

# On Application of Neural Networks' Modeling for Analytical Comparative Study between Two Optimally Selected Made Decisions by Ant Colony Systems

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**Abstract** This piece of research presents a comparative analytical study for two diversified, and challenging issues regarding decisions made by Ant Colony Systems. The presented comparative study considers two swarm intelligent collective decisions, which originated from two diverse, and interactive ACS lifestyles with the environment they are living in. By more details, this article introduces the application of Artificial Neural Networks (ANN<sup>S</sup>) modeling considered for analogical comparative analysis and evaluation of two optimal selectivity decisions performed due to two competitive, dynamical, and interactive environmental conditions as follows. Firstly, the decisional issue concerned with optimal selectivity of collective decision made for increasing the efficiency of Ant Colony's foraging process by optimally reaching the best selected food source. However, the second decision The second issue is observed while ant insects are famous for their elaborate nest architecture; less well-known is their skill at moving from one nest site to another. Some, like army ants, move so often that they make no permanent structure, bivouacking instead in simple natural shelters. When an ant was tethered inside an unfamiliar nest site location, and unable to move freely, it is capable to release an alarming pheromone from its mandibular gland that signaled other ants to reject this nest site as to avoid presumable danger. Interestingly, the presented realistic simulation of (ANN<sup>S</sup>) behavioral learning paradigms results in the analogy between number of neurons and number of ant mates in ant colony systems. Furthermore, realistic ANN modeling results in the analogy between the intelligent behavioral performance of two ACS versus the performance of two diverse ANN learning paradigms.

**Keywords:** Artificial Neural Networks Modeling, Swarm Intelligence, Tandem Running, House Hunting Ants, Computing Alarm Pheromone, Collective Decision Making, Temnothorax

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## 1. Introduction

The *Ant* is one type of social insects that have been evolved from wasp-like ancestors in the mid-Cretaceous of the period between 110 and 130 million years ago. It means they are as old as dinosaurs but unlike them, ants managed to survive. In a general sense, ant colonies as a social insect are living in a competitive, and dynamical environment. Which characterized by constantly changing food sources in their location (distributed sites), and variation of their quantity and quality. Most of 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 [1,2], and 2) Particle Swarm Optimization that investigates probabilistic algorithms inspired by the flocking and foraging behavior of birds and fish [3]. 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 Travelling Salesman Problem (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 at [4]. about ants as the particular insect has been selected as a title (Aayat) of a Surah No.27 "The Ants" in the Noble Qur'an. Therein, it has been shown some interesting findings regarding ants' decisions made interactively via their lifestyles' intercommunications with living environment's conditions as follows:

- 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 meet among themselves to have a 'chat'.
- d. They have an 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. Social insects have evolved impressively sophisticated solutions to some challenging environmental issues such as making nest site selection via building a leading model system of the collective intelligence of animal insect groups *Temnothorax* ants.

This manuscript is an interdisciplinary research article motivated by some behavioral observations for Ant Colony's optimal selective decision making. Firstly, the problem which considers selection between two food sources, one of these sources contains higher amount of sugar than the other. Both of sources are equidistantly sited at away from the original home nest Ant colony site [5]. Secondly, the observed problem while ant insects are famous for their elaborate nest architecture; less well-known is their skill at moving from one nest site to another. Some, like army ants, move so often that they make no permanent structure, bivouacking instead in simple natural shelters [6]. Herein, an evaluation of the two above suggested issues is presented at this paper, considering the involvement of tandem running, and the self-organized mechanism (collective decision making). That's pointing out to perform optimal convergence of tandem running process directing towards the either better source with trails marked by higher pheromone (for the first problem). Or directing the way to -even distant best nest site (for the second problem). In more details, the ants recruited as foragers visited the source higher in sugar marked results in the trail to it with greater amounts of pheromone than those visiting the source with lower in sugar. That optimal selective decision for food source is compared with finding of optimal (best) nest. That is following the tandem running regulation helping to carry over directions to new nests, in accordance with what has been recently announced by O'Shea-Wheller [6]: the process occurs in a decentralized fashion and is controlled by basic rules. Specifically, ants respond to the discovery rate of a new nest site, rather than by direct measurement of distance. "Colonies counteract the difficulty of finding a distant nest, simply by increasing the rate at which individuals give each other 'directions'," explains O'Shea-Wheller [6]. "This in turn increases the discovery rate, and contributes to a larger pool of informed workers. As such, the amount of directional information that a colony gathers increases as a function of migration distance, sort of like a *self-organizing route planner*." Specifically, the two problems achieve optimality of decisions by modulating the rate of 'tandem running', in which ants workers teach each other the route to either a better food source or a new nest site. In brief, both of the suggested problems are autonomously (Self-organizing) perform

selective searching considering speed-accuracy trade off for optimum decision to reach either best source or nest site. Briefly, this paper have demonstrated the comparison between two effective optimal selectivity decisions for: a) The best source location between two food sources that are equidistantly sited away from the original home nest, based upon pheromone trails and following the tandem running regulation [7,8], b) The balanced selection performance with the migration speed, in order to minimize exposure to a hostile environment to avoid presumable danger. That is based upon releasing alarming pheromone from the ants' mandibular gland and signaling other ants to reject dangerous nest site [8]. The rest of this paper is organized in four sections, in addition to this introduced first section. These sections are given in brief as follows. The revision of Artificial Neural Networks' learning models is briefly introduced at the second section. At the next second third section revising of the optimal selective process of a food source is presented. A review of organization strategies ant colony migration from the home nest to another non-vulnerable one to any potential danger is given at the fourth section. At the fifth section, the obtained realistic simulation results are introduced briefly. Finally, some interesting and conclusive remarks are presented at the last sixth section.

## 2. Revising of ANN's Learning Models [9]

This section introduces a brief revision for the conceptual basics associated with interactive Teaching /Learning processes performed by Artificial Neural Networks' (ANN<sup>s</sup>) Modeling. This revising section composed of four interrelated subsections denoted as (2.1, 2.2, 2.3, and 2.4), and briefly presented by follows.

At the subsection 2.1, relation between an artificial and biological single neuron model is considered along with illustration using basic mathematical formulae. The function and the structure of a Simplified Feed Forward Neural Network's Model are illustrated at the subsection 2.2. At the subsection 2.3., a generalized briefly overview is given for the block diagram describing interactive teaching/learning process that considers (face to face tuition). Finally, a mathematical formulation regarding the bidirectional interactive communications between any teacher and his learners is introduced. at the subsection 2.4 in details. That formulation considers two diverse learning paradigms models namely: guided with a teacher equivalently as error correction model (supervised), and learning model without teacher's guidance that equivalent to the self-organized (unsupervised) paradigm. [10,11].

### 2.1. Simplified Modeling of a Single Biological Neuron

Realistic modeling of biological neural system, is considered via distributed parallel information processing. However, a single biological neuron is the basic building block of any neural system. In more details, by referring to Figure 1, inside any single neuron performed information processing transferred among three basic structural components (*Dendrites, Soma, and Axon*) [12].

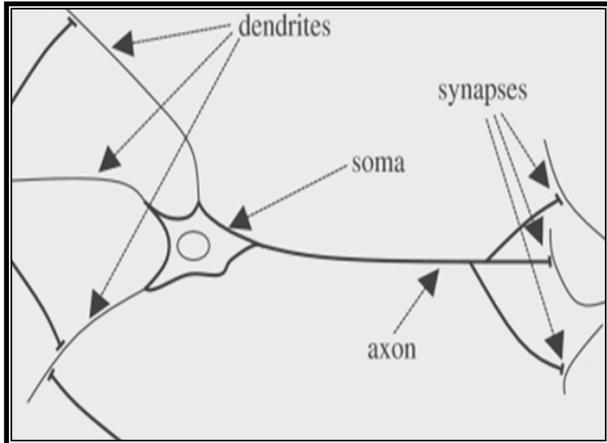


Figure 1. A simplified schematic structure of a single biological neuron adapted from [12]

Accordingly, realistic neuron model composed of three basic elements of that model given (by referring to the graphical presentation shown at Figure 2, in below) as follows:

- A set of weights, each of which is characterized by a strength of its own. A signal  $x_i$  connected to neuron  $k$  is multiplied by the weight  $w_{ki}$ . The weight of an artificial neuron may lie in a range that includes negative as well as positive values.
- An adder for summing the input signals, weighted by the respective weights of the neuron.
- An activation function for limiting the amplitude of the output of a neuron. It is also referred to as transfer function which squashes the amplitude range of the output signal to some finite value. Two types of the sigmoid transfer (activation) functions are commonly used in ANN applications. First one is the logistic sigmoid and the second other function is the odd sigmoid. Their values are given at any arbitrary time instant ( $n$ ) by equations (3) & (4) respectively.

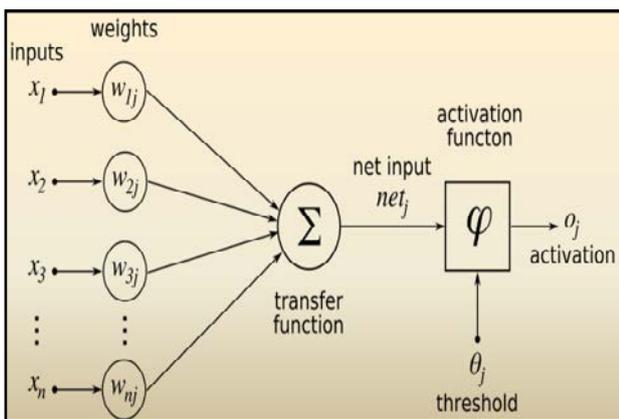


Figure 2. A single neuron ( $k$ ) model coupled with synaptic weights from other neurons  $w_{ki} (i, \dots, p)$

$$V_k = \sum_{i=1}^p w_{ki} x_i \tag{1}$$

$$y_k = \varphi(V_k + \theta_k). \tag{2}$$

The odd sigmoid function seemed to be well relevant for realistic simulation of learning brain performance as if this function input stimulus equals zero results in obtaining no output (zero).

$$y_k(n) = j(V_k(n)) = 1 / (1 + e^{-\lambda v_k(n)}) \tag{3}$$

$$y_k(n) = j(V_k(n)) = (1 - e^{-\lambda v_k(n)}) / (1 + e^{-\lambda v_k(n)}). \tag{4}$$

## 2.2. A Simplified Feed Forward Neural Network's Model

Neural Networks (NNs), have been extensively and successfully applied to pattern (speech/image) recognition, time-series prediction and modeling, function approximation, classification, adaptive control and other areas. As stated, a neural network consists of a pool of simple processing units, the 'neurons'. Within NNs three types of neurons are distinguished at Figure 3: input neurons (nodes, which receive data from outside the NN and are organized in the so called **input** layer, **output** neurons (nodes), which send data out of the NN called the output layer, and **hidden** neurons (nodes), whose input and output signals remain within the NN and form the so called hidden layer (or layers). The adopted neural model for simulation of reading brain performance evaluation is similarly following the most commonly known structural type of ANN. By referring to (Figure 3), it is noticed that: nine that depicted circles (3-4-2) are representing three distinct groups, or layers of biological neurons. For the four nodes represent Input layer, three nodes represent Hidden layer, and the Output two layer nodes (neurons). That is a structure of the Feed Forward Artificial Neural Network (FFANN) model consisted of three layers comprise nine nodes : an "input" layer of four nodes which denoted by ( $I_1, I_2, I_3,$  and  $I_4$ ) is connected to a "hidden" layer of three nodes, which is connected to an "output" layer of two nodes that denoted by ( $O_1,$  and  $O_2$ ). Obviously, any one of these nodes represents / simulates a single biological neuron, which illustrated schematically at (Figure 1). Generally, the activity function of that (FFANN) structure is briefly given as follows:

- 1) The activity of the input comprises three nodes, represents the raw information that is fed into the network.
- 2) The activity for each node of the hidden layer is determined by the activities provided by the three input layer's nodes and the synaptic weights' connections between the input nodes and the hidden layer's nodes.
- 3) The behavioral activity of the output two nodes depends on the activity of the four hidden nodes and the synaptic weights between the hidden and output nodes.

Artificial neural networks (ANN<sup>s</sup>) are mathematical models inspired by the organization and functioning of biological neurons. There are numerous artificial neural network variations that are related to the nature of the task assigned to the network. There are also numerous variations in how the neuron is modeled. In some cases, these models correspond closely to biological neurons [13,14] in other cases the models depart from biological functioning in significant ways.

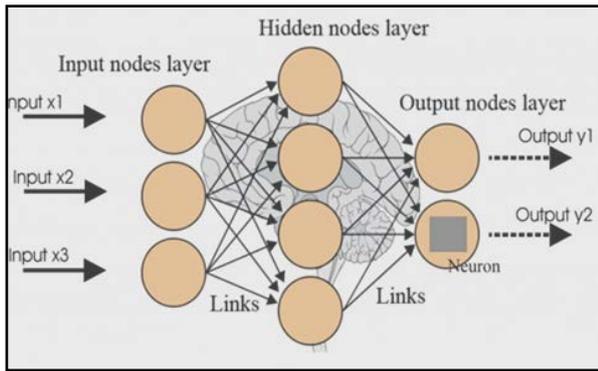


Figure 3. A simplified schematic diagram for a (FFANN) model (adapted from, [12])

### 2.3. Modeling of Interactive Learning Processes

Face to face tuition is illustrated as an interactive learning processes presented at Figure 4. Inputs to the neural network teaching model are provided as a signal provided by environmental stimuli (unsupervised learning). However, correction signal(s) in the case of learning using a teacher's guidance is/are given by output response(s) of the model that evaluated by either the environmental conditions (unsupervised learning) or by supervision of a teacher. Additionally, any tutor plays a role of improvement input data (stimulating learning pattern) by reducing the noise and redundancy of model pattern input. That is motivated by the tutor's experience while performing conventional (classical) learning. Consequently, the tutor provides the learning model with cleared data via maximizing of the signal to noise ratio [15]. Conversely, in the case of unsupervised/self-organized learning, which is based upon Hebbian learning rule [14], it is mathematically formulated by equation (11) presented at the next subsection (D).

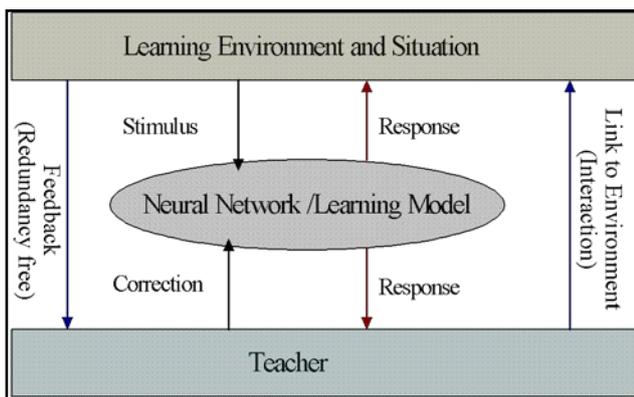


Figure 4. Simplified view for interactive learning process {Adapted from [11]}

### 2.4. Mathematical Formulation of Interactive Learning

At Figure 5, an interactive learning model through stimulating signals is well qualified in performing realistic simulation for evaluating learner's performance. This Figure illustrates inputs to the neural network learning

model which provided by stimuli unsupervised learning environment [11]. The correction signal for the case of learning with a teacher is given by responses outputs of the model will be evaluated by either the environmental conditions (unsupervised learning) [15,16] or by the instructor. The instructor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of learning model pattern input .In accordance with instructor's experience, he provides illustrated model with clear data by maximizing learning environmental signal to noise ratio [17]. By more details, referring to above Figure 5; the error vector  $\bar{e}(n)$  at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{5}$$

Where  $\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \dots\dots\dots$  is the error correcting signal vector that is controlling adaptively the learning process outcome,  $\bar{y}(n) \dots\dots$  is the obtained outcome (output) signal developed by ANN model, and  $\bar{d}(n) \dots\dots$  is the desired vector or numerical value(s). Moreover, the following four equations have been deduced:

$$V_k(n) = X_j(n)W_{kj}^T(n) \tag{6}$$

$$Y_k(n) = \phi(V_k(n)) = (1 - e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \tag{7}$$

$$e_k(n) = |d_k(n) - y_k(n)| \tag{8}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{9}$$

Where  $X$  is input vector and  $W$  is the weight vector.  $\phi$  is the activation function.  $Y$  is the output.  $e_k$  is the error value and  $d_k$  is the desired output. Note that  $\Delta W_{kj}(n)$  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:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \tag{10}$$

Where  $\eta$  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:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n). \tag{11}$$

Noting that  $e_k(n)$  equation (10) is substituted by  $y_k(n)$  at any arbitrary time instant (n) during the interactive learning process. Referring to Fig.1, the correction signal which provided by a tutor should take into consideration the noisy environmental level inside classrooms (such as

noisy crowdedness appears. In other words, that level is quantitatively measured as signal to noise (S/N) ratio or equivalently the additive noise power ( $\sigma$ ) to the ideally sensory clear signal. Consequently, the response time response measured by number of training cycles ( $n$ ) {as defined at the subsection in the above (B) by the two equations (10) & (11)}. Noting value of ( $n$ ) should have been increased until reaching learning convergence instant, when:

$$\Delta W_{kj}(n) = 0. \tag{12}$$

That above condition given by equation (8), could be fulfilled only if the desired output learning has been obtained after some number of training cycles (response time) in fulfillment of the two equations (10) & (11).

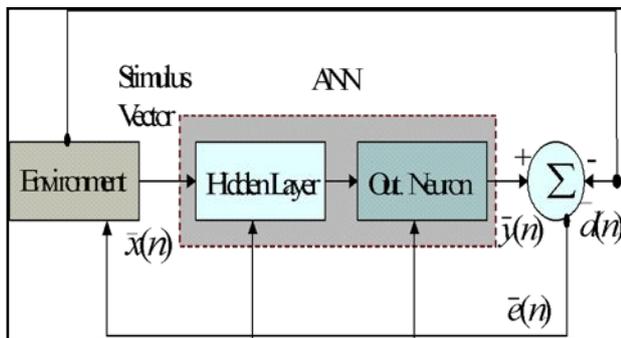


Figure 5. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [11].

### 3. Ant's Selection of Best Food Source

#### 3.1. Selection between Two Pathways Using Pheromones' Marking

If an experimenter offers a colony of mass recruiting ants, one of the species using pheromones to food trails, two food sources simultaneously and at equal distances from the nest, but one is higher in sugar content than the other, most of the foragers will usually go to the source higher in sugar. Some of the foragers will feed from the source lower in sugar, but on the average, their numbers will be much lower than those going to the better source. This is of course a good decision for the survival and reproduction of the colony: the ants concentrate on the food source that provides the most calories with the least amount of effort. But how do they do this? How do they “decide” which source is better and how do they coordinate their efforts so as to exploit it preferentially? [5]. Herein, a proposed explanation is currently introduced for how towards the better source containing the greatest amounts of pheromone and differentially choose these trails over those to lesser sources marked with smaller amounts of pheromone, illustration of how a group of ants able to optimally decide the selectivity of a shorter path to reach the food source via an asymmetrical simplified bifurcations network (referring to Figure 6.). It is noticed clearly that amount of artificial pheromone that is added depends on the length of the chosen path: the shorter the path, the higher the amount of added pheromone.

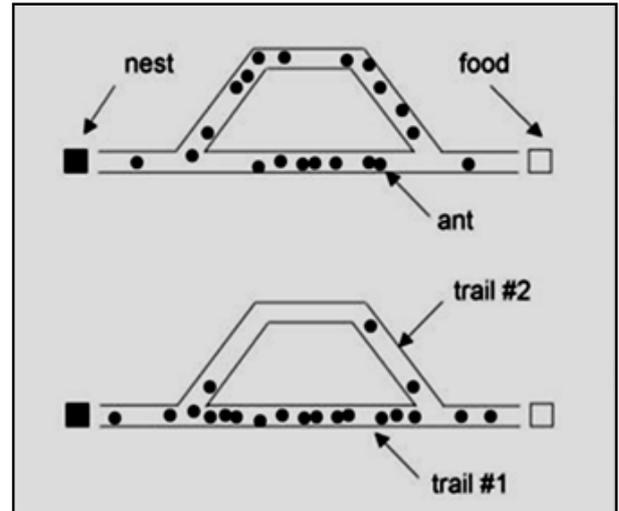


Figure 6. Schematic illustration of the ant algorithm. (At the top). Selection of a shorter path between a nest and a food source by natural ants. The ants travel between the nest and food through trail #1 and trail #2. Initially, ants are distributed equally on both trails. (At the bottom). Since trail #1 is shorter than trail #2, trail #1 becomes their favorite pathway with a higher pheromone concentration. (Adapted from [18])

#### 3.2. Selection of Minimum Pathway between Source and Nest

Referring to Figure 7, in the case of bifurcation occurrence due to an existence of an obstacle at some point placed on the pathway between the nest site and that of the source, the transportation process of food (from food source) to food store (nest). is illustrated behavioral ants' responses shown at the simplified sketched figure considering the pheromone trail between nest and food source.

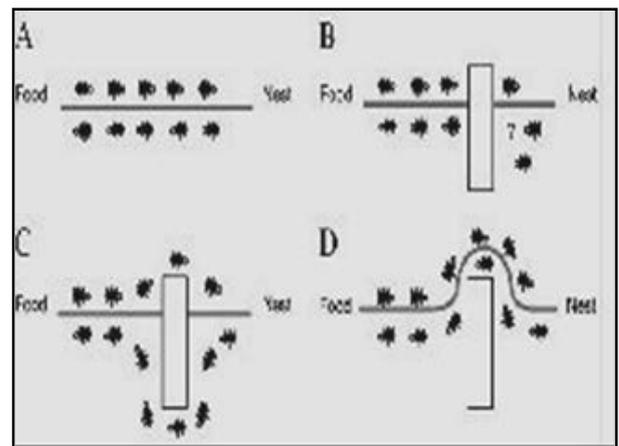


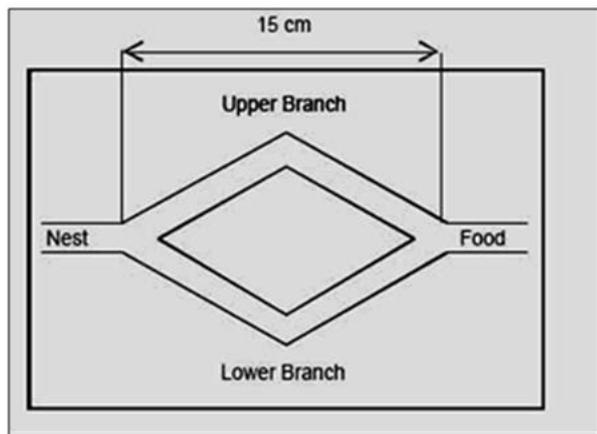
Figure 7. Ant Behavior A. Ants in a pheromone trail between nest and food; B. An obstacle interrupts the trail; C. Ants find two paths to go around the obstacle; D. A new pheromone trail is formed along the shorter path.

Accordingly, the persistent or recurring food sources may also be available, such as the aphids or scale insects ‘farmed’ by many ant species. The best strategy is often to remember rewarding foraging sites but also to be flexible enough to exploit newly discovered food and to select the better sources from those available. To this end, information directing nest mates to food also enables them

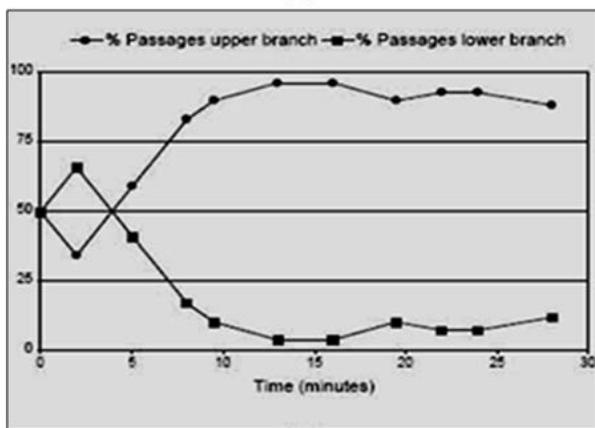
to select the highest quality food find when multiple resources are available [1].

### 3.3. Selection of One Path between Two Diamond's Branches

Referring to [19], it is announced that, one of the most striking features of an ant colony's behavior is its capacity for the spatial organization of foraging activity. The use of trail pheromone to guide fellow workers in the nest to a large food source or rich foraging zone has been extensively studied [20] and obviously contributes to foraging efficiency. We have recently, however, been able to show that trail laying and trail following behavior are more than just a means of communicating a food source's location. When more than one trail is present at a time, the interactions between foragers and the trails can lead to the collective selection of the shortest path or the best food source, despite the fact that individual foragers have no means of making such choices. Referring to the published research work at [21], it reveals the importance of the shape of trail networks for foraging in ants and emphasizes the underestimated role of the geometrical properties of transportation networks in general. At Figure 3, Ants moved searching the way to a food source via *Symmetrical Diamond Bridge* having two identical branches.

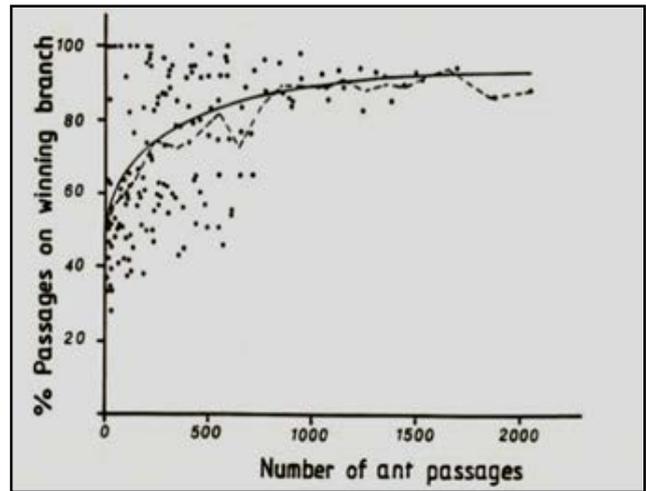


(a)



(b)

**Figure 8.** (a) illustrates a diamond bridge composed of two identical branches. The ants pass through that bridge adopting bifurcation (distributed) Strategy (b) Percentage of the ant workers per three minutes period that are passing on the two(upper and lower) branches of the diamond bridge (Adapted from [19])



**Figure 9.** Percentage of the ant workers that are passing on the collectivity selected winning branch of the diamond bridge {shown at the above Figure 3} resulting after 20 experiments measured every three minutes(dots). Noting that horizontal axis represents the cumulative number of ant passages on both branches of the diamond bridge. The dashed curve represents the average values. The solid curve represents the average of 200 Monte-Carlo Simulations (Adapted from [19])

## 4. Organization of Colony Migration

Migratory behavior forms an intrinsic part of the life histories of many organisms but is often a high-risk process. Consequently, varied strategies have evolved to negate such risks, but empirical data relating to their functioning are limited. In this section, recruitment of signals used by successful foragers or nest site scouts, concerned with but another fundamental type of communication is alarm signaling. In social insects [8], defensive behavior is closely connected with alarm signals that either recruit nest-mates to combat a potential-danger or warn them to stay away [8,23,24,25].

### 4.1. Selection between Two Target Nests

In the general sense, the social insects are famous for their elaborate nest architecture; less well-known is their skill at moving from one nest site to another. Some, like army ants, move so often that they make no permanent structure, bivouacking instead in simple natural shelters. Others, like honeybees and polybiine wasps, build elaborate nests, but emigrate to new homes during colony reproduction. Still others, like ants of the genus *Temnothorax*, are often forced to move because of the fragility of their nests. House-moving is one of the most challenging tasks a colony faces. Its future success depends on finding a home that offers the right physical environment, protection from enemies, and access to resources. At the same time, choosiness must be balanced with speed, to minimize exposure to a hostile environment, and to prevent delays in growth and reproduction. In most cases, consensus must be reached among hundreds or thousands of individuals, lest the colony should divide among multiple sites to the detriment of all. Finally, all of this must be achieved without well-informed leaders or central control. Instead, the work of selecting and moving to a home is distributed across a population of workers,

each informed about only a limited number of options, and influencing only a portion of its nest mates. More specifically, in this paper the model system of the house hunting ant *Temnothorax albipennis* is adopted, that to demonstrate a key strategy that can shorten migration exposure times in a group of social insects. Colonies of these ants frequently migrate to new nest sites, and due to the nature of their habitat, the distances over which they do so are variable, leading to fluctuating potential costs dependent on migration parameters.

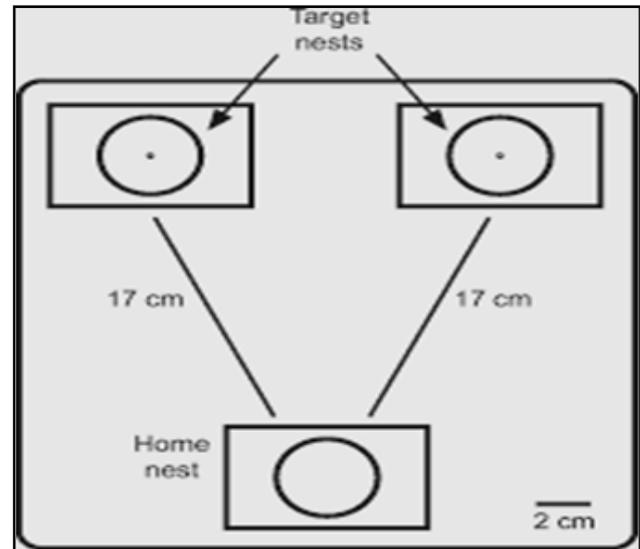
Referring to [8], the migratory behavior forms an intrinsic part of the life histories of many organisms but is often a high-risk process. Consequently, varied strategies have evolved to negate such risks, but empirical data relating to their functioning are limited. In this study, we use the model system of the house hunting ant *Temnothorax albipennis* to demonstrate a key strategy that can shorten migration exposure times in a group of social insects. Colonies of these ants frequently migrate to new nest sites, and due to the nature of their habitat, the distances over which they do so are variable, leading to fluctuating potential costs dependent on migration parameters. Regarding to the closest resemblance of ants' lifestyle with respect to that of human beings. local advanced intercommunication observed via chatting signaling among colonies' agents (ants). These signaling findings have been basically originated in accordance with the intercommunicative distributed collective cognition decisions among ants' colony members. Specifically, in the case of anticipated danger analysis, evaluation and deciphering of emerged alarm communication signals against predators resulting in variety of behavioral responses. In more details, considering the colony of *Temnothorax rugatulus*, it has been reported that alarm signaling pheromone while electing two different behaviors is dependable upon different context.

#### 4.2. Binary Choice between Two Nests [8]

Referring to Figure 10, when an ant was tethered inside an unfamiliar nest site and unable to move freely, she released a pheromone from her mandibular gland that signaled other ants to reject this nest as a potential new home, presumably to avoid potential danger. Accordingly, it is clearly possible that this pheromone's function can improve an emigrating behavioral response for colony's nest site selection performance. Colonies were given a binary choice between a nest with tethered ants and a nest that had five strings but no ants. By referring to Fig.8 concerned with test arena, were given a binary choice between a nest with tethered ants and a nest that had five strings but no ants. These two target nests were first placed adjacent to one another against one wall of the test arena. The home nest containing the colony from which the tethered ants were taken was then placed against the center of the wall opposite to the location of the target nests. Finally, the roof of the home nest was removed to induce migration.

The binary selection (choice) of one target nest between the equidistantly two targets is originally based upon the collective decision making [8]. That is carried out by ant workers' migratory performance from home nest towards the selected target nest in accordance with the signaling

originated from Alarm Pheromone to avoid dangerous hostile direction. Obviously, the ant workers' behavioral passing function (via selected target nest direction), results in performance closely resembling to the selected winning branch of the diamond bridge {shown at the above Figure 8, a & b), and (Figure 9), that adapted from [19]}.



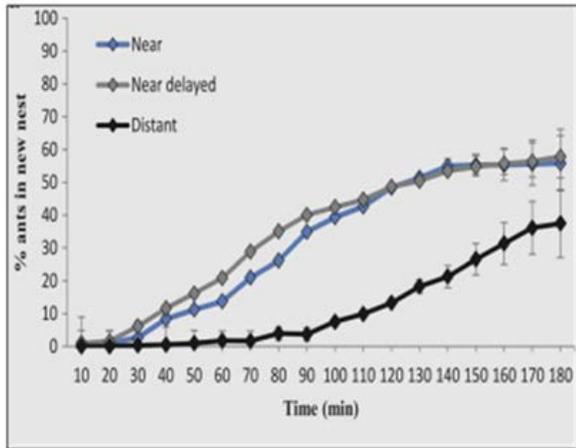
**Figure 10.** Experimental arena for nest choice tests. Colonies initially lived in the home nest, from which the roof was removed to induce migration. Colonies were allowed to choose between two target nests, which were identical in design but contained different materials (see Materials and methods for details). The arena size was 20×20 cm and 1 cm in height (Adapted from [8])

### 5. Simulation Result

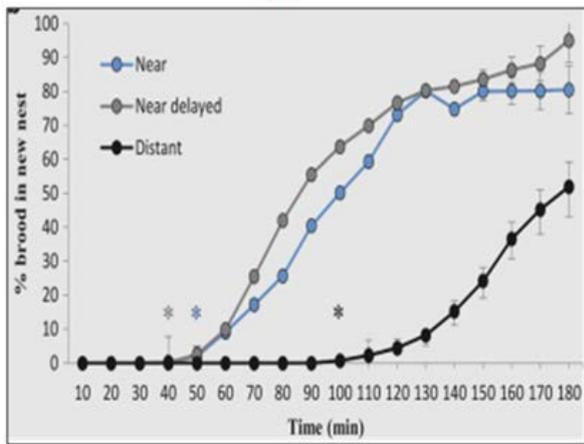
The presented simulation results considers the set of ten figures numbered as (from 11,12,.....18,19, and 20). Additionally, the obtained findings have been noticed to be in agreement with, and well supported by some other previously obtained realistic computer modeling results. In addition to other some other announced findings which published recently at a set of research manuscripts [7,9,27,30,31,32,33,34]. Referring to the above two Figures 8 & 9, the performance of an Ant Colony via the winning branch reaches some percentage value [%] after passing collectively a group of ant workers (supervised learning). This performance is dependable upon individual differences of ant colonies. These differences are clearly simulated by referring to two Figures 12, and Figure 13, while reaching the optimal solution of TSP with different values of either intercommunication parameters (Figure 13) among ant colony agents, or different learning rate values (Figure 17) . Referring to the two pair of figures (Figure & Figure 16 ), and (Figure 18, Figure 19) are simulating the performance of the first (Unsupervised) and second (Unsupervised) learning Paradigms' issues respectively. These cases are referred to different learning rate values {  $\eta = 0.05, 0.1, \text{ and } 0.2$  } analogous to different intercommunication values among ant agents.

Furthermore, it is noticed that resulted in convergence to different relative error values  $e(n)$  percentage values [%]. After any fixed time period {number of trials (n)}. Additionally, the two sets, each of three curves at

Figure 11, are analogous to the results shown at Figure 11. However, the rate corresponding to set in Figure 11(a) is less than that at the set in Figure 11(b). That is due the last set(b), is more valuable to danger than the former set (a) [6].



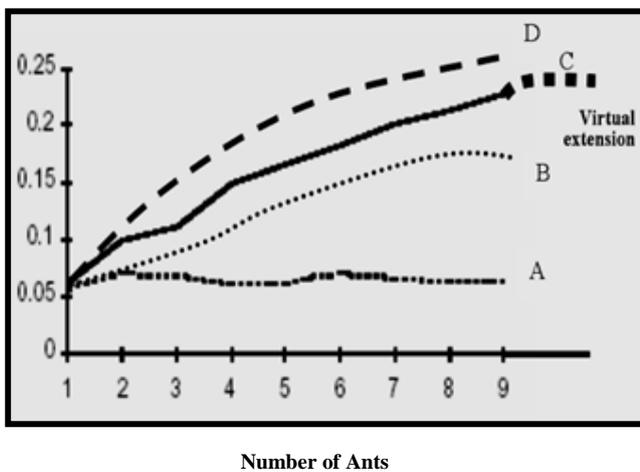
(a)



(b)

Figure 11. Mean percentage of total colony workers (a) and brood (b) in the new nests over time for each of the three treatment groups. Blue lines indicate the near treatment, grey lines indicate the near delayed treatment and black lines indicate the distant treatment, {Adapted from [6]}

Average Speed to Optimum Solution (1Sec.)



Number of Ants

Figure 12. Communication among ant mates (agents), determines the synergistic effect considering various intercommunication levels leading to different average speed values to reach the optimal TSP solution {Adapted from [26]}

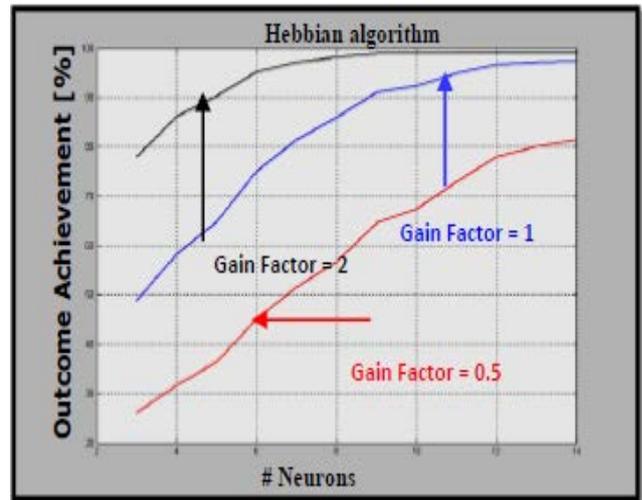
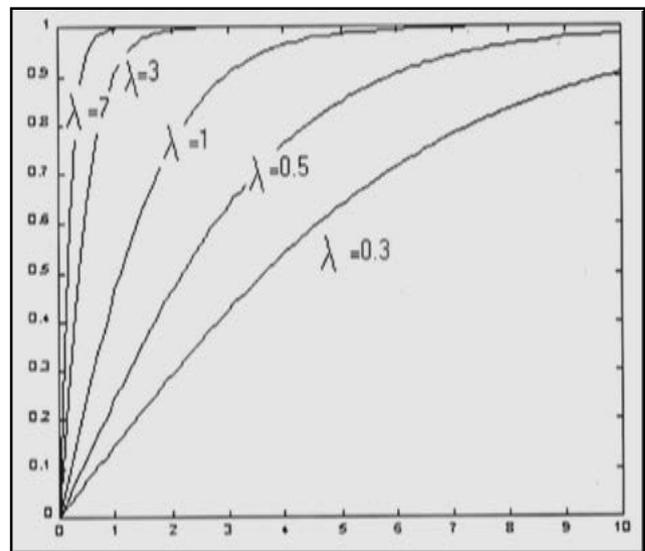


Figure 13. Learning performance to get accurate solution with different gain factors 0.05, 1, and 2, while #cycles = 300 and Learning Rate = 0.3

Normalized Output[y(n)]



Normalized Number of Training Time Cycles (n)

Figure 14. Graphical representation of learning performance of model with different gain factor values ( $\lambda$ )

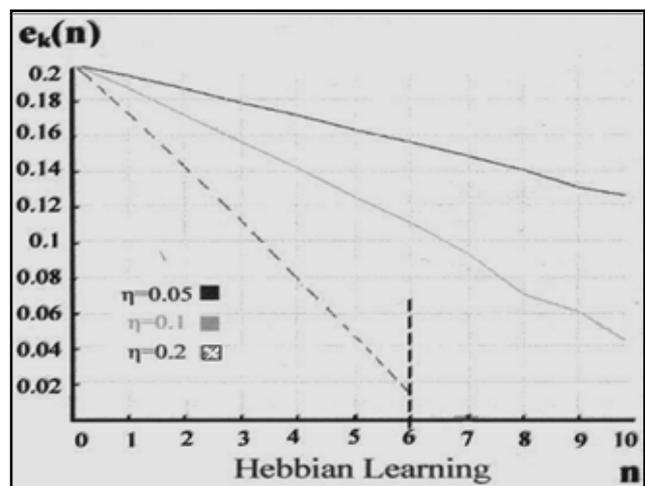


Figure 15. Adaptability performance concerned with Hebbian (self-organized) learning algorithm with learning rates (0.05, 0.1, 0.2). (Adapted from [24])

By referring to [27], the above depicted set of curves shown at Figure 12, are virtually reach different normalized optimal speed values to obtain the Traveling Sales-man Problem solutions (either virtually or actually). That solutions are obtained by different number of ants. Furthermore, this set of performance curves could be mathematically formulated (presented) by considering the following formula:

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

Where  $\alpha$ ..... is an amplification factors representing asymptotic value for maximum average speed to reach the optimized solutions of (T.S.P.), and  $\lambda$  in the gain factor changed in accordance with the intercommunication level among ant mates of the colony. Referring to the figure 13, in below the relation between number of neurons and the obtained achievement is given considering three different gain factor values (0.5, 1, and 2) Referring to Figure 15, it illustrates obtained neural modeling results which declares an interesting qualitative comparative analogy between performance evaluation of behavioral ANNs modeling; versus smart optimization performance of Ant Colony System as presented at Figure 13 & Figure 14. More precisely, the gain factor values given at Figure 13 are analogous with the intercommunication level values inside the ACS given at Figure 12.

However by the mathematical formulation of that normalized model behavior it is shown by various changes of communication levels (represented by  $\lambda$ ) that results in changing of the speeds for reaching optimum solutions. In given Figure 14. in blow, it is illustrated that normalized model behavior according to following equation:

$$y(n) = (1 - \exp(-\lambda i(n-1))) / (1 + \exp(-\lambda i(n-1))) \quad (14)$$

where  $\lambda i$  represents one of gain factors (slopes) for sigmoid function.

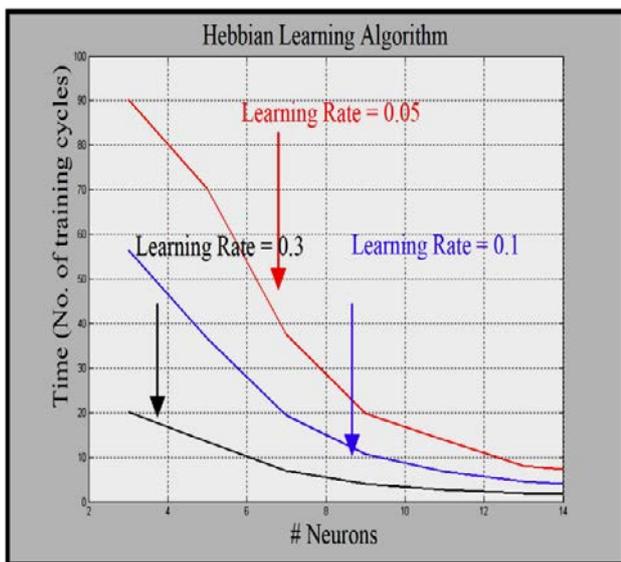


Figure 16. Hebbian learning performance and time factor with considering three different learning rates: 0.05, 0.1 and 0.3 for gain factor = 0.5, while #cycles = 300

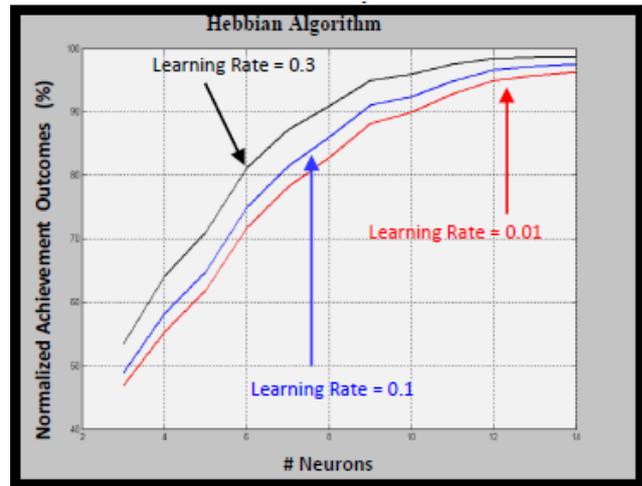


Figure 17. Illustrated the simulated output results presented as percentage degree [%] of normalized achievement outcomes versus # Neurons for different learning rate values  $\eta$  (0.01,0.1,and 0.3). and constant gain factor = 1

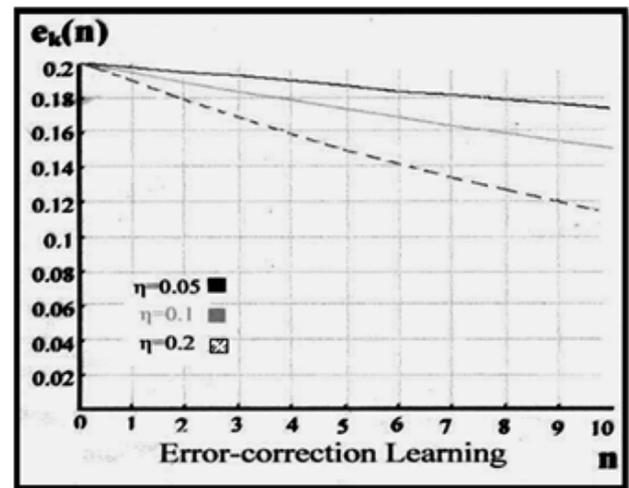


Figure 18. Adaptability performance concerned with error correction (supervised) learning algorithm with learning rates (0.05, 0.1, 0.2) (Adapted from [24])

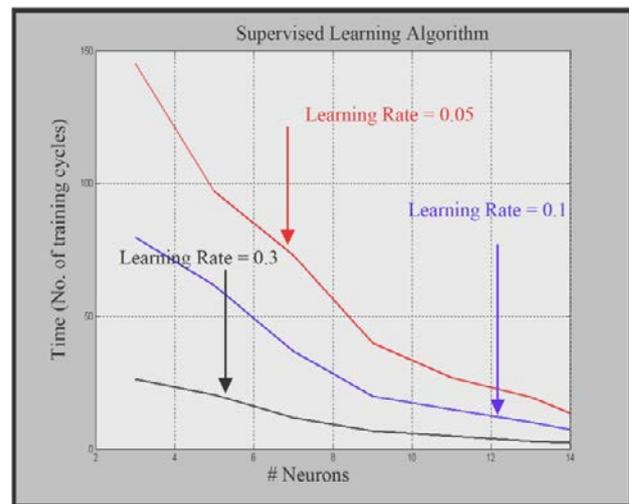
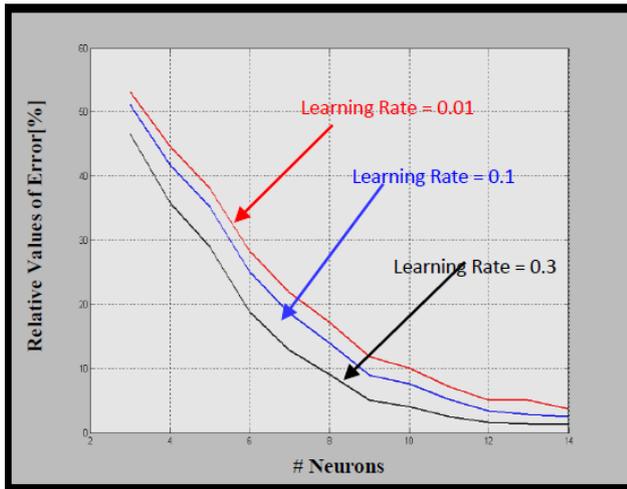


Figure 19. Error correction performance based on time response parameter with considering three different learning rates: 0.05, 0.1 and 0.3 for gain factor = 0.5, while #cycles = 300



**Figure 20.** Illustrates relative error values [%], versus # Neurons, that measures learning performance for different learning rates values  $\eta$  (0.01, 0.1, and 0.3), when #cycles = 300 and gain factor = 1

## 6. Conclusions

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

- The existence of an obstacle at some point of ants' pathway (Figure 7), results in various trailing pheromone tracing. Due to asymmetry of obstacles' shape, the time needed to find the shorter pathway is directly proportional to the discovery of the minimum path.

- Ant colony optimization algorithms have been applied to many combinatorial optimization problems, ranging from quadratic assignment to fold protein or routing vehicles and a lot of derived methods have been adapted to dynamic problems in real variables, stochastic problems, multi-targets and parallel implementations. It has also been used to produce near-optimal solutions to the travelling salesman problem.

- The humble ant is not only capable of solving difficult mathematical problems, but is even able to do what few computer algorithms can - adapt the optimal solution to fit a changing problem, deepen our understanding of how even simple animals can overcome complex and dynamic problems in nature, and will help computer scientists develop even better software to solve logistical problems and maximize efficiency in many human industries.

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