Comparative Performance Analysis and Evaluation for One Selected Behavioral Learning System versus an Ant Colony Optimization System

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ABSTRACT

This piece of research addresses an interesting comparative performance analysis and evaluation study for behavioral learning versus ant colony optimization. It considers two conceptual diverse algorithmic computational intelligence approaches. Both are related tightly to Neural and Non-Neural Systems respectively. The first algorithmic intelligent approach concerned with observed practically obtained results after one of neural animal systems' activities. Namely, a mouse's active trials to reach an optimal solution for a reconstruction problem during its movement inside figure of eight (8) maze. Conversely, the second approach originated from realistic simulation results observed for Non-Neural system's activities namely: Ant Colony System (ACS). Obtained results have been reached while ACS is searching for an optimal solution of Traveling Sales-man Problem (TSP).
Herein, some interesting observations have been introduced which concerned with similarity of enhancement for either learning systems under comparison. That enhanced/improved performance observed due to the effect of increase intelligent agent's number (either neurons or ants). Considering simulation of both adopted biological systems by Artificial Neural Network (ANN), results in very interesting findings. Furthermore, both have shown to be in agreement with learning convergence of an ANN learning model, while searching for optimal solution adopting Least Mean Square Error (LMS) Algorithm.

KEYWORDS

Artificial Neural Network Modeling, Animal Learning, Ant Colony System, Traveling Salesman Problem; Computational Biology.

1 INTRODUCTION

Investigational analysis and evaluation of two diverse adaptive behavioral phenomena in natural learning has been presented. Both phenomena have originated as result of creatures' interactions with their surrounding learning environmental conditions [1], and they obeyed the principle of learning without teacher. This Paper is classified to evolutionary algorithm (EA) approach [2]. Recently, one interdisciplinary work has been published which tightly associated to performances' analogy of both diverse behavioral learning phenomena considering a set of Neural animals' learning versus one Non-Neural (swarm intelligent) Systems [3], besides some other published interdisciplinary interesting research papers [4][5][6][7] [8][9].
More specifically, other works have been published which concerned with animal's learning at [10][11][12],and others related directly to ant colony system (ACS) at [13][14][15][16][17][18].
Two specific algorithmic examples have been selected herein for environmental behavioral learning systems. Firstly, that algorithm associated to adaptive neural behavioral learning originated inside hippocampus area of a Mouse's brain [12]. However, the second

algorithm is associated to analysis of behavioral learning of (ACS) optimization belonging to swarm intelligence phenomenon. The presented algorithm of (ACS) based on realistic simulation of foraging behavioral phenomenon observed by natural really biological (ACS) [13]. Analysis and evaluation of such interdisciplinary challenging learning issue is carried out using Neural Networks' Conceptual Approach. More specifically, both adopted behavioral learning models herein {either Mouse's or Ant Colony System (ACS)} improves its performance by consecutive trials to minimize response (learning convergence) time period [19][10] & [13][17].

The mouse's algorithmic learning model concerned with behavioral learning of mouse while performing trials for get out from inside figure eight (8) maze. That observed during its trials to solve reconstruction problem [12].

Briefly, this article presents analysis of all obtained introduced realistic simulation results of adopted both models considered input environmental stimulating actions. That are provided by external environmental conditions versus spontaneously adaptive responsive reactions carried by creatures' models [1][7][10][18]. Furthermore, behavioral intelligence & learning performance phenomena carried out by both nonhuman biological systems are characterized by their adaptive behavioral responses to their living environmental conditions. Accordingly, in other words, introduced diverse models for both approaches consider input stimulating actions provided by external environmental conditions versus adaptive reactions carried by creatures' models [1][3][10].The rest of this paper is organized as follows. At next section, revising of both adopted approaches*' concepts* and revising of ANN learning principles (Learning with, and without a teacher) have been presented. Behavioral mouse's learning algorithm is introduced at the third section in some details. The *fourth* section is dedicated to illustrate learning algorithm at ACS. Obtained simulation results compared with the experimental results for both learning paradigms are given at the fifth section. Finally, at the last sixth section, conclusions and valuable discussions are introduced.

2 A REVIEW FOR ADOPTED APPROACHES' CONCEPTS

Referring to [12], and [13]; therein, the analogy between two approaches is clear for two folds. Those folds are: learning performance, and dynamical adaptation equations. In more details, according to Fisher's information [12], 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, based on Bayesian rule, which seemed analogous to probabilistic formula named: Pseudo-random proportional to 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.In brief, this section reviews concepts of both adopted diverse approaches of algorithmic computational intelligence and introduced as follows:

2.1 First Algorithmic Learning Approach

The first behavioral algorithmic approach considers one of neural nonhuman (animal's learning) models. This neural creature's model has been inspired by observed behavioral learning in natural real world during performing some psychological experimental work on animals [19][20][21]. That presented learning approach via non-human (animals: Mice) behaves in similarity with two other natural real world models based on Pavlov's and Thorndike's psycho-experimental works. Brief, Pavlov's dog learns how to associate between two inputs sensory stimuli (audible and visual signals) [19]. However, Thorndike's cat behavioral learning tries to get out from a cage to reach food out of the cage [21].

2.2 Second Algorithmic Learning Approach

Herein, specifically, optimal solution of TSP considered using realistic simulation of Non-neural systems namely: ACS. The objective of that adopted simulation is to get benefit of swarm (ant) system' behavioral intelligence to reach optimality of TSP solution. The simulation process performed for the ACS' function of bringing food from different food sources to store (in cycles) at ants' nest. The first behavioral algorithmic approach considers one of neural nonhuman (animal's learning) models[6]. Additionally, analysis of previously obtained results leads to discovery of some interesting analogous relations between both adopted behavioral learning paradigms. That concerned with observed resulting errors, time responses, learning rate values, gain factor values versus number of trials, training dataset vectors intercommunication among ants and number of neurons as basic processing elements [3][7][22]. Interestingly, behavioral intelligence & learning performance phenomena carried out by both nonhuman biological systems are characterized by their adaptive behavioral responses to their living environmental conditions, as illustrated at next subsection.

2.3 Simplified Interactive Learning Process

Referring to Fig. 1, it illustrates a general view of a teaching model qualified to perform simulation of above mentioned brain functions. Inputs to the neural network teaching model are provided by environmental stimuli (unsupervised learning). However, correction signal(s) in the case of learning with a teacher given by output response(s) of the model that evaluated by either the environmental conditions (unsupervised learning) or by supervision of a teacher. Furthermore, the teacher plays a role in improving the input data (stimulating learning pattern) by reducing the noise and redundancy of model pattern input. That is in accordance with tutor’s experience while performing either conventional (classical) learning or CAL. Consequently, he provides the model with clear data by maximizing its signal to noise ratio [12]. Conversely, in the case of unsupervised/self-organized learning, which is based upon Hebbian rule [15], it is mathematically formulated by equation (7) given at the next subsection (D). For more details about mathematical formulation describing a memory association between auditory and visual signals, for more details the reader is referred to [10].

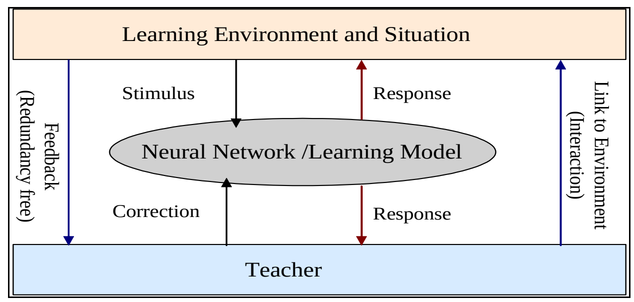

Figure 1 Simplified view for interactive learning process.

The presented model given in Figure 2 generally simulates two diverse learning paradigms. It presents realistically both paradigms: by interactive learning/ teaching process, as well as other self-organized (autonomous) learning. By some details, firstly is concerned with classical (supervised by a tutor) learning observed in our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between a teacher and his learners (supervised learning) [22]. However, the second other learning paradigm performs self-organized (autonomously unsupervised) tutoring process [1].

2.4 Interactive Mathematical Formulation of Learning Models

The presented model given in Figure 2 generally simulates two diverse learning paradigms. It presents realistically both paradigms: by interactive learning/ teaching process, as well as other self organized (autonomous) learning. By some details, firstly is concerned with classical (supervised by a tutor) learning observed in our classrooms (face to face tutoring). Accordingly, this learning model paradigm proceeds interactively via bidirectional communication process between a teacher and his learners (supervised learning) [22]. However, the second other learning paradigm performs self-organized (autonomously unsupervised) tutoring process [11].

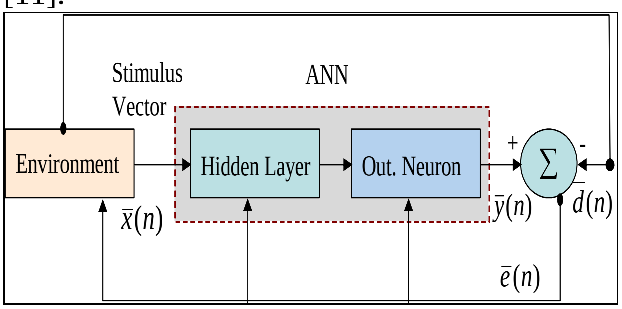

Figure 1. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [22].

Referring to above Figure 2; the error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

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

Where $\bar{e}(n)$ …… is the error correcting signal that adaptively controls the learning process,
$\bar{y}(n)$ …… is the output obtained signal from ANN model, and $\bar{d}(n)$ …… is the desired numeric value(s).
Moreover, the following four equations are deduced to illustrate generalized interactive learning process. These equations are commonly well valid for either guided with a teacher (supervised) or self-learning without a teacher (unsupervised):
Equation (2) considers the scalar product of two vectors the input vector (X) and internal weight vector (W) computed at the time instant (n).It is noticed that both are associated to neuron (k), and each has the same dimension (number of vector's components). The output of this neuron is given by equation (3).Which originated from the hyperbolic tangent function deduced from classical sigmoid function.
Equation (4) computes the error value which controls the guided learning process (supervised with a teacher) and so it does not valid in case of unsupervised (learning without a teacher).
The dynamic learning law at two subsequent time instances (n) & (n+1) is shown by equation (5).

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

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

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

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

Where X is input vector and W is the weight vector. φ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Note that ΔW_{kj}(n) is the dynamical change of weight vector value. Above four equations are commonly applied for both learning paradigms: supervised (interactive learning with a tutor), and unsupervised (learning though student's self-study). The dynamical changes of weight vector value specifically for supervised phase is given by:

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

Where η is the learning rate value during the learning process for both learning paradigms. At this case of supervised learning, instructor shapes child's behavior by positive/ negative reinforcement Also, Teacher presents the information and then students demonstrate that they understand the material. At the end of this learning paradigm, assessment of students' achievement is obtained primarily through testing results. However, for unsupervised paradigm, dynamical change of weight vector value is given by:

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

Noting that $e_k(n)$ equation (6) is substituted by $y_k(n)$ at any arbitrary time instant (n)during the learning process. Instructor designs the learning environment.

3 FIRST ALGORITHMIC LEARNING PERFORMANCE

3.1 Revising Function of Brain 's Hippocampus Area

In order to support adopted investigational research herein, and for more enlightening the function of brain's hippocampus area, three findings have been published recently, and herein they breifly introduced as follows:

3.1.1 First Finding

Referring to [23], 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.

3.1.2 Second Finding

The hippocampus is said to be involved in “navigation” and “memory” as if these were distinct functions [24]. 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.

3.1.3 Third Finding

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 [25]. However, an alternative explanation of apparent time coding is that hippocampal neurons "path integrates" 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 dominated an ongoing experience as illustrated at Fig.3 in below [25].

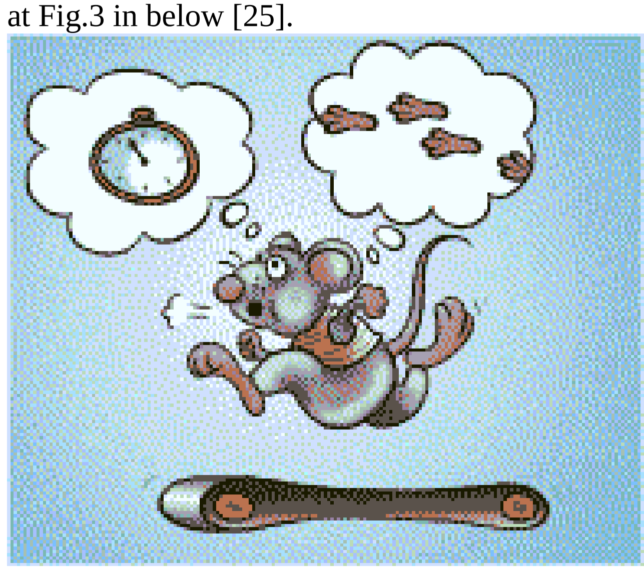

Figure 3. Dissociation between Elapsed Time and Path

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 [25].

3.2 Convergence of mouse's behavioral learning for Solving Reconstruction Problem

Referring to [12], [26] and [27], a pattern recognition problem is suggested as an example for reconstruction process. This example is given briefly as to revel 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 [12]. 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 [26]. 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 Fig.1. Assume that a population of N neurons encodes several variables (x1, x2 ……), which will be written as vector x. From the number of spikes n= (n1, n2, .nN) 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:

$$P\,(x \mid n) = P\,(n \mid x)\,P\,(x)\,/\,P\,(n) \qquad (8)$$

Assuming independent Poisson spike statistics. The final formula reads

$$P(x \mid n) = kP(x)\left(\prod_{i=1}^{N} f\,i(x)^{ni}\right)\exp\left(-\tau\sum_{i=1}^{N} f\,i(x)\right) \qquad (9)$$

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,

$$\hat{x} = \arg\max_{x} P\,(x \mid n) \qquad (10)$$

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 [19].

Referring to measured mean error results shown at Table1, for solving reconstruction (pattern recognition) problem by a mouse inside a figure of eight (8) maze [12][26]. Those results based on pulsed neuron spikes at hippocampus of the mouse brain. According to following table, the error value seems to decrease similar to exponential curve decays to some limit value versus (place field) cells. The value of mean error converges (by increase of number of cells) to some limit, excluded as Cramer-Rao bound. That limiting bound is based on Fisher's information given as tabulated results in the above that obtained after an experiment for trials to solve reconstruction process from a pattern recognition problem [12]. It is noticed that the algorithmic performance learning curve referred to Figure 1, converged to bounding limit (of minimum error value) fixed Cramer Rao bound (Limiting value). Referring to Fig.2, it is interesting to notice that absolute error values shown at vertical (y-axis) in Fig.4 are conversely corresponding to corrected image identification normalized values between [0 & 90] at vertical y-axis in Fig.4.Similarly, in Fig.3, neurons' number values increasing between [10 & 40] (at the x-axis), are in correspondence with horizontal x-axis in Fig. 4, which presents image resolution started at (2x5) pixels.

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

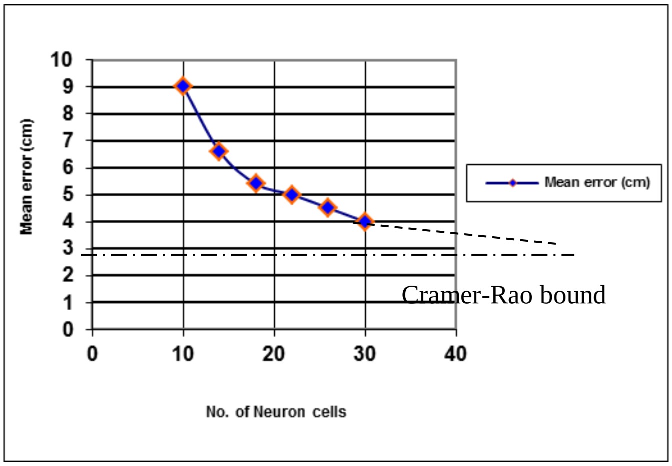

Figure 4. The dashed line indicates the approach to Cramer-Rao bound based on Fisher information adapted from [12].

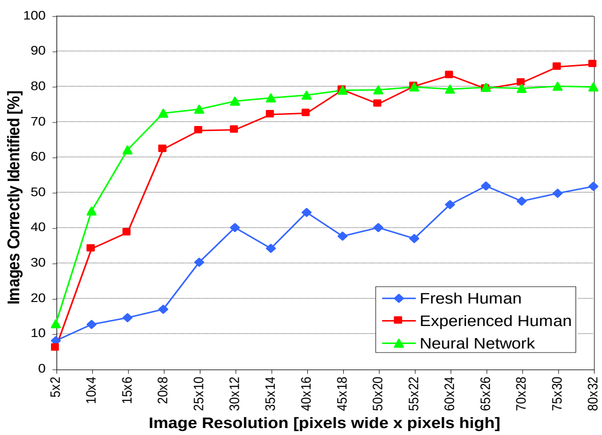

Figure 5. Obtained simulation results after running of neural network model compared versus measured human results considering basic images with different images' resolution (number of pixels). These results are illustrated in graphical form, adapted from [28].

4 SECOND ALGORITHMIC LEARNING PERFORMANCE

This algorithm adopts Swarm intelligence (SI) that defined as the collective behavior of decentralized, self- organized systems, natural or artificial. Its concept is employed in work on artificial intelligence, which shares a few features based on SI optimization algorithms [29], such as glowworm swarm optimization (GSO) [30][31], and ant colony system (ACS) optimization [13][32]. The agents in GSO are thought of as glowworms that carry a luminescence quantity called luciferin along with them. These glowworms function to encode the fitness of their current locations, evaluated using the objective function, into a luciferin value that they broadcast to their neighbors [31]. However, agents in ACS optimization behaves in order to reach optimization target considering foraging behavior based on pheromone communication among ant's agents regarding a good path between food source and colony's nest. Herein, a special attention has been considered for ACS's optimization [32].

4.1Revising Ant Colony System Performance

The Ant Colony System algorithm is inspired by the foraging behavior of ants, specifically the pheromone communication between ants regarding a good path between the colony and a food source in an environment. This mechanism is called stigmergy. Ants initially wander randomly around their environment. Once food is located an ant will begin laying down pheromone in the environment. Numerous trips between the food and the colony are performed and if the same route is followed that leads to food then additional pheromone is laid down. Pheromone decays in the environment, so that older paths are less likely to be followed. Other ants may discover the same path to the food and in turn may follow it and also lay down pheromone. A positive feedback process routes more and more ants to productive paths that are in turn further refined through use.
Referring to Fig.6 given in below, 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 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. 6B). 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. 6 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. 6 D). 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 behaviour: 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. This process is adapted with the existence of an obstacle through the pathway from nest to source and vice versa, however, more detailed illustrations are given through other published research work [17]. Therein, ACS performance obeys computational biology algorithm used for solving travelling salesman problem TSP optimally [13]. Referring to more recent work [33][34] 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 [22].

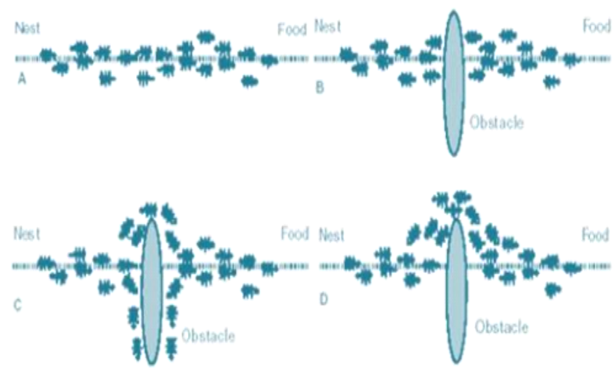

Figure 6. .Illustrates the process of transportation of food (from food source) to food store (nest) .Adapted from [13]

ACS optimization process compared versus MICE reconstruction problem. the relation between cooperative process in ACS and activity at hippocampus of the mouse brain is illustrated well at recently published work [3].

Referring to Fig. 7 (adapted from [33]), it illustrates the path taken by tandem running pair of ants (Temnothorax albipennis) 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. [33] At the start of a tandem run, the leader finds a naïve individual who is willing to follow her. But tandem runs are rather slow because the follower frequently pauses to look round for landmarks so that it can learn the route. Only when the follower has done this does it tap on the hind legs and abdomen of the leader to let it know that the tandem run can proceed.

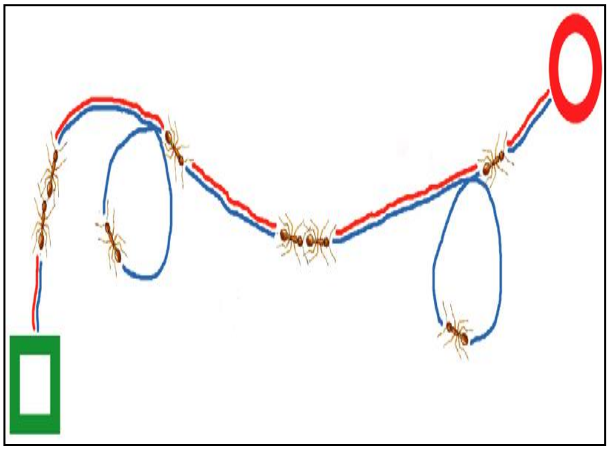

Figure 7. .Illustrates the supervised learning process of tandem running of pair ants Temnothorax albipennis, that obeys above equation (7) presented at second {section (c)}in the above. Adapted from [30]

4.2 Algorithmic Steps Analogy for Mouse's Behavioral Learning Versus ACS Optimization

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**
Figure 8. 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 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**
Figure 9. Illustrates training process in ANN models considering latency time phenomenon having two loops with iterative learning cycles.

Figure 8 gives the algorithmic steps for solving basically the Travelling Sales Man (TSP) considering the process of transportation of food (from food source) to food store (nest) shown at Figure 6. Interestingly, it clear that both algorithmic steps presented at Figure 8 and Figure 9 are analogous to each other. Furthermore, the algorithmic steps shown at Figure 9 are describing behavioural learning in Pavlov's iterative work processes based on neural network model presenting Hebbian learning as introduced at [10]. The results obtained after performing the original psych-experimental work concerned with Pavlov's dog, are nearly well analogous to the behavioural learning of mouse's trail for solving reconstruction problem That is illustrated during the while detailed comparative evaluation for learning creativity of Cats, Dogs, Ants, and Rats presented at [7].

Referring to Figure 11, which has been 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 sigmoid function as shown at given by the end of this manuscript (at Figure 13).

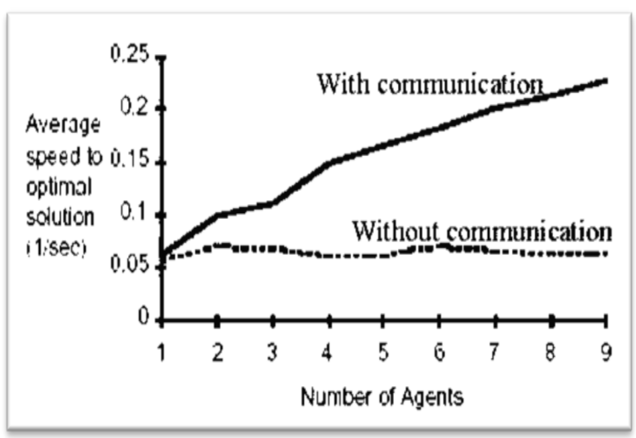

Figure 10. Illustrates performance of ACS considering either with or without intercommunication among ant agents {adapted from [13]}.

5 SIMULATION RESULTS

5.1 Intercommunication Among Ants

Referring to Fig. 9, the relation between tour lengths versus the CPU time is given [29]. It is observed the effect of ant cooperation level on reaching optimum (minimum tour). Obviously, as level of cooperation among ants increases (better communication among ants) the CPU time needed to reach optimum solution is decreased. So, that optimum solution is observed to be reached (with cooperation) after 300 (msec) CPU the while that solution is reached after 600 (msec) CPU time (without cooperation).

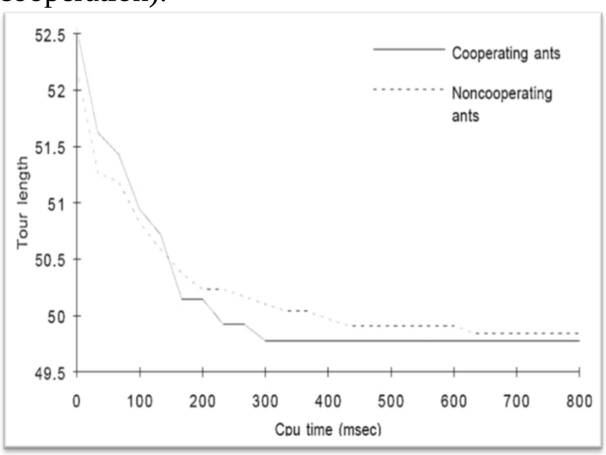

Figure 11. Cooperating ants find better solutions in a shorter time. Average value obtained after 25 runs. The number of ants was set to m=4, adapted from [29].

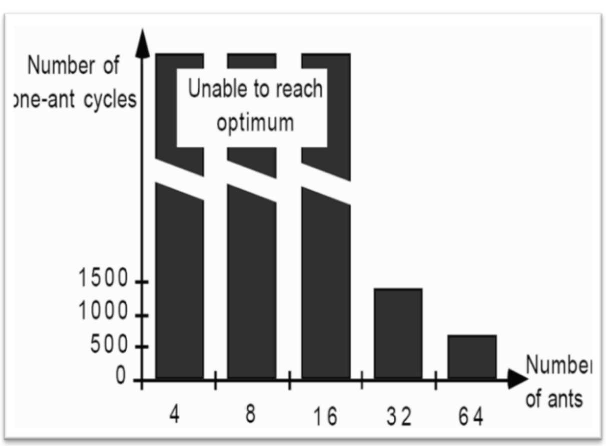

Figure 12. Number of cycles required to reach optimum rated to the total number of ants adapted from [29].

In other words, by different levels of cooperation (communication among ants) the optimum solution is reached after CPU time τ placed somewhere between above two limits 300-650 (M. sec). Referring to [24], cooperation among processing agents (ants) is a critical factor affecting ACS performance as illustrated at Fig. 9. So, the number of ants required to get optimum solution differs in accord with cooperation levels among ants. This number is analogous to number of trials in OCR process. Interestingly, in natural learning environment, the (S/N) signal to noise ratio is observed to be directly proportional to leaning rate parameter in self-organized ANN models. That means in less noisy learning environment (clearer) results in better outcome learning performance given in more details at [19][25]. More precisely, such learning environment with better (S/N) ratio, implicitly results in increasing of stored experience (inside synaptic connectivity) while nonhuman creatures are adopting self-organized learning via interaction with environment [15]. Referring to equation (11) introduced for solving reconstruction problem (corresponding to the most probable value of x) has great similarity to the equation presented to search for optimal solution considering TSP reached by ACS (for random variable S) as follows.

$$s = \begin{cases} \arg\max_{u \in M_k} \left\{ \left[\tau(r,u)\right] \cdot \left[\eta(r,u)\right]^{\beta} \right\} & \text{if } q \le q_0 \\ S & \text{otherwise} \end{cases} \tag{12}$$

where τ(r,u) is the amount of pheromone trail on edge (r,u) , η(r,u) is a heuristic function, which was chosen to be the inverse of the distance between cities r and u, β is a parameter which weighs the relative importance of pheromone trail and of closeness, q is value chosen randomly with uniform probability in [0, 1], q_0 ($0 \le q_0 \le 1$) is a parameter, M_k is memory storage for k ants activities, and S is a random variable selected according to some probability distribution [26][24]. Synergistic effect by Ant colony intercommunications is given by mathematical formulation for ACS optimization as follows. At recent previous work analogy between ACS performance and ANNs has been illustrated at [2][5][6][27][28]. The performance of the synergistic effect of ACS referring to the generalized sigmoid function is given as function of discrete integer (+ve) value representing for number of ants as follows:

$$f(n) = \alpha\left(\frac{1-e^{-\lambda n}}{1+e^{-\lambda n}}\right) \quad (13)$$

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. 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. More appropriate that declares the slope (gain factor) for suggested sigmoid function is a direct measure for intercommunications level among ants in ACS in other words, the slope, λ is directly proportional to pheromone trail mediated communication among agents of ACS. Consequently, ACS global performance has become nearly parallel (slope =0) to the X-axis (number of ants), nevertheless increasing of ants comprising tested colony (slope, λ=0), that's the case when no intercommunications between ants exists. Fig. 6 illustrates the normalized behavioral model following the equation.

y (n)= (1-exp(-λi(n-1)))/ (1+exp(-λi(n-1))) (14)

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.13, and Fig.14 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 [5][7]. 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) [5][17]. The above equation (14) presents a set of curves changes in accordance with different gain factor values (λ).In this equation,

λi represents one of gain factors (slopes) for sigmoid function which considered being analogous to communication level, n….. is the number of training cycles. This set of curves is illustrated graphically at Fig.11, they considered as normalization of output response values. 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 (-η_i(n-1)) (15)

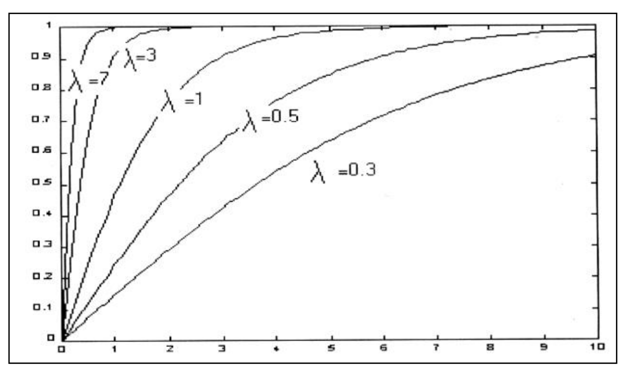

Figure 13. Graphical representation of learning performance of model with different gain factor values (λ).The Figure analogously represents behavioral learning performance of ACS model corresponding to the various communication levels values (λ).

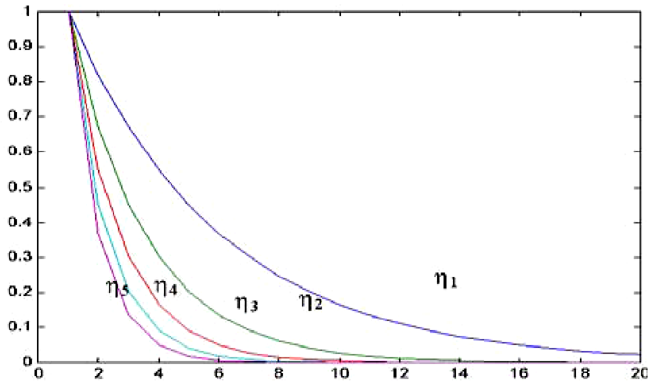

Figure 14. illustrates different learning performance curves for different learning rate values (η).

5.2 Realistic Simulation Program

Figure 15 introduces the flowchart for simulation program which applied for performance evaluation of behavioral learning processes. Considering the two biological creatures adopted herein that having either neural or non-neural systems, simulation by artificial neural networks results in very interesting findings. That Figure presents a simplified macro-level flowchart which briefly describes the algorithmic steps for realistic simulation program of adopted Artificial Neural Networks' model for different number of neurons using. These results are shown at the three figures (16, 17, 18, and 19) after running of that program.

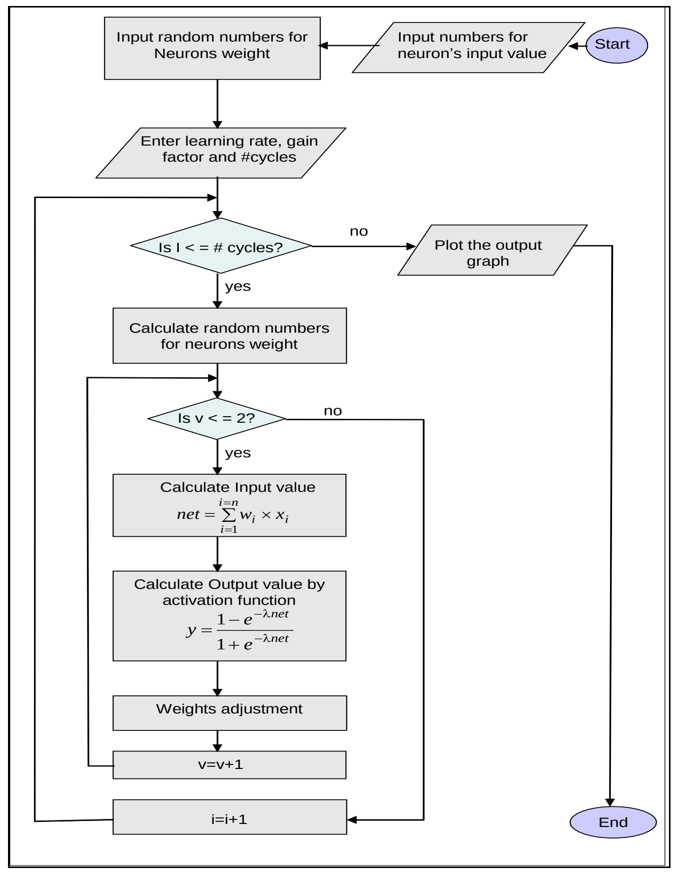

Figure 15. A simplified macro level flowchart that describing algorithmic steps for Artificial Neural Networks modeling considering various neurons' numbers

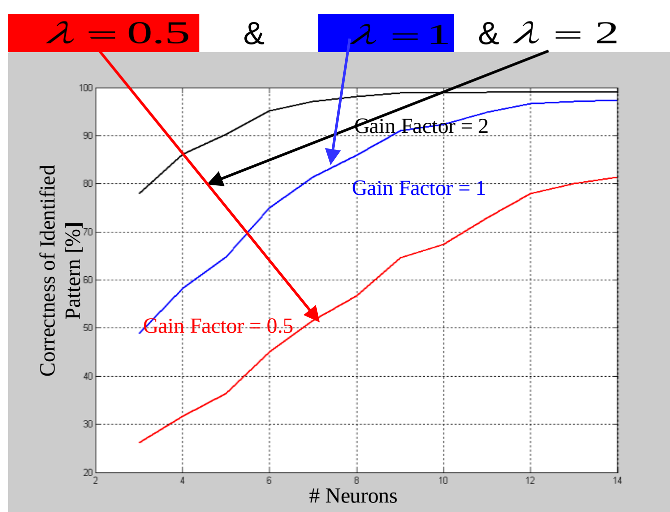

Figure 16. Illustrate the learning achievement for different gain factors and intrinsically various number of neurons which measured for constant learning rate value = 0.3.

The set of Figures (16, 17, 18, and19) illustrates obtained simulation results after running of a program having its flowchart at Figure 15.
This set considers the learning performance of an ANN based on either intrinsic (individual differences' achievement) by gain factor effect at Figures (16, 17, and19) or environmental effect given by learning rate in Figure 18.

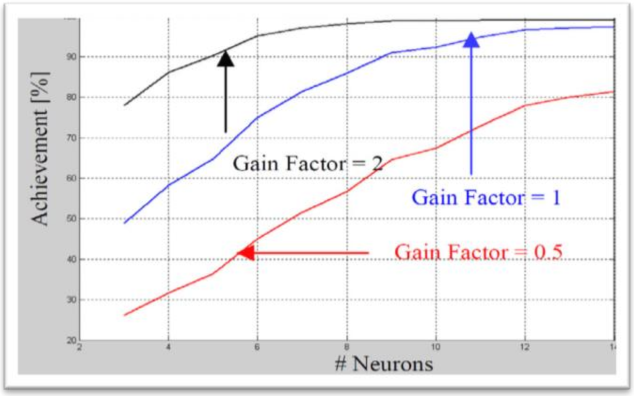

Figure 17. Illustrates the performance of error correction algorithm versus learning convergence time for different gain factor values.

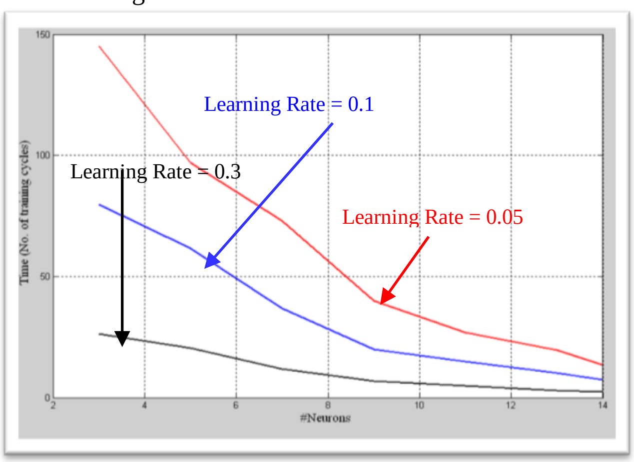

Figure 18. Illustrates the performance of error correction algorithm versus learning convergence time for different learning rate values.

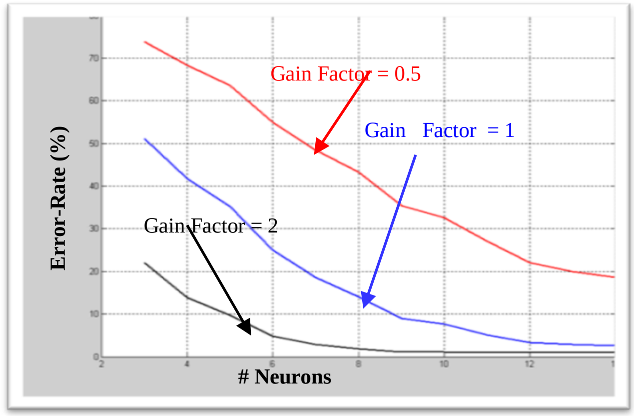

Figure 19. Illustrate learning performance to get accurate solution with different gain factors 0.05, 1, and 2, while #cycles = 300 and Learning rate = 0.3

Interestingly, the solution of mouse's reconstruction problem inside a Figure of eight maze (8), could be classified as one of a pattern recognition problems which could be performed with similarity to solving Optical Character Recognition (OCR) problems studied at [35][36].

5.3 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 [22]. 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 [10][11][12].

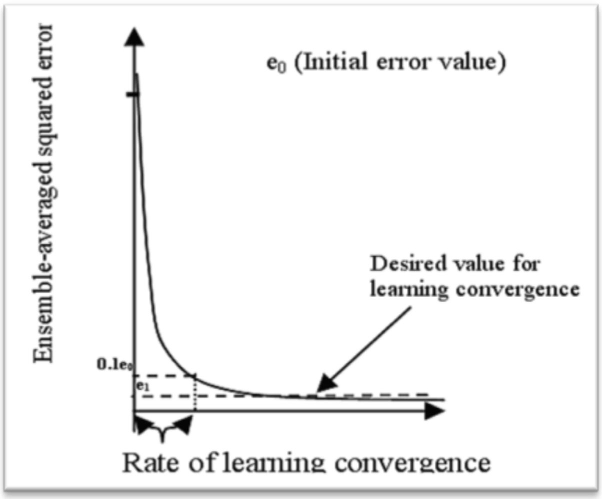

Figure 20. Idealized learning curve of the LMS algorithm adapted from [22].

6 CONCLUSIONS AND DISCUSSIONS

According to above animal learning experiments, 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 the simulation results given at [11] therein it is shown that both learning performance curves presenting both work for Thorndike , Pavlov and mouse's solving of reconstruction problem solving are commonly characterized by their hyperbolic decay and also, both obeys generalized (LMS) for error minimization by learning convergence.

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. Additionally, the learning algorithms for the presented four models 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. Noting that, increase on number of artificial ants is analogous to number of trials in Pavlov's work.

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