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RESEARCH ARTICLE

ON COMPARATIVE STUDY OF NEURAL NETWORKS' APPLICATION FOR THREE BEHAVIORAL LEARNING SYSTEMS' ACTIVITIES VERSUS SWARM INTELLIGENCE PERFORMANCE.

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Abstract

This piece of research addresses an interesting comparative analytical study. Which considers two concepts of diverse algorithmic computational intelligence approaches related tightly with Neural and Non-Neural Systems. The first algorithmic intelligent approach concerned with observed obtained practical results after three neural animal systems' activities. Namely, they are Pavlov's, and Thorndike's experimental work. Besides a mouse's trial during its movement inside figure of eight (8) maze, to reach an optimal solution for reconstruction problem. Conversely, second considers algorithmic Swarm Intelligent (SI) approach originated from resulting activities of Non-Neural Ant Colony System (ACS). These results obtained after reaching an optimal solution while solving Traveling Sales-man Problem (TSP).
Interestingly, the effect of the increase for agents' number (either neurons or ants) on learning systems' performance shown to be in agreement of each other for both (neural and non-neural) systems. Finally, performance of both intelligent learning paradigms shown to be in agreement with learning convergence process searching for Least Mean Square LMS error algorithm. That's during application of training phase of three Artificial Neural Network (ANN) models. Accordingly, adopted ANN modeling is a relevant and realistic tool to investigate observations and analyze performance for both selected computational intelligence (biological behavioral learning) systems.

Introduction:-

Investigational analysis and evaluation of two adaptive diverse phenomena in natural learning environmental paradigms. They consider two typical behavioral learning performance algorithms of non-human creatures' which biologically classified as Neural (animals), and Non-Neural (ant colonies) Systems [1][2][3][4][5][6]. The first algorithm is associated to adaptive neural behavioral learning inside three animals' brain: a Dog, a Cat, and a Mouse. However, the second belongs to analysis of behavioral learning algorithm associated to ant colony optimization for observed swarm intelligence phenomenon. Which based on realistic simulation foraging of behavioral phenomenon observed by real Ant Colony System. Analysis and evaluation of such interdisciplinary challenging learning issue is carried out using Neural Networks' Conceptual Approach. Herein, this paper presents analytical details for both intelligent behavioral approaches, which considered via two hand folds as follows. Firstly, at one hand: autonomous inferences and perceptions performed in nature by non-human brain (animals: Dogs, Cats, and Mice). Secondly, the other hand is inspired by source of ant colony optimization originated from intelligent

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foraging behavioral phenomenon of real ant colonies. This behavior is exploited in artificial ant colonies for the search of approximate solutions to optimization problems such as Traveling Salesman Problem (TSP).

A. First Algorithmic Learning Approach

More specifically, the first behavioral algorithmic approach considers three nonhuman models. All three neural creatures' models have been inspired by observed behavioral learning performance in natural real world. Two of introduced models based on Pavlov's and Thorndike's excremental work. In some 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. Both behavioral learning models improves its performance by trial to minimize response time period. The third model concerned with behavioral learning of mouse while performing trials for get out from inside figure 8 maze. That by trial to solve reconstruction problem [7].

B. Second Algorithmic Learning Approach

The third algorithm concerned with searching for optimal solution of TSP by using Non-neural systems namely, colony system ACS. That model simulates a swarm (ant) intelligent system used for solving optimally traveling sales man problem TSP. That by bringing food from different food sources to store (in cycles) at ant's nest. Moreover, three learning models based on pulsed neurons criterion parallel genetic algorithmic programming, and modified Hebbian learning paradigm (Oja's rule). Interestingly, all of other models shown to behave analogously to previous suggested Pavlov's, Thorndike's and ACS models.

Principles of biological information processing concerned with learning convergence for both bio-systems have been published at [8]. By some details, in this work an interesting comparative analysis introduced for concepts of behavioral learning phenomenon, versus optimal solution of TSP using swarm intelligence optimization (ACS) [1][10][11][12]. In other words, an investigational analytical overview is presented herein to get insight with behavioral intelligence of non-human creatures' performance as Neural and Non-Neural Systems [1][4][5][12].

Briefly, analysis of obtained results by such recent research work leads to discovery of some interesting analogous relations between both 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 [5][13][14]. However, it seems to observe diversity of behavioral learning curves performance (till reaching optimum state) for proposed biological systems, both are similar to each other (considering normalization of performance curves) [3][6]. 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. So, all introduced models for both approaches consider input stimulating actions provided by external environmental conditions versus adaptive reactions carried by creatures' models [1][9][15].

The rest of this paper is organized as follows. At next section, a simple interactive learning model is presented along with a generalized ANN block diagram simulating learning process. Revising of Thorndike's, Pavlov's, and mouse's behavioral learning are introduced briefly at the third section. The fourth section is dedicated to illustrate learning algorithm at ACS.

Obtained simulation results compared with the experimental results are given at the fifth section. Finally, at the last sixth section, some conclusions and valuable discussions are introduced.

INTERACTIVE LEARNING MODEL:-

C. Simplified interactive learning process

Referring to Figure 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). For more details about mathematical formulation describing a memory association between auditory and visual signals, please refer to [17].

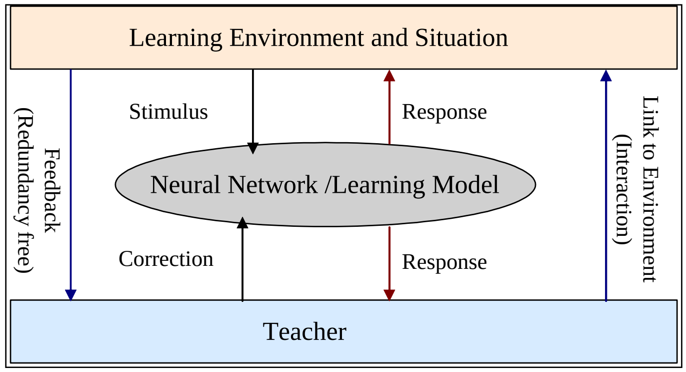


Figure 1:- Simplified view for interactive learning process.

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) [16] [17]. However, the second other learning paradigm performs self-organized (autonomously unsupervised) tutoring process [17].

D. Mathematical Formulation of learning paradigms

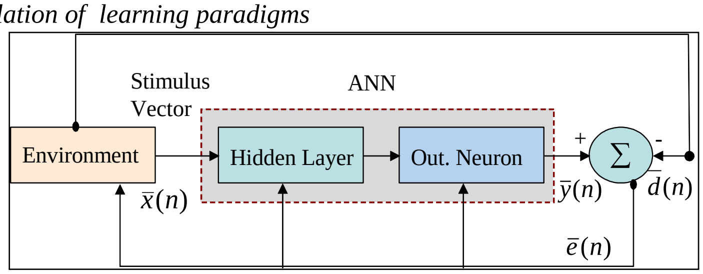


Figure 2:- Generalized ANN block diagram simulating two diverse learning paradigms adapted from [18].

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

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

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:

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

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

$$e_k(n) = |d_k(n) - y_k(n)| \quad (4)$$

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

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:

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

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:

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

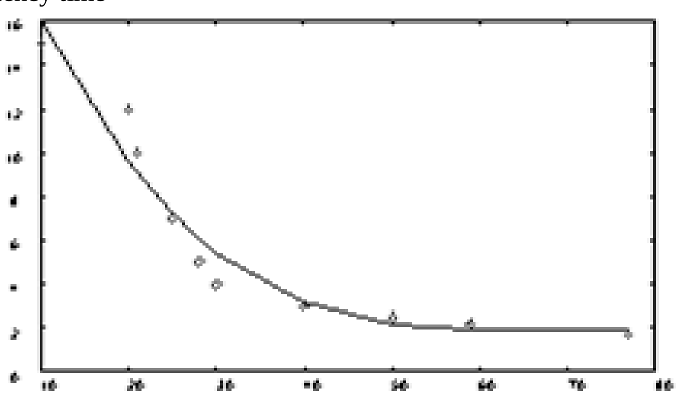
Noting that e_k(n) equation (6) is substituted by y_k(n) at any arbitrary time instant (n)during the learning process. Instructor designs the learning environment.

MODELS OF FIRIST LEARNING ALGORITHM:-

E. Revising of Pavlov's work [10]

The psycho-experimental work of Pavlov is known for classical conditioning. It is characterized by following two aspects: A spontaneous reaction that occurs automatically to a particular stimulus, and to alter the "natural" relationship between a stimulus and a reaction response was viewed as a major breakthrough in the study of behavior [15][20]. By referring to the original Pavlov's work, let us define what is meant by latency time. This time is briefly, 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 [3] [4]. Conversely, on the basis of Pavlov's obtained experimental results, it is well observed mathematical interrelationship between latency time period versus subsequent number of trials can be illustrated explicitly in the form of hyperbolic function curve that mathematically expressed by following equation: $t(n) = \dfrac{\alpha}{n^{\beta}}$ (8) 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 figure 3 in blow.

Latency time



Training cycles

Figure 3:- Fitting curve for latency time results observed by Pavlov's experimental work.

F. Revising of Thorndike's Work [11]

Referring to behaviorism learning theory presented at [20] ,Thorndike had suggested three principles, which instructors (who adopted teaching based on behaviorism learning theory) should apply in order to promote effectiveness of behavioral learning process. These 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.

Furthermore, building on these he proposed an alternative teaching technique called programmed learning/instruction and also a teaching machine that could present programmed material. Initially, cat's performance trials results in random outputs. By sequential trials, following errors observed to become minimized, by increasing number of training (learning) cycles. Referring to Fig.4, which illustrates original Thorndike's work results. This figure presents the relation between response time and number of trials. Furthermore, referring to that original Thorndike’s experimental results given at Fig.4, represent behavioral learning performance of Thorndike's work. However, normalized learning curve that presents performance curve of experimental work is given approximately at figure 5. Interestingly, the comparative analogy between performance curves of Pavlov’s and Thorndike’s work shown to behave similar to each other [4].

In general, principle of adaptive learning process (observed during creatures' interaction with environment) illustrated originally at [15].

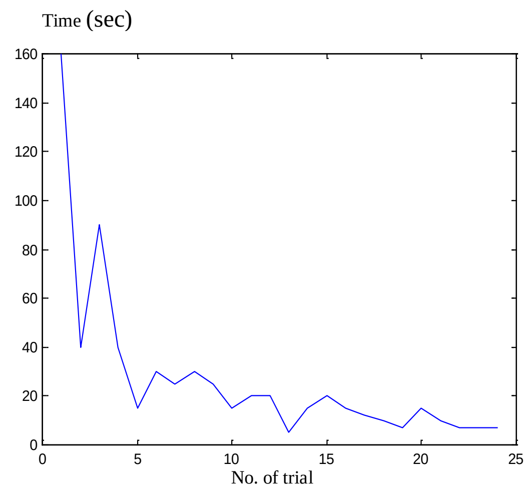
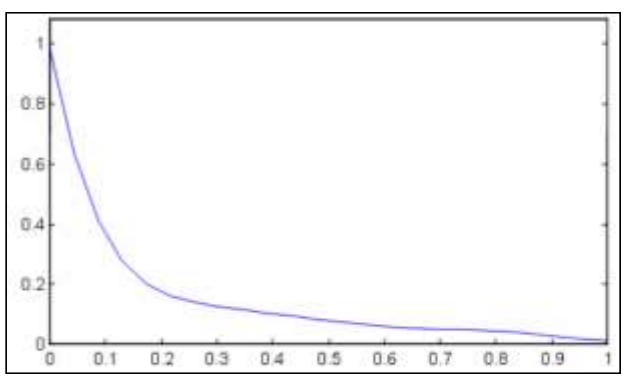


Figure .4:- The original result of Thorndike representing learning performance for a cat to get out from the cage for reaching food.

Normalized Time Response (Cycles)

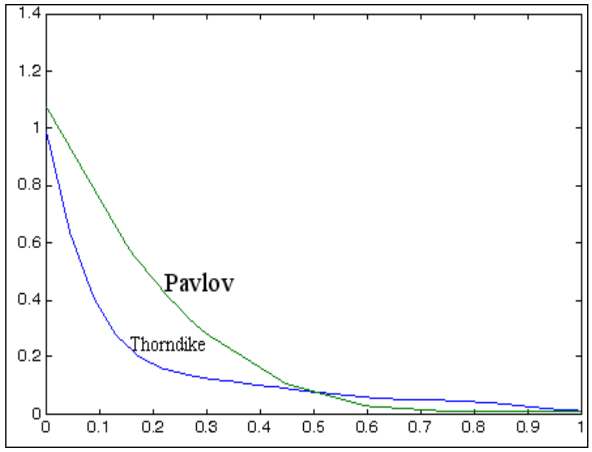


Normalized No. of Trials

Fig. 5:- Thorndike normalized results seem to be closely similar to exponential time decay

Referring to Figure 6, it observed that by increasing number of training cycles, the first learning algorithm converges to some fixed limiting values (for normalized time response). That observed results consider normalization of both number of trials values versus their corresponding normalized time response (for both original experimental work of Pavlov and Thorndike given at Figure 3 & Figure 4 respectively).

Normalized Time
Response (Cycles)



Normalized no. of trials (training cycles)

Figure 6:- Comparison between Pavlov and Thorndike work. Considering normalized results after application of ANN.

G. Mouse's Learning For Solving Reconstruction Problem

Referring to [18], 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 mouse [7]. 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 [20]. 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 [6]. 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 (x|n) = *P* (n|x) *P* (x) / *P* (n) (9)

Assuming independent Poisson spike statistics. The final formula reads

$$P(x \mid n) = kP(x)\left(\prod_{i=1}^{N} fi\,(x)^{ni}\right)\exp\left(-\tau\sum_{i=1}^{N} fi\,(x)\right) \quad (10)$$

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,

$$\hat{x} = \arg\max P(x \mid n) \quad (11)$$

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 [7][21]. That measured 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.

Table 1:- 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 based on Fisher's information given as tabulated results in the above and derived from [21].That implies LMS algorithm is valid and obeys the curve shown at in blow.

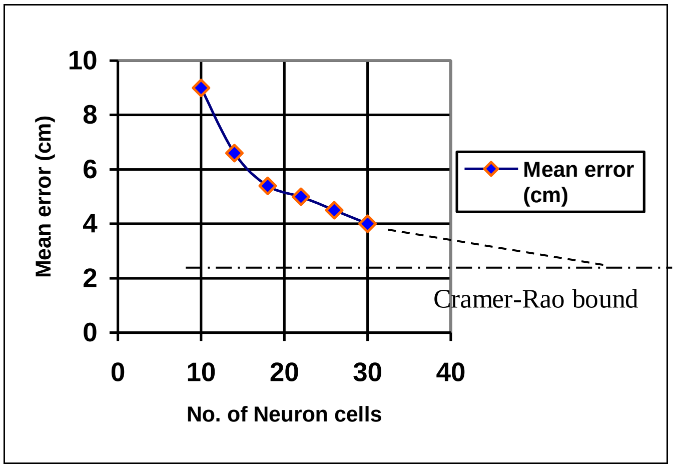


Figure7:- The dashed line indicate the approach to Cramer-Rao bound based on Fisher information adapted from [6].

Furthermore, it is noticed that the algorithmic performance learning curve referred to Figure 7, 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 referring to above Figure 2. Interestingly, considering comparison between learning curve performances at Figure 7 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 given herein at the simulation results' section V.

SECOND ALGORITHMIC LEARNING PERFORMANCE :-

H. Revising Ant Colony System Performance

Referring to Fig.1 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. 1B). 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. 1C). 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. 1D). 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, [1].Therein, ACS performance obeys computational biology algorithm used for solving optimally travelling salesman problem TSP [1].

Referring to two more recent research [2][22], 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] [23] [24].

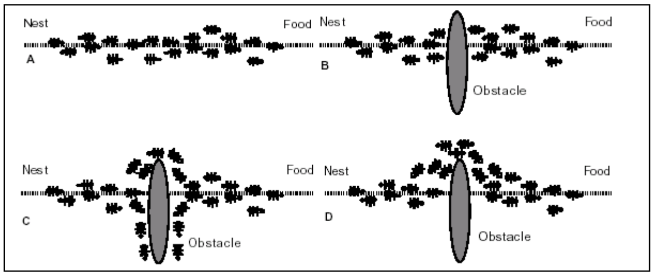


Figure 8:- Illustrates the process of transportation of food (from food source) to food store (nest).

ACS optimization process versus MICE reconstruction problem. Finally the relation between cooperative process in ACS and activity at hippocampus of the mouse brain is illustrated well at two recently published works [3] [4].

I. Cooperative Learning By ACS For Solving TSP

Cooperative learning by Ant Colony System for solving TSP

Referring to Figure 9, which adapted from [1], 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 equation (13) in below. This analogy seems to be illustrated well as referring to fig.4 where the output salivation signal is increased depending upon the value of no of training cycles. 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.

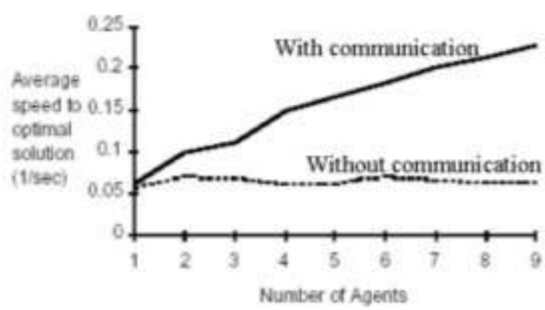


Figure 9:- Illustrates performance of ACS with and without communication between ants {adapted from [1]}

SIMULATION RESULTS:-

J. Intercommunication Among Ants

Referring to Figure 10 shown in below, the relation between tour lengths versus the CPU time is given. 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).

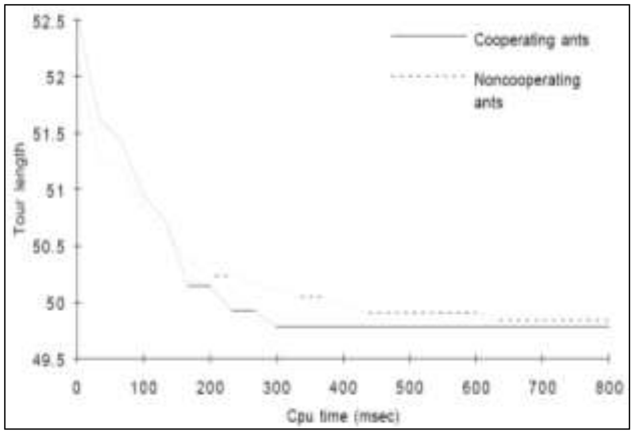


Figure 10:- Cooperating ants find better solutions in a shorter time. Average on 25 runs. The number of ants was set to m=4, adapted from [24].

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 Figure 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.

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

where $\tau(r,u)$ is the amount of pheromone trail on edge (r,u) , $\eta(r,u)$ 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:

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

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.

In given figure 6 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))) (14)
Where λi represents one of gain factors (slopes) for sigmoid function.

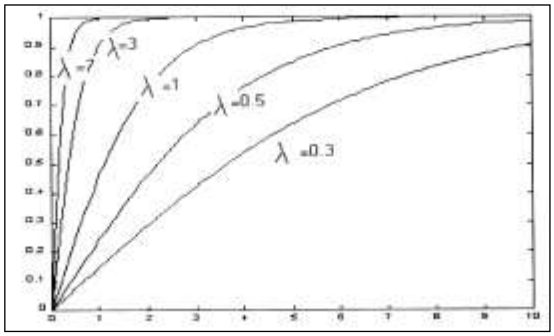


Figure 11:- Graphical representation of learning performance of ACS model with different communication levels (λ).

K. Realistic Simulation Program

Figure 12 introduces the flowchart for simulation program which applied for performance evaluation of behavioral learning processes. Considering the two adopted cases of biological creatures having either neural or non-neural systems. That Figure presents a simplified macro-level flowchart which describes briefly algorithmic steps for realistic simulation program of adopted Artificial Neural Networks' model for different number of neurons using. The results are shown at the three figures (13, 14, and 15) after that program running.

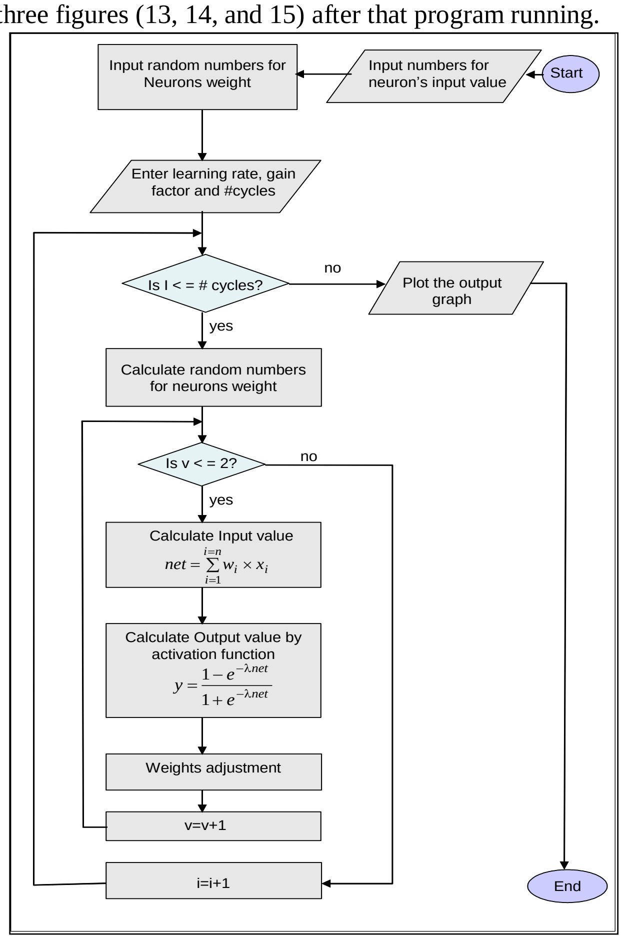


Figure 12:- A simplified macro level flowchart describing algorithmic steps for Artificial Neural Networks modeling considering various neurons' number.

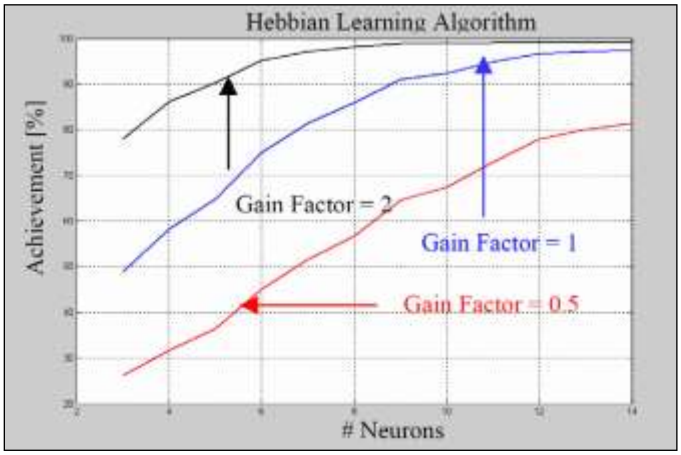


Figure 13:- Illustrate learning performance to get accurate solution with different gain factors 0.05, 1, and 2, while #cycles = 300 and Learning rate = 0.3

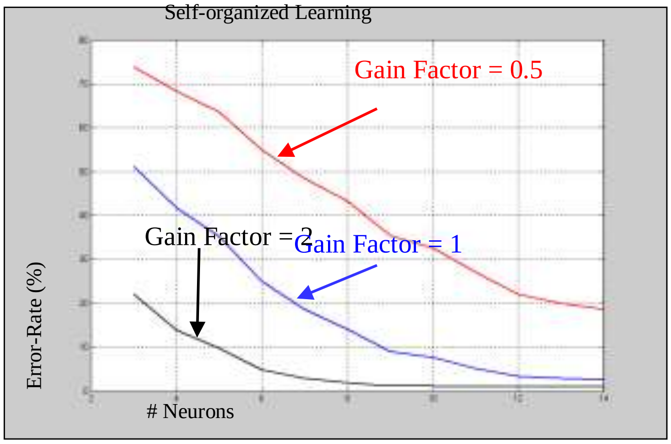


Figure 14:- Illustrate learning performance error-rate with different gain factors when #cycles = 300 and Learning rate = 0.3

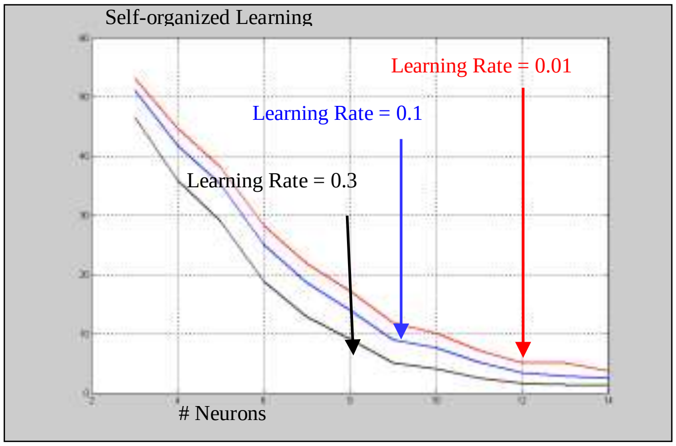


Figure 15:- Illustrate learning performance error-rate with different learning rates when #cycles = 300 and gain factor = 1

L. Least Mean Square LMS Algorithm

At the Figure 14, it presents the learning convergence process for least mean square error as used for training of ANN models [17]. It is clear that this process performed similarly as ACS searching for minimum tour when solving TSP [1]. Furthermore, it obeys the learning performance observed during psycho experimental work carried for animal learning [3].

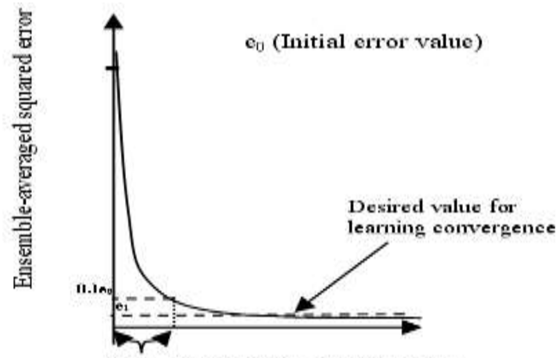


Figure 16:- Idealized learning curve of the LMS algorithm adapted from [17].

CONCLUSIONS AND DISCUSSION:-

According to above animal learning experiments (dogs, cats, and mice), 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 Figure 6, it is shown that both learning performance curves presenting both work for Thorndike and Pavlov are commonly characterized by their hyperbolic decay and also, both obeys generalized (LMS) for error minimization by learning convergence.

In this context, that algorithm agrees with the behavior of brainier mouse behavior (that is genetically reformed) as illustrated at [17]. Generally, the four introduced nonhuman models in this work perform their behavioral learning functions similar to LMS error algorithm, which introduced at Figure 16.

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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