorndike's work, as well as Pavlov's seem to be similar to rat's behavior when solving reconstruction problem inside figure 8 maze [7]. Additionally, that original work performance agrees with experimental results of misclassification error performance versos number of generations in parallel genetic programming approach [18].

In natural world it is observed some diverse learning aspects for the two suggested natural biological system (crenatures types for dogs, cats and ants). However, both are shown to behave similar to each other, considering there learning performance carves. In details, simulations of learning performance curves behave as exponential decay function till reaching stable minimum error value or minimum time response. Conversely, this minimum error implies maximum optimum speed for both models. That conversed performance shown to agree well with odd sigmoid function performance. Conclusively, reaching to maximum speed for cat to get out from cage at Thorndike's work, is analogously corresponding well to optimum speed reaching solution of TSP solved by ACS model. Moreover, at the end of this manuscript some other models considering pattern reconstruction problem and genetic programming are also given in comparison with all presented models herein. The rest of this paper is organized as follows. At the next second section revising of adopted research work motivations are presented. These motivations have been composed of two folds given in two subsections (A&B). Both are respectively associated with the two previously introduced learning system paradigms. Thorndike's work is presented briefly. Description of modeling process of Thorndike's work is illustrated at third section. The fourth section is dedicated to illustrate ant colony system modeling. Two more learning models are presented at the section five, where they are related to: parallel genetic programming approach for solving some classification problems , and Oja's rule algorithm searching for Principal Component Analysis (PCA). Finally, at last sixth section some conclusive remarks and discussions are given.

II. RESEARCH MOTIVATIONS

This piece of research has been motivated by two motivational folds which tightly related to two learning system paradigms. It is noticed both paradigms are conceptually originated from computational intelligence biology. two motivational folds given at the following two subsections(A&B). The first motivational fold shown at the next subsection (A), It concerned with ANN^s modeling paradigms relevant to educational applications at practical field environment (at classrooms). However, the second motivational fold deals with the of second paradigm' conceptual view that associated to obtained simulation results after the performing of foraging process by ACS. That means bringing food from different food sources (in cycles) to store at ants' nest.

A. First Motivational Fold

The field of learning sciences is represented by a growing community conceiving knowledge associated with educational system performance as well as the assessment of technology-mediated learning processes. Therefore, a recent evolutionary trend has been adopted by educationalists as well as learners due to rapid technological and social changes. Therefore, they are facing increasingly challenges which arise in this time considering modifications of educational field applications. This research work is mainly motivated by what has been announced in U.S. as referred to the WHITE HOUSE REPORT in 1989. Therein, it has been considered the decade (1990-2000) as Decade of the brain [19]. Furthermore, the overwhelming majority of neuroscientists have adopted the concept which suggests that huge number of neurons in addition to their synaptic interconnections constituting the central nervous system with its synaptic connectivity performing dominant roles for learning processes in mammals besides human [20]. More specifically, this motivation is supported by what revealed by National Institutes of Health (NIH) in USA that children in elementary school, may be qualified to learn "basic building blocks" of cognition and that after about 11 years of age, children take these building blocks and use them [21][22]. The extremely composite biological structure of human brain results in everyday behavioral learning brain functions. At the educational field, it is observable that learning process performed by the human brain is affected by the simple neuronal performance mechanism [23]. In this context, neurological researchers have recently revealed their findings about increasingly common and sophisticated role of Artificial neural networks (ANN[s]). Mainly, this role has been applied for systematic and realistic modeling of essential brain functions (learning and memory) [24]. Accordingly, neural network theorists, neurobiologists, and educationalists have focused their attention for making interdisciplinary contributions to investigate observed educational phenomena associated with brain functional performance. Such as cognitive learning styles aiming to reach the optimality of learning processes' performance [25]. More specifically, this first learning paradigm approach considers three neural based nonhuman creatures' (animals') models. All of these three creatures' models have been inspired by observed behavioral learning performance in real natural world. Two of presented models based on Pavlov's and Thorndike's excremental work [6]. By more details, Pavlov's dog learns how to associate between two inputs sensory stimuli (audible, and visual signals). However, Thorndike's cat behavioral learning tries to get out from a cage to reach food out of the cage [11]. Both behavioral learning models improves its performance by trial and error in order to minimize response time period [6]. Furthermore, the third model concerned with behavioral learning of mouse while performing consecutive trials for get out from inside figure 8 maze, it tries to solve reconstruction problem [12].

B. Second Motivational Fold

In a general sense, social insect colonies live in a dynamic, competitive environment in which food sources of variable quality are constantly changing in location. Most ant species are dependent upon ephemeral food finds. In such an environment, there is an advantage to sharing information if it can help the colony direct its workers quickly to the best food sources.

The second paradigm considers collective intelligence as a behavior that emerges through the interaction and cooperation of large numbers of lesser intelligent agents (such as ants). This paradigm composed of two dominant sub-fields 1) Ant Colony Optimization that investigates probabilistic algorithms inspired by the foraging behavior of ants [26][27], and 2) Particle Swarm Optimization that investigates probabilistic algorithms inspired by the flocking and foraging behavior of birds and fish [28]. Like evolutionary computation, swarm intelligence-based techniques are considered adaptive strategies and are typically applied to search and optimization domains. That simulation the foraging behavioral intelligence of a swarm (ant) system used for reaching optimal solution of TSP a cooperative learning approach to the traveling salesman problem optimal solution of TSP considered using realistic simulation of Non-neural systems namely: ACS.

In the context of intercommunications and cooperative learning among ants inside ACS, some interesting findings have been announced recently [29]. In more details, several facts about the lifestyle of ants, which were not known earlier to mankind. Moreover, recent research has shown that the animals or insects whose lifestyle is closest in resemblance of the lifestyle of human beings are the ants.

This can be seen from the following findings regarding ants:

a. The ants bury their dead in a manner similar to the humans.
b. They have a sophisticated system of division of labor
c. Once in a while they me et among themselves to have a 'chat'.
d. They have adopted an internal and advanced method of communication among themselves.
e. They hold regular markets wherein they exchange goods.
f. They store grains for long periods in winter and if the grain begins to bud, they cut the roots, If the grains stored by them get wet due to rains, they take these grains out into the sunlight to dry, and once these are dry, they take them back inside.

Interestingly, it is noticed by referring to the above lifestyle finding (d) that colonies of ants are employed by cooperative learning approach which based on active cooperative intercommunication performance aiming to solve optimally the traveling salesman problem [30].

Finally, it is worthy to note that ACS behavior by considering the following Holy Islamic Qur'anic verses:

At length, when they came to a (lowly) valley of ants, one of the ants said: 'Oye ants, get into your habitations, lest Solomon and his hosts crush you (Under foot) without knowing it." (Al-Qur'an 27:17-18).

III. REVISING OF THE FIRST LEARNING PARADIGM' MODELS

This section is dedicated to present some details about three models given at subsections *(A, B, and C)* related to the first adopted paradigm, referred respectively to Pavlov's, Thorndike's, and Mouse's Maze learning processes. They are belonging to learning behaviorism observed phenomenon, and related to obtained some results of psycho- learning experimental work. That work performed by three nonhuman animals' (Dog, Cat, and Mouse) interaction with external environment [7][31][32]. The adopted three behavioral learning models have been performed through consecutive number of trials and errors' correction in repetitive steps (iterative number of cycles) [4][6][10][12][33-37].

A. Pavlov's work revised [8][9][10]

In order to reach relevant, realistic, and accurate comparison for the two practical and simulated resulting data cases, pre-normalization of both data has been considered. Referring to Fig.1, the practical and simulation results seems to be very similar to each other. However, it is obvious that practically obtained results are influenced varying by the individual differences of dogs' salivation response. That's to external stimulating pairings{Sound (heard) stimulus and visual (sight) stimulus}.

Firstly, referring to original Pavlov's work, let us define what is meant by latency time. Briefly, this time is defined as the delay period elapsed since acquisition of two input stimulating signals (pairings), till developing output response signals [10].In more details, responding signals are held to be of zero value during their correlated latency time periods. Hence, by the end of these periods, output actions are spontaneously developed in a form of some number of salivation drops representing response signals intensities. These intensities observed to be in proportionality with the increase of the subsequent number of trials. So, this relation agrees with odd sigmoid function curve as reaching saturation state [5][10].

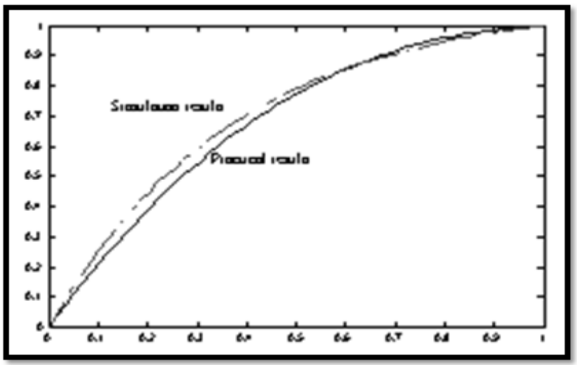


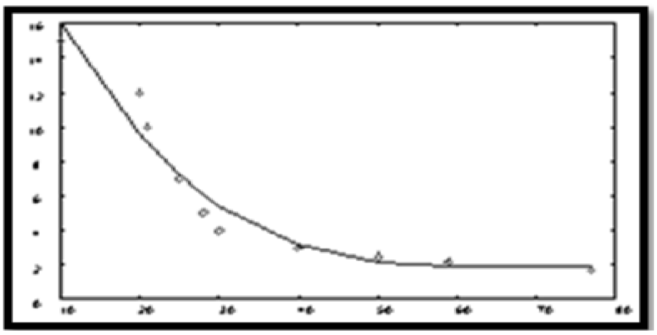
Fig 1. Comparison between simulation and practical result

Conversely ,on the basis of Pavlov's experimental results, it is clear that relationship between latency time period, and the number of subsequent trials could be expressed as hyperbolic curve relation as follows:

$$t(n) = \frac{\alpha}{n^{\beta}} \qquad (1)$$

where α and β are arbitrary positive constant in the fulfillment of some curve fitting to a set of points as shown by graphical relation illustrated at Fig.2 in blow.

Latency time



Training cycles

Fig.2 Fitting curve for latency time results observed by Pavlov's experimental work.

- ***Phonics reading model based on Pavlov's classical conditioning learning concept.***

Referring to the two figures shown in below, an interesting application given for reading model which obeys Pavlov' learning concept. By more details, considering at Fig. 3, the two inputs I_1 and I_2 represent sound (heard) stimulus and visual (sight) stimulus respectively. The outputs O_1 and O_2 are representing pronouncing and image recognition processes respectively. In order to justify the superiority and optimality of phonic approach over other teaching to read methods, an elaborated mathematical representation is introduced for two different neuro-biologically based models. Any of models needs to learn how to behave (to perform reading tasks). Somebody has to teach (for supervised learning)- not in our case – or rather for our learning process is carried out on the base of former knowledge of environment problem (learning without a teacher). The model obeys the original Hebbian learning rule. The reading process is simulated at that model in analogues manner to the previous simulation for Pavlovian conditioning learning. The input stimuli to the model are considered as either conditioned or unconditioned stimuli. Visual and audible signals are considered interchangeably for training the model to get desired responses at the output of the model. Moreover the model obeys more elaborate mathematical analysis for Pavlovian learning process [9]. Also, the model is modified following general Hebbian algorithm and correlation matrix memory [33]. The adopted model is designed basically following after simulation of the previously measured performance of classical conditioning experiments. The model design concept is presented after the mathematical transformation of some biological hypotheses. In fact, these hypotheses are derived according to cognitive/ behavioral tasks observed during the experimental learning process. Generally, the output response signal varies as shown in the original Pavlov experimental work [10], where the output response signal is measured quantitatively in the exactness of pronouncing letter/ word. In accordance with biology, the output of response signal is dependent upon the transfer properties of the output motor neuron stimulating pronouncing as unconditioned response (UCR) for heard phoneme (sound signal). However, this pronouncing output is considered as conditioned response (CR) when input stimulus is given by only sight (seen letter/ word). The structure of the model following the original Hebbian learning rule in its simplified form (single neuronal output) is given in Fig.4, where A and C represent two sensory neurons (receptors)/ areas and B is nervous subsystem developing output response. The below simple structure drives an output response (pronouncing) that is represented at Fig.4 as O_1. However the other output response represented at Fig.3 as O_2 is obtained when input sound is considered as conditioned stimulus. Hence visual recognition as condition response of the heard letter/ word is obtained as output O2. In accordance with biology, the strength of response signal is dependent upon the transfer properties of the output motor neuron stimulating salivation gland. The structure of the model following the original Hebbian learning rule in its simplified form is given in Fig.4.The 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 y_1 and y_2 respectively.

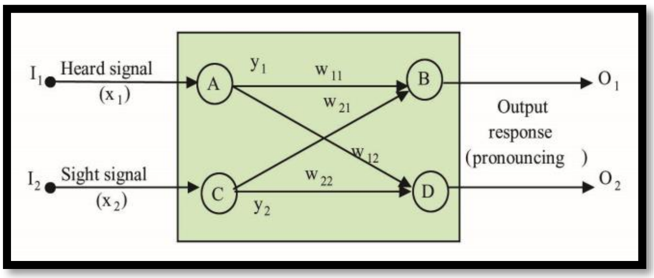


Fig. 3. Generalized model considering input stimuli and output responses, (adapted from [5]).

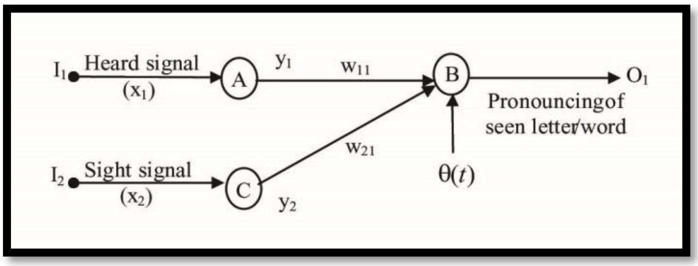


Fig. 4. The structure of the first model where reading process is expressed by conditioned response for seen letter/ word (adapted from [10]).

B. Thorndike's work revised [11]

Initially, cat's performance trials results in random outputs. By sequential trials, following errors observed to become minimized, as number of learning cycles increases. Referring to Fig. 5, original Thorndike's work results, are shown as relation between response time and number of trials. So, results shown at Fig.5.

represent behavioral learning performance of Thorndike's work. However, normalized learning curve presenting performance is approximately given at figure 6.

Conversely to above given presentation of learning performance curve, response speed curve (for Thorndike's work) introduced at figure 7. Interestingly, this curve seems to behave similarly, as well known sigmoid function behavior, which simulates neuronal response, [33]. Generally, principle of adaptive learning process (observed during creatures' interaction with environment) illustrated originally at [32].Moreover, this principle has been adopted for modeling of learning phenomenon and its applications, at more recently published research papers [38-44].

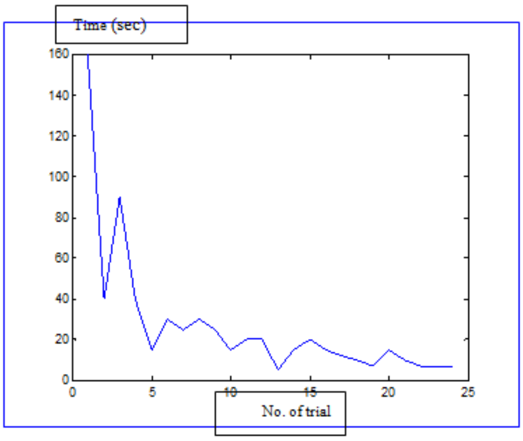


Fig. 5. The original result of Thorndike representing learning performance for a cat to get out from the cage for reaching food.

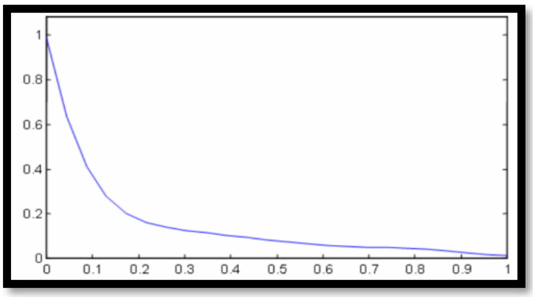


Fig. 6 . Thorndike normalized results seem to be similar as an exponential decay curve.

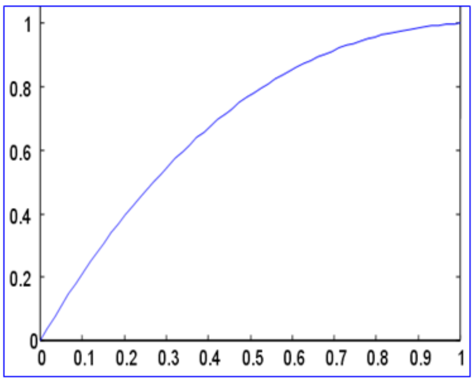


Fig. 7 Illustrates normalized performance curve presenting response speed derived conversely from the original curve results of response time presented at figure 3.

- ***More about Thorndike's experimental work***

On the basis of original observed experimentally measured performance, realistic modeling for Thorndike's work is presented at this section. The behavioral learning process of the original experiments is considered to belong to learning by interaction with environment principle.

However, any of detected errors, during cat's learning process, is corrected spontaneously depending upon stored experience inside cat's internal neural system. In other words, cat's experience has to be dynamically modified following synaptic adaptation (plasticity) of its internal weights' connectivity. Consequently, the suggested model for Thorndike's work. Considers dynamical changes of learning rate of as number of learning steps increases. The statistical analysis of model results proved the consistency of learning performance distribution as shown at following Table 1.

Table 1. Illustrates statistical analysis of model results representing Thorndike's work:

Learning rate value η	Average number of training cycles	Variance σ	Standard deviation $\sqrt{\sigma}$	Coefficient of variation ρ
0.1	100.7	93.7889	9.6845	0.0962
0.2	51.3	22.6778	4.7621	0.0928
0.3	34.8	10.1778	3.1903	0.0917
0.4	26.5	6.2778	2.5055	0.0945
0.5	21.5	2.9444	1.7159	0.0798
0.6	18.2	2.4	1.5492	0.0851
0.7	15.8	1.5111	1.2293	0.0778
0.8	14.2	1.2889	1.1353	0.08
0.9	12.6	1.1556	1.0750	0.0853

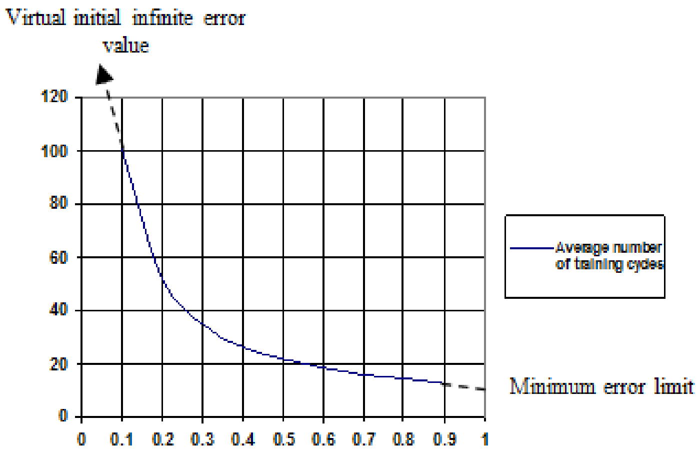


Fig. 8. Illustrates the relations between error values and adaptive learning rate values indicating the increase of stored experience in biological neural systems.

The model performance learning curve is shown at the above figure. This figure illustrate, modeling similarity to the approximated original learning performance curve shown at Fig. 6. The learning rate parameter (η (m)) is changed as a function of training cycles number (m) in accord with the following formula:

$$\eta(m) = \eta_0 \left(\frac{1 - e^{\frac{-m}{\tau}}}{1 + e^{\frac{-m}{\tau}}} \right) \qquad (2)$$

where m is number of training cycles during learning process simulating Thorndike's experimental work. η_0 is maximum learning rate for our case equals 0.9, and τ is the search time for the cat to get out from its cage to obtain food it is suggested to equals unity.

Referring to this formula, it is noticed that maximum value of learning rate parameter converges to 0.9, as number of learning cycles increases. So, this model provides realistic description of original work performance results. In the context of behaviorism learning theory which applied at [34 - 44]. Additionally, Thorndike had suggested three principles, which instructors (who adopted teaching based on behaviorism learning theory) should consider in order to promote effectiveness of behavioral learning processes. These suggested principles are given as follows:

- Present the information to be learned in small behaviorally defined steps
- Give rapid feedback to pupils regarding the accuracy of their learning. (Learning being indicated by overt pupil responses).
- Allow pupils to learn at their own pace.

C. Maze Reconstruction Problem

Referring to [12], 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 mouse 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 mouse [37]. 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 mouse in the figure-8 maze shown at Figure 7, which adapted from [12]. Assume that a population of N neurons encodes several variables (x_1, x_2 ……), which will be written as vector x. From the number of spikes n=(n_1,n_2,…….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:

$$P\,(\mathrm{x}|\mathrm{n}) = P\,(\mathrm{n}|\mathrm{x})\,P\,(\mathrm{x}) \,/\, P\,(\mathrm{n}) \qquad (3)$$

Assuming independent Poisson spike statistics. The final formula reads

$$(4)\; P(x\,|\,n) = kP(x)\left(\prod_{i=1}^{N} fi(x)^{ni}\right)\exp\left(-\tau\sum_{i=1}^{N} fi(x)\right)$$

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,

$$\hat{x} = \arg\max P(x\,|\,n) \qquad (5)$$

By sliding the time window forward, the entire time course of x can be reconstructed from the time varying-activity of the neural population. This appendix illustrates well Referring to results for solving reconstruction (pattern recognition) problem solved by a mouse in figure (8) maze [37]. That measured results based on pulsed neuron spikes at hippocampus of the mouse brain. In order to support obtained investigational research results and lightening the function of mouse's brain hippocampus area, three findings have been announced recently as follows:

1- Referring to [45], experimental testing performed for hippocampal brain area observed neural activity results in very interesting findings. Therein, ensemble recordings of 73 to 148 rat hippocampal neurons were used to predict accurately the animals' movement through their environment, which confirms that the hippocampus transmits an ensemble code for location. In a novel space, the ensemble code was initially less robust but improved rapidly with exploration. During this period, the activity of many inhibitory cells was suppressed, which suggests that new spatial information creates conditions in the hippocampal circuitry that are conducive to the synaptic modification presumed to be involved in learning. Development of a new population code for a novel environment did not substantially alter the code for a familiar one, which suggests that the interference between the two spatial representations was very small. The parallel recording methods outlined here make possible the study of the dynamics of neuronal interactions during unique behavioral events.
2- The hippocampus is said to be involved in “navigation” and “memory” as if these were distinct functions [46]. In this issue of *Neuron* this research paper evidence has been provided that the hippocampus retrieves spatial sequences in support of memory, strengthening a convergence between the two perspectives on hippocampal function.
3- Recent studies have reported the existence of hippocampal "time cells," neurons that fire at particular moments during periods when behavior and location are relatively constant as introduced at [47]. However, an alternative explanation of apparent time coding is that hippocampal neurons "path integrate" to encode the distance an animal has traveled. Here, we examined hippocampal neuronal firing patterns as rats ran in place on a treadmill, thus "clamping" behavior and location, while we varied the treadmill speed to distinguish time elapsed from distance traveled. Hippocampal neurons were strongly influenced by time and distance, and less so by minor variations in location. Furthermore, the activity of different neurons reflected integration over time and distance to varying extents, with most neurons strongly influenced by both factors and some significantly influenced by only time or distance. Thus, hippocampal neuronal networks captured both the organization of time and distance in a situation where these dimensions neuronal networks captured both the organization of time and distance in a situation where these dimensions dominated an ongoing experience as illustrated at Fig. 9 in below [47].

Figure. 9 Dissociation between Elapsed Time and Path Integration in the Hippocampus During the delay period of a working memory task required the mouse to run on a treadmill for either a fixed amount, adapted from [47]

By referring to Table 2,it is shown that mean error value seems to be decreased - versus number of place field cells at the hippocampus brain area - in a similar manner as exponential curve decays to some limit value.

Table 2. Relation between number of cells and mean error in solving reconstruction problem.

No. of neuron cells	10	14	18	22	26	30
Mean error (cm)	9	6.6	5.4	5	4.5	4

Noting that, the value of mean error converges (by increase of number of cells) to some limit, excluded as Cramer-Rao bound. That limiting bound is originated from Fisher's information given in tabulated results at Table 2.

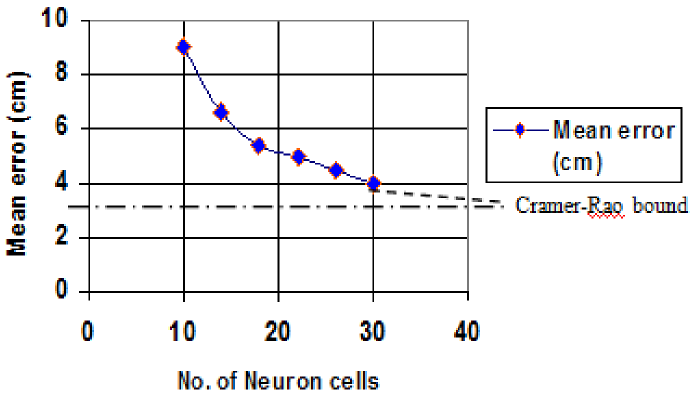


Fig.10 The dashed line indicate the approach to Cramer-Rao bound based on Fisher information adapted from [37].

Furthermore, it is noticed that the algorithmic performance learning curve referred to Fig.10, converged to bounding limit (of minimum error value) fixed Cramer Rao bound (Limiting value). That is analogous to minimum time response corresponding to maximum number of trials limit by referred to Fig.1 & Fig.2, Interestingly, considering comparison between learning curve performances at Figure 8 and learning that at ACS. It observed the analogy when comparing number of place field cells (at hippocampus mouse's brain area) versus the number of cooperative ants while searching for optimized TSP solution adopting ACS. More details are presented at the simulation results' section V

First model considers the reconstruction problem solved by rat moving inside figure 8 maze. This model is based on pulsed spike's neuronal behavior at hippocampus rat's brain area [46][47]. Learning performance of that model measured by dependence of minimizing of mean error value upon number of place field neurons.

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IV. REVISING OF SECOND LEARNING PARADIGM

A. Shortest Path Criterion Adopted by ACS

By referring to Fig. 8, this criterion is briefly illustrated as follows. Considering Fig. 8-A 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. This elementary behavior 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. 8 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. 8 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. 6D). The most interesting aspect of this autocatalytic process is that finding the shortest path around the obstacle seems to be an emergent property of the interaction between the obstacle shape and ants distributed behavior: Although all ants move at approximately the same speed and deposit a pheromone trail at approximately the same rate, it is a fact that it takes longer to contour obstacles on their longer side than on their shorter side which makes the pheromone trail accumulate quicker on the shorter side. It is the ants' preference for higher pheromone trail levels which makes this accumulation still quicker on the shorter path [26].

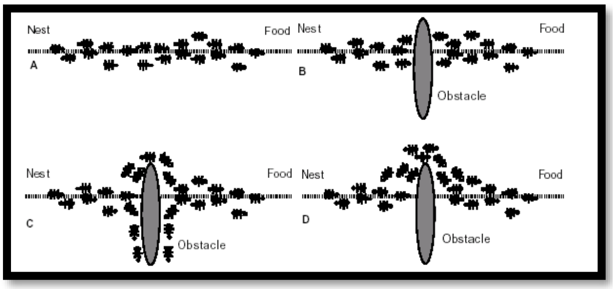

Fig. 11 illustrates the process of transportation of food (from food source) to food store (nest). This process is adapted with the existence of an obstacle through the pathway from nest to source and vice versa.

B. Cooperative Learning by ACS

Cooperative learning by Ant Colony System for solving TSP referring to Figure 10 which adapted from [13], the difference between communication levels among agents (ants) develops different outputs average speed to optimum solution. The changes of communication level are analogues to different values of λ in odd sigmoid function as shown at equation (6) in below. This analogy sis well illustrated well by referring to Fig.1, where the output salivation signal is increased depending upon the value of no of training cycles. Furthermore, this analogy is illustrated at Fig.7 referring to normalized performance curve presenting response speed derived conversely from the original curve results of response time presented at figure 6.

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 [16]. 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 λ at figure 13.

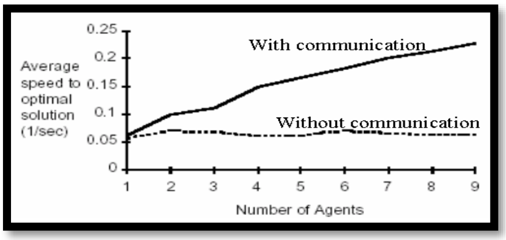

Figure 12. Illustrates performance of ACS with and without communication between ants {adapted from [1]}

This different response speed to reach solution is analogous to different communication levels among agents (artificial ants) as shown at the Fig.13. It is worthy to note that communication among agents of artificial ants model develops different speed values to obtain an optimum solution of TSP, considering variable number of agents (ants).

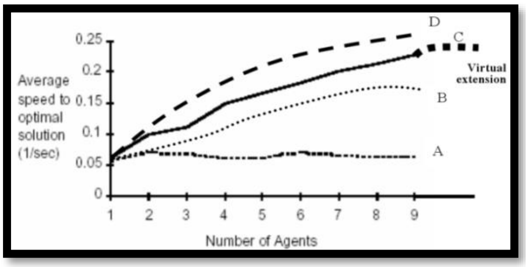

Fig.13. Communication determines a synergistic effect with different communication levels among agents leads to different values of average speed.

Consequently as this set of curves 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:

$$f(n) = \alpha\left(\frac{1-e^{-\lambda n}}{1+e^{-\lambda n}}\right) \qquad (6)$$

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 accords with communication between ants.

C. Analogy between Gain factor values and intercommunication levels

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. 14. in blow, it is illustrated that normalized model behavior according to following equation.

y(n)= (1-exp(-λi(n-1)))/ (1+exp(-λi(n-1))) (7)

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

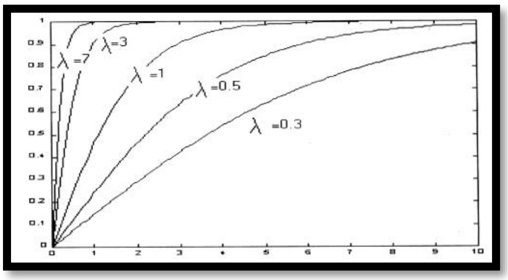

Fig. 14. Graphical representation of learning performance of ACS model with different communication levels (λ).

D. Algorithmic steps for micro level flowchart of suggested ANN model.

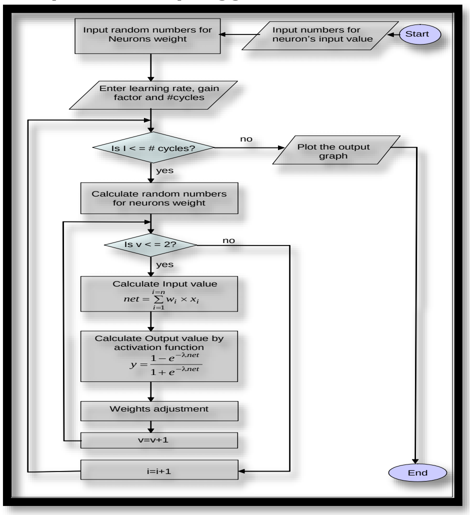

Fig. 15 A simplified macro level flowchart describing algorithmic steps using Artificial Neural Networks modeling

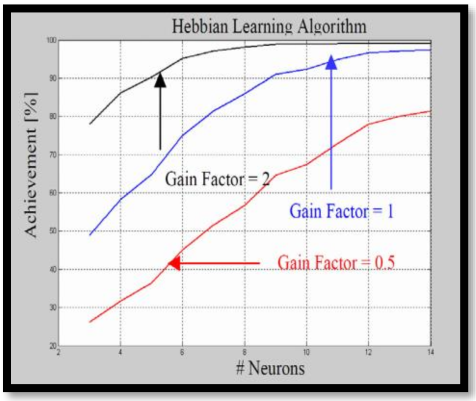

Figure 16 lustrates learning performance to get accurate solution with different gain factors 0.05, 1, and 2, for fixed number of training #cycles = 300 and Learning rate = 0.3.

The above set of sigmoid functions could be conversely presented as a set of normalized decay exponential curves given by following formula where suggested (η_i) as individual differences factor. These differences are suggested to be as one of factors (η_i). These factors could be presented in case of considering different learning performance curves(when normalized) as follows:

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

where (n) is the number of training cycles. That set of curves is illustrated graphically at figure 8 given in blow.

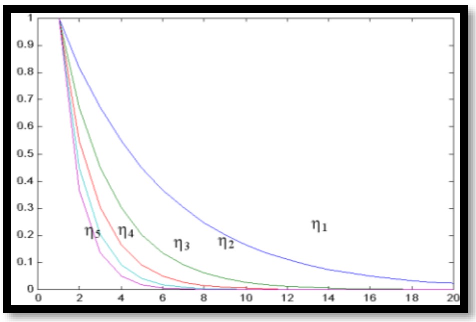

Fig. 17 Illustrates different learning performance curves for the examples given considering normalization of output response values adapted from [6].

V. MORE L EARNING MODELS

This section introduces two models deal closely with approaches applied for solving learning problems associated with patterns' recognition and classification, as follows:

*A. **Learning process in genetic algorithms [17][18]***

This model based on genetic algorithm approach. Learning process performed by this model is given at Table 3.

Table 3: Illustrates misclassification error for some fixed population size for segment data set.

Error %	25	17	13	12	11	10
Generations	20	40	80	120	160	200

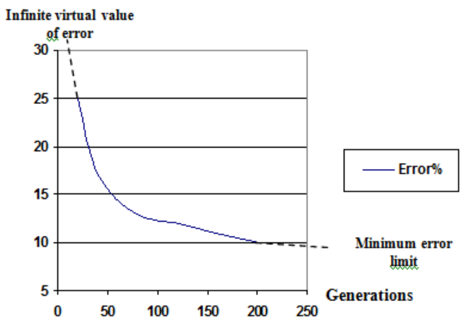

Fig. 18. Illustrates decay curve for misclassification error value versus the increase of generation in parallel genetic algorithm (for some constant population size) adapted from [18].

B. Oja's rule algorithm searching for PCA [33][49]

Referring to the statistical nature of learning processes, (Haykin 1999) an example of dynamic recognition model is presented. That model is based on principal component analysis (PCA) or equivalently referred as Karhunen-Loeve transform. Which is a mathematical way of determining linear transformation of a sample of points in N-dimensional space. So, it exhibits properties of the sample most clearly along the coordinate axes. Along the new axes the sample variances are extremes (maxima and minima), and uncorrelated. The name comes from the principal axes of an ellipsoid (e.g. the ellipsoid of inertia), which are just the coordinate axes in question. Additionally that system continuously enlarges in real time, and it is possible to recompute PCA using an iterative gradient search method (Roseborough and Murase 2000). This iterative steps (computing eigen values λi) corresponds to increasing of eigen vectors (e_i) rank, derived from some randomized data set.

The following figure 15, illustrates the conversion of searching process to obtain PCA for a given randomized data set vectors. At this figure it is noticed that, the magnitude of λi equals the variance in the data set that is spanned by its corresponding e_i. So, it is obvious that higher order eigenvectors account for less energy ion the approximation of data set since their Eigen value have low magnitude corresponding to better signal to noise ratio (S/N).

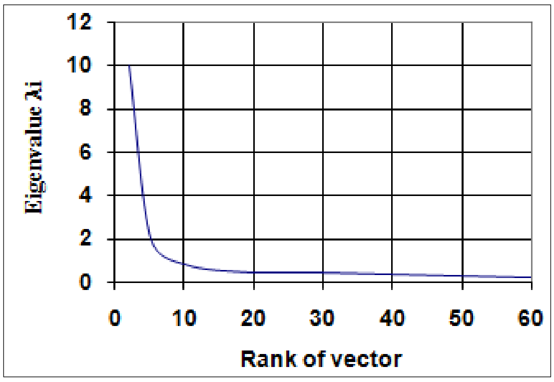

Fig. 19. The ordered Eigen values of data set randomized vectors

C. Least Mean Square LMS Algorithm

The following figure presents the learning convergence process for least mean square error as used for training of ANN models [33]. It is clear that this process performed similarly as ACS searching for minimum tour when solving TSP. [13]. Furthermore, it obeys the behavioral learning performance observed during psycho-experimental work carried for animal learning as well as the realistic simulation results [5][6][12].

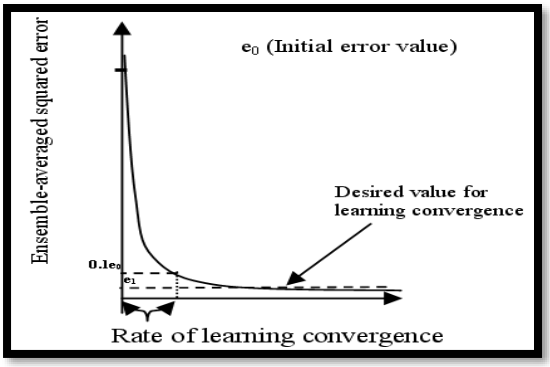

Fig. 20. Idealized learning curve of the LMS algorithm adapted from [33].

VI. CONCLUSION

This section introduces some interesting concluding remarks and comments based on mutual analogy observed among all introduced results of above four models (classified in two paradigms). This analogy considers at one hand, three behavioral learning models presented at the 3rd section related to first paradigm. However, at the other hand, ACS model presented at preceded 4th section related to second paradigm. According to above animal learning experiments (dogs, cats, and mouse), their performance analysis and evaluation by ANNs behavioral learning modeling, all of them agree well as for ACS optimization process. Also, it is noticed that performance of both types (ant and animals) is similar to latency time tending to be minimized as number of trials increases.

Recently, some interesting findings have been published at [51],concerned with the analogy between ACS while solving TSP versus mouse activity while solving reconstruction problem inside figure 8 Maze.

Referring to [6], therein, shown that both work for Thorndike and Pavlov [10][11] are supporting each other considering there learning performance [10[11][12]. So, it is obvious that both obeys generalize (LMS) for error minimization by learning convergence [33]. Also, that algorithm agrees with the behavior of brainier mouse behavior (that is genetically reformed) as shown at [17], [18]. Additionally; adaptation equations for all of presented systems in the above are running in agreement with dynamic behavior of each other. Moreover, the learning algorithms for these systems are close to each other with similar iterative steps (either explicitly or implicitly). Finally, it is precious to note that the rate of increase of speed of response is analogous to rate for reaching optimum average speed in ACS optimization process. Moreover, the increase on number of artificial ants is analogous to number of trials in Pavlov's work [10]. Conclusively, performances of three models(at this fifth section) agree well , with behavioral adaptive processes ,presented by other animal learning models. Those previously shown, at sections III. & IV. ,presenting experimental work applied on dogs ,cats , mouse, and ants respectively.

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