

Stigmergic Optimization: Inspiration, Technologies and Perspectives

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Summary. This Chapter summarizes some of the well known stigmergic computational techniques inspired by nature, mainly for optimization problems developed by mimicking social insects' behavior. Some facts about social insects namely ants, bees and termites are presented with an emphasis on how they could interact and self organize for solving real world problems. We focused on ant colony optimization algorithm, bees behavior inspired algorithms, particle swarm optimization algorithm and bacterial foraging algorithm.

1.1 Introduction

Nature has inspired researchers in many different ways. Airplanes have been designed based on the structures of birds' wings. Robots have been designed in order to imitate the movements of insects. Resistant materials have been synthesized based on spider webs. The fascinating role that insects play in our lives is obvious. It is interesting how these tiny insects can find the shortest path for instance between two locations without any knowledge about distance, linearity, etc.

Biologists studied the behavior of social insects for a long time. For decades, entomologists have known that insect colonies are capable of complex collective action, even though individuals adhere to straightforward routines. When foraging, for example, workers appear to march to a drumbeat that dictates when to turn and when to lay down pheromone to guide other workers. As simple as these rules are, they create an effective dragnet to haul in food as efficiently as possible. In this manner, ants have been solving problems very skillfully every day of their lives for the last 100 million years [120].

After millions of years of evolution all these species have developed incredible solutions for a wide range of problems. Biologically inspired systems have been

gaining importance and it is clear that many other ideas can be developed by taking advantage of the examples that nature offers.

Some social systems in nature can present an intelligent collective behavior although they are composed by simple individuals with limited capabilities. The intelligent solutions to problems naturally emerge from the self-organization and indirect communication of these individuals. These systems provide important techniques that can be used in the development of distributed artificial intelligent systems [7].

Rest of this Chapter is organized as follows. Section 1.2 introduces Entomology and Stigmergy followed by some factual contents about social insects in Section 1.3. Some nature inspired computational algorithms are depicted in Section 1.4 and conclusions are provided in Section 1.5.

1.2 Entomology and Stigmergy

Entomology is the scientific study of insects. Hogue [79] noted that Entomology has long been concerned with survival (economic or applied Entomology) and scientific study (academic Entomology), but the branch of investigation that addresses the influence of insects (and other terrestrial Arthropoda, including Arachnids, Myriapods, etc) in literature, language, music, the arts, interpretive history, religion, and recreation has only recently been recognized as a distinct field. This is referred to as *cultural entomology*.

Over the last fifty years biologists have unraveled many of the mysteries surrounding social insects, and the last decade has seen an explosion of research in the fields variously referred to as *collective intelligence*, *swarm intelligence* and *emergent behavior*. Even more recently the swarm paradigm has been applied to a broader range of studies, opening up new ways of thinking about theoretical Biology, Economics and Philosophy.

The South African Scientist - Eugène Marais (1872-1936) - is considered as one of the first scientists who paid attention to the behavior of social insects. His work on termites led him to a series of stunning discoveries. He developed a fresh and radically different view of how a termite colony works, and indeed of what a termite colony is. In 1923 he began writing a series of popular articles on termites for the Afrikaans press and in 1925 he published a major article summing up his work in the Afrikaans magazine *Die Huisgenoot*. In 1925 Marais published an original research article and some conclusions about the white ant. In 1927, Maurice Maeterlinck (1862-1949), a Nobel Prize winner, lifted half of Marais's work and published it without any acknowledgement, as the book "*The Life of the White Ant*" [94]. This plagiarization may well have been a major factor in Marais's final collapse. Plagued for many years by ill-health and an addiction to morphine, he took his own life in March 1936. Marais's book "*The Soul of the White ant*" was published posthumous in 1937 [110].

Konrad Lorenz (1903-1989) is widely credited as being the father of Ethology, the scientific study of animal behavior, with his early work on imprinting and

instinctive behavior. Although Marais had created a detailed document on termites, he was unaware of the mechanics of termite communication. How is it that a group of tiny, short-sighted, simple individuals are able to create the grand termite mounds, sometimes as high as six meters, familiar to inhabitants of dry countries? The answer to this question was first documented by the French Biologist, Pierre-Paul Grassé in his 1959 study of termites [76]. Grassé noted that termites tended to follow very simple rules when constructing their nests.

- First, they simply move around at random, dropping pellets of chewed earth and saliva on any slightly elevated patches of ground they encounter. Soon small heaps of moist earth form.
- These heaps of salivated earth encourage the termites to concentrate their pellet-dropping activity and soon the biggest heaps develop into columns which will continue to be built until a certain height, dependent on the species, is reached.
- Finally, if a column has been built close enough to other columns, one other behavior kicks in: the termites will climb each column and start building diagonally towards the neighboring columns.

Obviously, this does not tell the whole story but a key concept in the collective intelligence of social insects is revealed: the termites' actions are not coordinated from start to finish by any kind of purposive plan, but rather rely on how the termite's world appears at any given moment. The termite does not need global knowledge or any more memory than is necessary to complete the sub-task in hand; it just needs to invoke a simple behavior dependent on the state of its immediate environment. Grassé termed this *stigmergy*, meaning 'incite to work', and the process has been observed not just in termites, but also in ants, bees, and wasps in a wide range of activities. Writing about termites, he offered a more general definition of stigmergy - "the stimulation of the workers by the very performances they have achieved" [80].

Grassé quoted "*Self-Organization in social insects often requires interactions among insects: such interactions can be direct or indirect. Direct interactions are the "obvious" interactions: antennation, trophallaxis (food or liquid exchange), mandibular contact, visual contact, chemical contact (the odor of nearby nestmates), etc. Indirect interactions are more subtle: two individuals interact indirectly when one of them modifies the environment and the other responds to the new environment at a later time. Such an interaction is an example of stigmergy*".

Studying nest reconstruction in termites, Grassé showed that it doesn't rely on direct communication between individuals. The nest structure itself coordinates the workers' tasks, essentially through local pheromone concentrations. The state of the nest structure triggers some behaviors, which then modify the nest structure and trigger new behaviors until the construction is over [70].

According to Gordon [70], the application of stigmergy to computation is surprisingly straightforward. Instead of applying complex algorithms to static datasets, through studying social insects we can see that simple algorithms can often do just as well when allowed to make systematic changes to the data in question [70]. A famous example of stigmergy is pheromonal communication, whereby ants

engaging in certain activities leave a chemical trail which is then followed by their colleagues.

This ability of ants to collectively find the shortest path to the best food source was studied by Jean-Louis Deneubourg ([36]-[44], [71]-[75], [104]-[108]). He demonstrated how the Argentine ant was able to successfully choose the shortest between the two paths to a food source. Deneubourg was initially interested in self organization, a concept which until then had been the fare of chemists and physicists seeking to explain the natural order occurring in physical structures such as sand dunes and animal patterns ([1]-[4], [5], [6], [8], [14]-[19], [26], [62], [84], [111], [133]-[135], [138]). Deneubourg saw the potential for this concept, which by 1989 had turned into a sizeable research project amongst Physicists, to be applied to Biology. In his experiments, a group of ants are offered two branches leading to the same food source, one longer than the other. Initially, there is a 50% chance of an ant choosing either branch, but gradually more and more journeys are completed on the shorter branch than the longer one, causing a denser pheromone trail to be laid. This consequently tips the balance and the ants begin to concentrate on the shorter route, discarding the longer one. This is precisely the mechanism underpinning an ant colony's ability to efficiently exploit food sources in sequential order: strong trails will be established to the nearest source first, then when it is depleted and the ants lose interest, the trails leading to the next nearest source will build up [70].

1.3 Facts About Social Insects

Among all social insects, the ants, social bees, social wasps, and termites, dominate the environment in most terrestrial habitats.

1.3.1 Facts about Ants

Shortly, while talking about ants, we can use Charlotte Sleigh's words: "Ants are legion: at present there are 11,006 species of ants known; they live everywhere in the world except the polar icecaps; and the combined weight of the ant population has been estimated to make up half the mass of all insects alive today" [123].

Like all insects, ants have six legs. Each leg has three joints. The legs of the ant are very strong so they can run very quickly. If a man could run as fast for his size as an ant can, he could run as fast as a racehorse. Ants can lift 20 times their own body weight. An ant brain has about 250,000 brain cells. Mushroom shaped brain appendages have function similar to the gray-matter of human brains. A human brain has 10,000 million so a colony of 40,000 ants has collectively the same size brain as a human [137].

The average life expectancy of an ant is 45-60 days. Ants use their antennae not only for touch, but also for their sense of smell. The head of the ant has a pair of large, strong jaws. The jaws open and shut sideways like a pair of scissors. Adult ants cannot chew and swallow solid food. Instead they swallow the juice which they squeeze from pieces of food. They throw away the dry part that is left over. The

ant has two eyes; each eye is made of many smaller eyes called compound eyes. The abdomen of the ant contains two stomachs. One stomach holds the food for itself and second stomach is for food to be shared with other ants. Like all insects, the outside of their body is covered with a hard amour this is called the exoskeleton. Ants have four distinct growing stages, the egg, larva, pupa and the adult. Biologists classify ants as a special group of wasps - (*Hymenoptera Formicidae*). There are over 10000 known species of ants. Each ant colony has at least one or more queens. The job of the queen is to lay eggs which the worker ants look after. Worker ants are sterile; they look for food, look after the young, and defend the nest from unwanted visitors. Ants are clean and tidy insects. Some worker ants are given the job of taking the rubbish from the nest and putting it outside in a special rubbish dump. Each colony of ants has its own smell. In this way, intruders can be recognized immediately. Many ants such as the common Red species have a sting which they use to defend their nest. The common Black Ants and Wood Ants have no sting, but they can squirt a spray of formic acid. Some birds put ants in their feathers because the ants squirt formic acid which gets rid of the parasites. The Slave-Maker Ant (*Polyergus Rufescens*) raids the nests of other ants and steals their pupae. When these new ants hatch they work as slaves within the colony [81].

When searching for food, ants initially explore the area surrounding their nest in a random manner. While moving, ants leave a chemical pheromone trail on the ground. Ants are guided by pheromone smell. Ants tend to choose the paths marked by the strongest pheromone concentration . When an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the quantity of pheromone that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source.

The indirect communication between the ants via pheromone trails enables them to find shortest paths between their nest and food sources as illustrated in Figure 1.1.

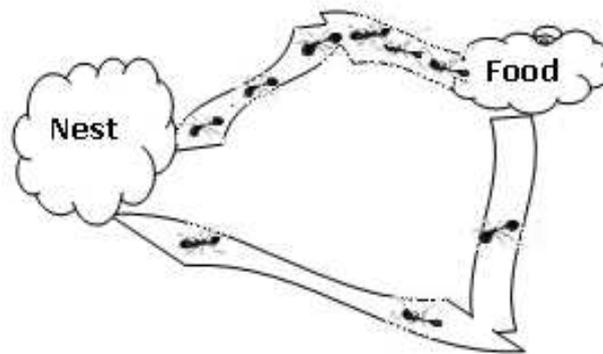


Fig. 1.1. The ants taking the shortest path can perform a greater number of trips between nest and food; implicitly the pheromone trail will be more than the one released by the ants following the longest path.

According to Truscio [137] both ants and humans share these endeavors:

- *livestock farming*: herd aphids and "milk" them for nectar-like food
- *cultivation*: growing underground gardens for food
- *childcare*: feeding young and providing intensive nursery care
- *education*: teaching younger ants the tricks of the trade
- *climate control*: maintaining a strict 77° F for developing ants
- *career specialization*: changing and learning new careers
- *civic duties*: responding with massive group projects
- *armed forces*: raising an army of specialized soldier ants
- *security*: warding off other ants, insects, and animals
- *earth movers*: move at least as much soil as earthworms
- *social planning*: maintain ratio of workers, soldiers, and reproductives
- *engineering*: tunnel from 2 directions and meet exactly midway
- *communications*: complex tactile, chemical communication system
- *flood control*: incorporate water traps to keep out rain
- *limited free will*: inter-relationships more symbiotic than coercive

1.3.2 Facts about Bees

There are two well known classes of bees: *European bees* and *Africanized bees*. A comparison between the two classes of bees is given in Table 1.1. The ancestors of the Africanized bee live throughout Africa, south of the Sahara Desert. African bees were accidentally introduced into the wild in South and North America during 1956. Brazilian scientists were attempting to create a new hybrid bee in the hopes of creating improved honey production. The Africanized bee escaped and began to attack the honey bees.

European Honey Bees	Africanized Bees
Pollinate flowers and crops	More aggressive
Calmed by smoke	Attack in larger groups
Swarm only when crowded	Make less honey
	Make less wax
	Hate high pitched sounds
	Swarm more often

Table 1.1. African and European honey bees: a comparison

Drones usually live five to ten weeks. Workers usually live about fifty days and all the workers are females. Queens live an average about three years and there is only one surviving queen bee in each colony. She mates over with many drones (male bees), and may lay 1500 eggs per day. The queen releases a pheromone that identifies her as the queen. When the beehive is overpopulated, Africanized Bees swarm to a local area to start a new hive. Too much warm or cold weather may cause swarming. Only one queen bee will rule. When the two queens reach the adult stage,

they battle to the death for control of the hive. The cycle of swarming continues until the hive is worn out. An extremely aggressive Africanized bee colony may attack any 'threat' within 100 ft. and pursue for up to one-fourth a mile.

Africanized bees react to disturbance around the hive. They can stay angry for days after being disturbed. If one bee stings, it releases an alarm that smells like bananas. This pheromone causes the other bees to become agitated and sting. The Africanized bee, like the honey bee, dies when it stings. The tiny barbs on the stinger stick in the victim. When the bee tries to fly away, it rips its abdomen and eventually dies [82].

It is said that there is a relationship between bees and Fibonacci numbers. Fibonacci described the sequence "encoded in the ancestry of a male bee." This turns out to be the Fibonacci sequence. The following facts are considered:

- If an egg is laid by a single female, it hatches a male.
- If, however, the egg is fertilized by a male, it hatches a female.
- Thus, a male bee will always have one parent, and a female bee will have two.

If one traces the ancestry of this male bee (1 bee), he has 1 female parent (1 bee). This female had 2 parents, a male and a female (2 bees). The female had two parents, a male and a female, and the male had one female (3 bees). Those two females each had two parents, and the male had one (5 bees). If one continues this sequence, it gives a perfectly accurate depiction of the Fibonacci sequence. However, this statement is mostly theoretical. In reality, some ancestors of a particular bee will always be sisters or brothers, thus breaking the lineage of distinct parents [147].

1.3.3 Facts about Termites

Termites have been on Earth for over 50 million years. Some of their fossils date back to the Oligocene, Eocene, and Miocene periods. They have evolved into many different species. As of 1995 there were approximately 2,753 valid names of termite species in 285 genera around the world. The word 'termites' comes from the Latin word '*Tarmes*'. The Latin word was given to a small worm that makes holes in wood.

The *M. bellicosus* termites live in colonies but really they are more like families. Of some thirty or so insect orders, termites are the only one in which all species are categorized as highly social. They are very unique due to the fact that their colonies are based on monogamy. As far as entomologists know, they are the most sophisticated families ever to evolve in the universe. The termite colony has three separate stages: juvenile, adult, and senile. The survival of their species depends on their caste system. The smallest in size, yet most numerous of the castes are the workers. They are all completely blind, wingless, and sexually immature. Their job is to feed and groom all of the dependent castes. They also dig tunnels, locate food and water, maintain colony atmospheric homeostasis, and build and repair the nest. The soldiers' job is to basically defend the colony from any unwanted animals. Soldiers have larger heads that are longer and wider than that of the workers because it contains more muscles. The soldiers cannot feed themselves and must rely on the workers for this.

During swarming season the young males and females that are leaving the nest to make new colonies are exposed to birds, bats, reptiles and amphibians. One of the most dangerous predators of the *M. bellicosus* are driver ants. If their path crosses a mound of the *M. bellicosus* they will invade it by entering at the top where the building material is soft. Once inside the ants find little resistance since they have better eye sight and greater agility. It is rare that the colony is completely destroyed because some of the worker termites hide in the royal chamber. These termites continue the colony and before long life has returned to usual [82].

1.4 Nature Inspired Algorithms

Inspired by Nature became now a well known syntagma. Nature is offering models and humans are exploiting any interesting idea from this.

1.4.1 Ant colonies inspired algorithms

Ant colony optimization (ACO) was introduced around 1991-1992 by M. Dorigo and colleagues as a novel nature-inspired metaheuristic for the solution of hard combinatorial optimization problems [45], [50]-[54], [56]. Dorigo [56] was intrigued to learn how these virtually brainless creatures could create highly sophisticated messaging systems and build extremely complex architectural structures. Although an individual ant is quite small (measuring only 2.2 to 2.6 mm in length) and wanders quite aimlessly in isolation, a group of many ants exhibits extraordinarily intelligent behavior, recognizable to humans as meaningful pathways to food sources. This emergent intelligence can be summarized in the pseudocode below [83]:

1. At the outset of the foraging process, the ants move more or less randomly – this “random” movement is actually executed such that a considerable amount of surface area is covered, emanating outward from the nest.
2. If it is not carrying food, the ant “deposits” a nest pheromone and will prefer to walk in the direction of sensed food pheromone.
3. If it is carrying food, the ant deposits a food pheromone and will prefer to walk in the direction of sensed nest pheromone.
4. The ant will transport food from the source to the nest.

As a pheromone “trail” becomes stronger, the more ants follow it, leaving more pheromone along the way, which makes more ants follow it, and so on.

ACO is implemented as a team of intelligent agents which simulate the ants behavior, walking around the graph representing the problem to solve using mechanisms of cooperation and adaptation. ACO algorithm requires to define the following [57]:

- The problem needs to be represented appropriately, which would allow the ants to incrementally update the solutions through the use of a probabilistic transition rules, based on the amount of pheromone in the trail and other problem specific

knowledge. It is also important to enforce a strategy to construct only valid solutions corresponding to the problem definition.

- A problem-dependent heuristic function η that measures the quality of components that can be added to the current partial solution.
- A rule set for pheromone updating, which specifies how to modify the pheromone value τ .
- A probabilistic transition rule based on the value of the heuristic function η and the pheromone value τ that is used to iteratively construct a solution.

According to Dorigo et al. [49], the main steps of the ACO algorithm are given below:

1. *pheromone trail initialization*
2. *solution construction using pheromone trail*

Each ant constructs a complete solution to the problem according to a probabilistic

3. *state transition rule*

The state transition rule depends mainly on the state of the pheromone [136]

4. *pheromone trail update.*

A global pheromone updating rule is applied in two phases. First, an evaporation phase where a fraction of the pheromone evaporates, and then a reinforcement phase where each ant deposits an amount of pheromone which is proportional to the fitness of its solution [136]. This process is iterated until a termination condition is reached. ACO was first introduced using the Traveling Salesman Problem (TSP) [?], [29]-[32], [46]-[49], [66], [67], [126]-[128], [130], [21]. Starting from its start node, an ant iteratively moves from one node to another. When being at a node, an ant chooses to go to a unvisited node at time t with a probability given by

$$p_{i,j}^k(t) = \frac{[\tau_{i,j}(t)]^\alpha [\eta_{i,j}(t)]^\beta}{\sum_{l \in N_i^k} [\tau_{i,l}(t)]^\alpha [\eta_{i,l}(t)]^\beta} \quad j \in N_i^k \quad (1.1)$$

where N_i^k is the feasible neighborhood of the ant_k , that is, the set of cities which ant_k has not yet visited; $\tau_{i,j}(t)$ is the pheromone value on the edge (i, j) at the time t , α is the weight of pheromone; $\eta_{i,j}(t)$ is a priori available heuristic information on the edge (i, j) at the time t , β is the weight of heuristic information. Two parameters α and β determine the relative influence of pheromone trail and heuristic information. $\tau_{i,j}(t)$ is determined by

$$\tau_{i,j}(t) = \rho \tau_{i,j}(t-1) + \sum_{k=1}^n \Delta \tau_{i,j}^k(t) \quad \forall (i, j) \quad (1.2)$$

where ρ is the pheromone trail evaporation rate ($0 < \rho < 1$), n is the number of ants, Q is a constant for pheromone updating. A generalized version of the pseudo-code for the ACO algorithm with reference to the TSP is illustrated in Algorithm 1.1.

Algorithm 1.1 Ant Colony Optimization Algorithm

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01. Initialize the number of ants n , and other parameters.
 02. While (the end criterion is not met) do
 03. $t = t + 1$;
 04. For $k= 1$ to n
 05. ant_k is positioned on a starting node;
 06. For $m= 2$ to $problem_size$
 07. Choose the state to move into
 08. according to the probabilistic transition rules;
 09. Append the chosen move into $tabu_k(t)$ for the ant_k ;
 10. Next m
 11. Compute the length $L_k(t)$ of the tour $T_k(t)$ chosen by the ant_k ;
 12. Compute $\Delta\tau_{i,j}(t)$ for every edge (i, j) in $T_k(t)$ according to Eq.(??);
 13. Next k
 14. Update the trail pheromone intensity for every edge (i, j) according to Eq.(1.2);
 15. Compare and update the best solution;
 16. End While.
-

Other applications of the ACO algorithm include: sequential ordering problem [68], quadratic assignment problem [95]-[99], [69], [129], [132], vehicle routing problem [22]-[24], scheduling problems [33], [63], [65], [100], [10], [11], graph coloring [34], partitioning problems [92], [93], timetabling [124], shortest subsequence problem [101], constraint satisfaction problems [125], maximum clique problem [20], edge-disjoint paths problem [9].

Perrotto and Lopez use ant colonies optimization for reconstruction of phylogenetic trees, which are developed in order to help unveil the evolutionary relationships among species, taking into account the Darwinian principle of the natural evolution of species. That is, by analyzing a set of amino acid sequences (or proteins) of different species, it can be determined how these species probably have been derived during their evolution. A phylogenetic tree can be considered as a binary tree, whose leaf nodes represent the species to be analyzed and inner nodes the ancestral species from which the current species have evolved. Also, phylogenetic trees may or may not have a root that indicates the oldest ancestor. A tree is constructed using a fully connected graph and the problem is approached similarly to the traveling salesman problem [109].

ACO was successfully applied for routing and road balancing problems. Schoonderwoerd et al. [113]-[115] designed an ant based control system (ABC) was designed to solve the load-balancing problem in circuit-switched networks [117], [119].

One of the ramifications of the ABC system is the adaptation of Guérin's *smart ants* to solve the problems of routing and load-balancing in circuit-switched networks by Bonabeau et al. [13], [77]. While an ant in ABC updates only the entry corresponding to the source node in the pheromone table of each node it passes, Bonabeau smart ants update the pheromone table at each node, all entries

corresponding to *every* node they pass. Two other ramifications of the ABC system are the work of Subramanian et al. [131] and Heusse et al. [78], [112].

Caro and Dorigo [27] proposed the AntNet algorithm, designed for routing in packet-switched networks. Unlike traditional routing algorithms (such as OSPF and RIP) which focused on minimal or shortest path routing, routing in AntNet was carried out with the aim of optimizing the performance of the entire network. In AntNet, routing was achieved by launching forward ants at regular intervals from a source node to a destination node to discover a feasible low-cost path and by backward ants that travels from to destination node to source node update pheromone tables at each intermediate node [117].

ACO algorithms are also applied in the bioinformatics field for the problems such as: protein folding [121], [122], to multiple sequence alignment [102], and to the prediction of major histocompatibility complex (MHC) class II binders [85].

Sim and Sun [118]proposed a *Multiple Ant Colony Optimization (MACO)* technique, in which more than one colony of ants are used to search optimal paths, and each colony of ants deposits a different type of pheromone represented by a different color.

1.4.2 Bees' behavior inspired algorithms

Farooq et al. [61], [139]-[145] developed a bee inspired algorithm for routing in telecommunication network. The work is inspired by the way these insects communicate. He is also using “dance” quality of the bees, as illustrated in the book *The Dance Language and Orientation of Bees* [64].

The worker bees in a honey bee colony are grouped as food-storer, scout and forager. The food collection is organized by the colony by recruiting bees for different jobs. The recruitment is managed by the forager bees which can perform dances to communicate with their fellow bees inside the hive and recruit them. At the entrance of the hive is an area called the dance-floor, where dancing takes place [116]. Different types of dances have been identified:

- *Waggle dance* - is an advertisement for the food source of the dancer. Another forager can leave her food source and watch out for a well advertised food source [116]. A forager randomly follows dances of multiple recruiting foragers and seems to respond randomly as well. Especially she does not compare several dances. A dance does not seem to contain any information that helps to choose a food source [143].
- *Tremble dance* - foragers are more likely to perform the tremble dance if they have to wait long for a food-storer bee to unload their nectar after their arrival at hive. Foragers perform the tremble dance on the dance-floor and in the brood nest as well, whereas the waggle dance is limited to the dance-floor. So maybe bees in the hive are addressed, too [143]. According to Seeley [116] worker bees in the hive are ordered by the tremble dancers to give up their jobs and to unload nectar.

Upon their return from a foraging trip, bees communicate the distance, direction, and quality of a flower site to their fellow foragers by making waggle dances on a dance floor inside the hive. By dancing zealously for a good foraging site they recruit foragers for the site. In this way a good flower site is exploited, and the numbers of foragers at this site are reinforced. A honey bee colony has many features that are desirable in networks:

- efficient allocation of foraging force to multiple food sources;
- different types of foragers for each commodity;
- foragers evaluate the quality of food sources visited and then recruit optimum number of foragers for their food source by dancing on a dance floor inside the hive;
- no central control;
- foragers try to optimize the energetic efficiency of nectar collection and foragers take decisions without any global knowledge of the environment.

For solving the routing problem [61] the following hypothesis are considered: if a honey bee colony is able to adapt to countless changes inside the hive or outside in the environment through simple individuals without any central control, then an agent system based on similar principles should be able to adapt itself to an ever changing network environment in a decentralized fashion with the help of simple agents who rely only on local information. Problem is modeled as a honey bee colony and as a population based multi-agent system, in which simple agents coordinate their activities to solve the complex problem of the allocation of labor to multiple forage sites in dynamic environments. The agents achieve this objective in a decentralized fashion with the help of local information that they acquire while foraging. The proposed algorithm for routing problem is called *BeeHive* and uses the following principles of a honey bee colony [61]:

1. Each node in the network is considered as being a hive that consists of bee agents. Each node periodically launches its bee agents to explore the network and collect the routing information that provides the nodes visited with the partial information on the state of the network. These bee agents can be considered as scouts that explore and evaluate the quality of multiple paths between their launching node and the nodes that they visit.
2. Bee agents provide to the nodes which they visit, with the information on the propagation delay and queuing delay of the paths they explored. These lead to their launching node from the visited nodes. One could consider the propagation delay as distance information, and the queuing delay as a direction information (please remember bee scouts also provide these parameters in their dances): this reasoning is justified because a data packet is only diverted from the shortest path to other alternate paths when large queuing delays exist on the shortest path.
3. A bee agent decides to provide its path information only if the quality of the path traversed is above a threshold. The threshold is dependent on the number of hops that a bee agent is allowed to take. Moreover, the agents model the quality of a

- path as a function of the propagation delay and the queuing delay of the path; lower values of the parameters result in higher values for the quality parameter.
4. The majority of the bee agents in the BeeHive algorithm explore the network in the vicinity of their launching node and very few explore distant part of the network. The idea is borrowed from honey bee colony resulting in not only reducing the overhead of collecting the routing information but also helping in maintaining smaller/local routing tables.
 5. We consider a routing table as a dance floor where the bee agents provide the information about the quality of the paths they traversed. The routing table is used for information exchange among bee agents, launched from the same node but arriving at an intermediate node via different neighbors. This information exchange helps in evaluating the overall quality of a node as it has multiple pathways to a destination) for reaching a certain destination.
 6. A nectar forager exploits the flower sites according to their quality while the distance and direction to the sites is communicated to it through waggle dances performed by fellow foragers on the dance floor. In our algorithm, we map the quality of paths onto the quality of nodes for utilizing the bee principle. Consequently, we formulate the quality of a node, for reaching a destination, as a function of proportional quality of only those neighbors that possibly lie in the path toward the destination.

Data packets are interpreted as foragers. Once they arrive at a node, they access the information in the routing tables, stored by bee agents, about the quality of different neighbors of the node for reaching their destinations. They select the next neighbor toward the destination in a stochastic manner depending upon its goodness. As a result, not all packets follow the best paths. This will help in maximizing the system performance although a data packet may not follow the best path.

Craig [35] borrowed the following idea from bees colonies behavior and used it for Internet Server Optimization: each colony must collect extra nectar during the warm season to make and store enough honey – usually 20 to 50 kg – in order to survive the winter. Efficient nectar collection is thus crucial for the colony survival. It is inefficient, in general, for all of the colony’s foragers to collect from the same flower patch. A large number of bees at one patch can “swamp out” the flowers’ capacity to generate nectar. On the other hand, some flower patches are richer or more productive than others. To maximize nectar intake, the honey bee colony must ‘decide’ in some decentralized but intelligent fashion how many bees will forage at each flower patch.

1.4.3 Particle swarm optimization algorithm

The Particle Swarm Optimization (PSO) model [58]-[60], [86]-[91] consists of a swarm of particles, which are initialized with a population of random candidate solutions. They move iteratively through the d -dimension problem space to search the new solutions, where the fitness, f , can be calculated as the certain qualities measure. Each particle has a position represented by a position-vector \mathbf{x}_i (i is the

index of the particle), and a velocity represented by a velocity-vector \mathbf{v}_i . Each particle remembers its own best position so far in a vector $\mathbf{x}_i^\#$, and its j -th dimensional value is $x_{ij}^\#$. The best position-vector among the swarm so far is then stored in a vector \mathbf{x}^* , and its j -th dimensional value is x_j^* . During the iteration time t , the update of the velocity from the previous velocity to the new velocity is determined by Eq.(1.3). The new position is then determined by the sum of the previous position and the new velocity by Eq.(1.4).

$$v_{ij}(t+1) = wv_{ij}(t) + c_1r_1(x_{ij}^\#(t) - x_{ij}(t)) + c_2r_2(x_j^*(t) - x_{ij}(t)). \quad (1.3)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1). \quad (1.4)$$

where w is called as the inertia factor, r_1 and r_2 are the random numbers, which are used to maintain the diversity of the population, and are uniformly distributed in the interval $[0,1]$ for the j -th dimension of the i -th particle. c_1 is a positive constant, called as coefficient of the self-recognition component, c_2 is a positive constant, called as coefficient of the social component. From Eq.(1.3), a particle decides where to move next, considering its own experience, which is the memory of its best past position, and the experience of its most successful particle in the swarm. In the particle swarm model, the particle searches the solutions in the problem space with a range $[-s, s]$ (If the range is not symmetrical, it can be translated to the corresponding symmetrical range.) In order to guide the particles effectively in the search space, the maximum moving distance during one iteration must be clamped in between the maximum velocity $[-v_{max}, v_{max}]$ given in Eq.(1.5):

$$v_{ij} = \text{sign}(v_{ij})\min(|v_{ij}|, v_{max}). \quad (1.5)$$

The value of v_{max} is $p \times s$, with $0.1 \leq p \leq 1.0$ and is usually chosen to be s , i.e. $p = 1$. The pseudo-code for particle swarm optimization algorithm is illustrated in Algorithm 1.2.

The end criteria are usually one of the following:

- Maximum number of iterations: the optimization process is terminated after a fixed number of iterations, for example, 1000 iterations.
- Number of iterations without improvement: the optimization process is terminated after some fixed number of iterations without any improvement.
- Minimum objective function error: the error between the obtained objective function value and the best fitness value is less than a pre-fixed anticipated threshold.

1.4.4 Bacteria foraging algorithm

Since selection behavior of bacteria tends to eliminate animals with poor foraging strategies and favor the propagation of genes of those animals that have successful foraging strategies, they can be applied to have an optimal solution through methods for locating, handling, and ingesting food. After many generations, a foraging animal takes actions to maximize the energy obtained per unit time spent foraging. That is,

Algorithm 1.2 Particle Swarm Optimization Algorithm

-
01. Initialize the size of the particle swarm n , and other parameters.
 02. Initialize the positions and the velocities for all the particles randomly.
 03. While (the end criterion is not met) do
 04. $t = t + 1$;
 05. Calculate the fitness value of each particle;
 06. $\mathbf{x}^* = \operatorname{argmin}_{i=1}^n (f(\mathbf{x}_1^*(t-1)), f(\mathbf{x}_1(t)), f(\mathbf{x}_2(t)), \dots, f(\mathbf{x}_i(t)), \dots, f(\mathbf{x}_n(t)))$;
 07. For $i=1$ to n
 08. $\mathbf{x}_i^\#(t) = \operatorname{argmin}_{i=1}^n (f(\mathbf{x}_i^\#(t-1)), f(\mathbf{x}_i(t)))$;
 09. For $j=1$ to *Dimension*
 10. Update the j -th dimension value of \mathbf{x}_i and \mathbf{v}_i according to Eqs.(1.3), (1.4), (1.5);
 12. Next j
 13. Next i
 14. End While.
-

poor foraging strategies are either eliminated or shaped into good ones. To perform social foraging an animal needs communication capabilities and it gains advantages that can exploit essentially the sensing capabilities of the group, so that the group can gang-up on larger prey, individuals can obtain protection from predators while in a group, and in a certain sense the group can forage a type of collective intelligence [103].

Escherichia Coli (E. Coli) normally lives inside the intestines, where it helps to body break down and digest the food. Its behavior and movement comes from a set of six rigid spinning (100-200 r.p.s) flagella, each driven as a biological motor. An E. coli bacterium alternates through running and tumbling. When the flagella rotate clockwise (counterclockwise), they operate as propellers and hence an E. Coli may run or tumble. Passino et al. [103] has modeled the chemotactic actions of the bacteria as follows:

- If in neutral medium, alternate tumbles and runs it is considered as search.
- If swimming up a nutrient gradient (or out of noxious substances), swim longer (climb up nutrient gradient or down noxious gradient) then it is considered as seeking increasingly favorable environments.
- If swimming down a nutrient gradient (or up noxious substance gradient), then search is considered as avoiding unfavorable environments.

In this way, it can climb up nutrient hills and at the same time avoid noxious substances. E. coli occasionally engages in a conjugation that affects the characteristics of a population of bacteria. There are many types of taxes that are used by bacteria. For instance, some bacteria are attracted to oxygen (aerotaxis), light (phototaxis), temperature (thermotaxis), or magnetic lines of flux (magnetotaxis). Some bacteria can change their shape and number of flagella based on the medium to reconfigure so as to ensure efficient foraging in a variety of media. Bacteria can form intricate stable spatio-temporal patterns in certain semisolid nutrient substances

and they can eat radially their way through a medium if placed together initially at its center. Moreover, under certain conditions, they will secrete cell-to-cell attractant signals so that they will group and protect each other.

1.5 Conclusions and Some Potential Areas for Exploration

This chapter reviewed some of the well known nature inspired stigmergic computational models which has evolved during the last few decades. We presented some facts about social insects namely ants, bees and termites and how they could interact and self organize for solving real world problems. We focused on ant colony optimization algorithm, bees behavior inspired algorithm, particle swarm optimization algorithm and bacterial foraging algorithm.

The subject of copying, imitating, and learning from biology was coined *Biomimetics* by Otto H. Schmitt in 1969 [28]. This field is increasingly involved with emerging subjects of science and engineering and it represents the studies and imitation of nature's methods, designs and processes. Nature, through billions of years of trial and error, has produced effective solutions to innumerable complex real-world problems. Even though there are several computational nature inspired models, there is still a lot of room more research, at least in the form of finding some collaborations and interactions between the existing systems as well as developing new systems by borrowing ideas from nature. Butler [25] suggests some potential research areas:

1. Spiders spin silk that is stronger than synthetic substances developed by man but require only insects as inputs.
2. Diatoms, microscopic phytoplankton responsible for a quarter of all the photosynthesis on Earth, make glass using silicon dissolved in seawater.
3. Abalone, a type of shellfish, produces a crack-resistant shell twice as tough as ceramic from calcium found in seawater using a process known as biomineralization.
4. Trees "turn sunlight, water, and air into cellulose, a sugar stiffer and stronger than nylon, and bind it into wood, a natural composite with a higher bending strength and stiffness than concrete or steel," as noted by Paul Hawken, Amory and L. Hunter Lovins in *Natural Capitalism*.
5. Countless plants generate compounds that fight off infection from fungi, insects, and other pests.

References

1. Aron S, Pasteels JM, Deneubourg JL, Boevé JL (1986). Foraging recruitment in *Leptothorax unifasciatus*: The influence of foraging area familiarity and the age of nest-site. *Insectes Sociaux*, 33, 338-351.

2. Aron S, Pasteels JM, Deneubourg JL (1989). Trail-laying behaviour during exploratory recruitment in the argentine ant, *Iridomyrmex humilis* (Mayr). *Biology of Behaviour*, 14, 207-217.
3. Aron S, Deneubourg JL, Goss S, Pasteels JM (1990). How Argentine ants establish a minimal-spanning tree to link different nests. In *Social Insects and the Environment*, Eds. G.K. Veeresh, B. Mallik and C.A. Viraktamath, Oxford & IBH, New Delhi, 533-534.
4. Aron S, Deneubourg JL, Goss S, Pasteels JM (1990). Functional self-organisation illustrated by inter-nest traffic in the argentine ant *Iridomyrmex humilis*. In *Biological Motion*, Eds W. Alt and G. Hoffman. *Lecture Notes in Biomathematics*, Springer-Verlag, Berlin, 533-547.
5. Beckers R, Goss S, Deneubourg JL, Pasteels JM (1989). Colony size, communication and ant foraging strategy, *Psyche*, 96, 239-256.
6. Beckers R, Deneubourg JL, Goss S (1990). Changing foraging strategies inherent to trail recruitment. In *Social Insects and the Environment*, Eds. G.K. Veeresh, B. Mallik and C.A. Viraktamath, Oxford & IBH, New Delhi, 549.
7. Benzatti D, *Collective Intelligence (Ants)*, Available at: <http://ai-depot.com/CollectiveIntelligence/Ant.html>
8. de Biseau JC, Deneubourg JL, Pasteels JM (1992). Mechanisms of food recruitment in the ant *Myrmica sabuleti* : an experimental and theoretical approach. In *Biology and Evolution of Social Insects*, Ed. J. Billen. Leuven University Press, Leuven (B), 359-367.
9. Blesa M, Blum C (2004) Ant colony optimization for the maximum edge-disjoint paths problem. In: Raidl GR, Cagnoni S, Branke J, Corne DW, Drechsler R, Jin Y, Johnson CG, Machado P, Marchiori E, Rothlauf R, Smith GD, Squillero G, editors. *Applications of evolutionary computing, proceedings of EvoWorkshops 2004. Lecture Notes in Computer Science*, vol. 3005. Berlin: Springer, 160-9.
10. Blum C. Beam (2005) ACO-Hybridizing ant colony optimization with beam search: An application to open shop scheduling. *Computers & Operations Research*, 32(6), 1565-1591.
11. Blum C, Sampels M (2004) An ant colony optimization algorithm for shop scheduling problems. *Journal of Mathematical Modelling and Algorithms*, 3(3), 285-308.
12. Blum C (2005) Ant colony optimization: Introduction and recent trends. *Physics of Life Reviews*, 2, 353-373.
13. Bonabeau, E, Hénaux F, Guérin S, Snyer D, Kuntz P, Théraulaz G (1998) Routing in telecommunications networks with ant-like agents. In *Proceedings of Intelligent Agents Telecommunications Applications*, Berlin, Germany.
14. Bonabeau E, Dorigo M, Theraulaz G (2000) Inspiration for optimization from social insect behavior, *Nature*, 406, 39-42.
15. Bonabeau E, Theraulaz G, Deneubourg JL (1995). Phase diagram of a model of self-organizing hierarchies. *Physica A*, 217, 373-392.
16. Bonabeau E, Theraulaz G, Deneubourg JL (1996). Mathematical model of self-organizing hierarchies in animal societies. *Bulletin of Mathematical Biology*, 58, 661-717.
17. Bonabeau E, Theraulaz G, Deneubourg JL (1996). Quantitative study of the fixed threshold model for the regulation of division of labour in insect societies. *Proceedings of the Royal Society of London Series B*, 263, 1565-1569.
18. Bonabeau E, Theraulaz G, Fourcassié V, Deneubourg JL (1998). Phase-ordering kinetics of cemetery organization in ants. *Physical Review E*, 57, 4568-4571.
19. Bonabeau E, Theraulaz G, Deneubourg JL, Lioni A, Libert F, Sauwens C, Passera L (1998). Dripping faucet with ants. . *Physical Review E*, 57, 5904-5907.

20. Bui TN, Rizzo JR (2004) Finding maximum cliques with distributed ants. In: Deb K, et al., editors. Proceedings of the genetic and evolutionary computation conference (GECCO 2004). Lecture Notes in Comput Sci, vol. 3102. Berlin: Springer, 24-35.
21. Bullnheimer B, Hartl RF, Strauss C (1999). A New Rank Based Version of the Ant System: A Computational Study, *Central European Journal for Operations Research and Economics*, 7(1):25-38.
22. Bullnheimer B, Hartl RF, Strauss C (1997) An Improved Ant system Algorithm for the Vehicle Routing Problem. Sixth Viennese workshop on Optimal Control, Dynamic Games, Nonlinear Dynamics and Adaptive Systems, Vienna (Austria).
23. Bullnheimer B., R.F. Hartl and C. Strauss (1999) Applying the Ant System to the Vehicle Routing Problem. In Voss S., Martello S., Osman I.H., Roucairol C. (eds.), *Meta-Heuristics: Advances and Trends in Local Search Paradigms for Optimization*, Kluwer:Boston.
24. Bullnheimer B. (1999). *Ant Colony Optimization in Vehicle Routing*. Doctoral thesis, University of Vienna, January 1999.
25. Butler R, *Biomimetics, technology that mimics nature*, available online at: mongabay.com
26. Calenbuhr V, Deneubourg JL (1990). A model for trail following in ants: Individual and collective behaviour. In *Biological Motion*, Eds. W. Alt and G. Hoffman. *Lecture Notes in Biomathematics*, Springer-Verlag, Berlin, 453-469.
27. Caro GD, Dorigo M (1998) AntNet: Distributed stigmergetic control for communications networks, *Journal of Artificial Intelligence Research*, 9, 317-365.
28. Cohen YB (2005), *Biomimetics: Biologically Inspired Technologies*, CRC Press.
29. Colomi A, Dorigo M, Maffioli F, Maniezzo V, Righini G, Trubian M (1996). Heuristics from Nature for Hard Combinatorial Problems. *International Transactions in Operational Research*, 3(1):1-21.
30. Colomi A, Dorigo M, Maniezzo V (1992). Distributed Optimization by Ant Colonies. *Proceedings of the First European Conference on Artificial Life*, Paris, France, F.Varela and P.Bourgine (Eds.), Elsevier Publishing, 134-142.
31. Colomi A, Dorigo M, Maniezzo V (1992). An Investigation of Some Properties of an Ant Algorithm. In *Proceedings of the Parallel Problem Solving from Nature Conference (PPSN 92)*, Brussels, Belgium, R.Männer and B.Manderick (Eds.), Elsevier Publishing, 509-520.
32. Colomi A, Dorigo M, Maniezzo V (1995). New Results of an Ant System Approach Applied to the Asymmetric TSP. In *Proceedings of the Metaheuristics International Conference*, Hilton Breckenridge, Colorado, I.H.Osman and J.P. Kelly (Eds.), Kluwer Academic Publishers, 356-360.
33. Colomi A, Dorigo M, Maniezzo V, Trubian M (1994). Ant system for Job-shop Scheduling. - *Belgian Journal of Operations Research, Statistics and Computer Science*, 34(1):39-53.
34. Costa D, Hertz A (1997). Ants Can Colour Graphs. *Journal of the Operational Research Society*, 48, 295-305.
35. Tovey CA (2004) HONEY BEE Algorithm: A Biologically Inspired Approach to Internet Server Optimization, *Engineering Enterprise*, Spring, 13-15
36. Deneubourg JL, Aron S, Goss S, Pasteels JM (1990) The self-organizing exploratory pattern of the argentine ant, *Journal of Insect Behavior*, 3, 159-168.
37. Deneubourg JL, de Palma A (1980) Self-organization and architecture in human and animal societies. In *International Conference on Cybernetics and Society*, IEEE, 1126-1128.
38. Deneubourg JL, Pasteels JM, Verhaeghe JC (1983). Probabilistic behaviour in ants: a strategy of errors? *Journal of Theoretical Biology*, 105, 259-271.

39. Deneubourg JL, Aron S, Goss S, Pasteels JM, Duerinck G (1986). Random behaviour, amplification processes and number of participants: how they contribute to the foraging properties of ants. *Physica D*, 22, 176-186.
40. Deneubourg JL, Aron S, Goss S, Pasteels JM (1987). Error, communication and learning in ant societies. *European Journal of Operational Research*, 30, 168-172.
41. Deneubourg JL, Goss S, Pasteels JM, Fresneau D, Lachaud JP (1987). Self-organization mechanisms in ant societies (II): learning in foraging and division of labor. In *From individual to collective behavior in social insects*, Eds J.M. Pasteels and J.L. Deneubourg. *Experientia Supplementum*, 54, Birkhäuser, Bâle, 177-196.
42. Deneubourg JL, Aron S, Goss S, Pasteels JM (1990). The self-organizing exploratory pattern of the argentine ant. *Journal of Insect Behavior*, 3, 159-168.
43. Deneubourg JL, Theraulaz G, Beckers R (1991). Swarm made architectures. In *Proceedings of the 1st European Conference on Artificial Life*, Paris 1991, Eds P. Bourguin and E. Varela. MIT Press, Cambridge (Mass.), 123-133.
44. Deneubourg JL, Camazine S, Detrain C (1999) Self-organization or individual complexity: a false dilemma or a true complementarity In *Information processing in social insects*, Detrain C., Deneubourg J.L. and Pasteels J.M. (eds), Birkhauser Verlag, 401-408.
45. Dorigo M, Blum C (2005) Ant colony optimization theory: A survey, *Theoretical Computer Science*, 344, 243-278.
46. Dorigo M, Maniezzo V, Colomi A (1991) Positive feedback as a search strategy, Tech. Report 91-016, Dipartimento di Elettronica, Politecnico di Milano, Italy.
47. Dorigo M, Maniezzo V, Colomi A (1996) Ant system: optimization by a colony of cooperating agents, *IEEE Transaction on Systems, Man and Cybernetics-Part B*, 26(1), 29-41.
48. Dorigo M, Gambardella LM (1997) Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem. *IEEE Transactions on Evolutionary Computation*, 1(1):53-66.
49. Dorigo M, Gambardella LM (1997) Ant Colonies for the Traveling Salesman Problem. *BioSystems*, 43, 73-81.
50. Dorigo M, Caro GD, Gambardella LM (1999) Ant algorithms for discrete optimization, *Artificial Life*, 5(2), 137-172.
51. Dorigo M, Bonabeau E, Theraulaz G (2000) Ant algorithms and stigmergy, *Future Generation Computer Systems*, 16(8) 851-871.
52. Dorigo M, Caro GD (1999) The ant colony optimization metaheuristic, *New Ideas in Optimization*, D. Corne, M. Dorigo, and F. Glover, Eds. New York: McGraw-Hill.
53. Dorigo M, Stutzle T (2002) The ant colony optimization metaheuristic: Algorithms, applications, and advances, *Handbook of Metaheuristics*, F. Glover and G. Kochenberger, Eds. Norwell, MA: Kluwer.
54. Dorigo M, Maniezzo V, Colomi A (1991) Positive Feedback as a Search Strategy, Dipartimento Elettronica, Politecnico Milano, Italy, Tech. Rep. 91-016.
55. Dorigo M, Gambardella LM (1997) Ant colony system: A cooperative learning approach to the travelling salesman problem, *IEEE Transaction on Evolutionary Computation*, 1, 53-66.
56. Dorigo M, Caro DG (1999) Ant colony optimization: a new meta-heuristic. *Proceeding of the 1999 Congress on Evolutionary Computation (CEC)*, 1470-1477.
57. Dorigo M, Bonabeau E, Theraulaz G (2000) Ant algorithms and stigmergy, *Future Generation Computer Systems*, 16, 851-871.
58. Eberhart RC, Kennedy J (1995) A new optimizer using particle swarm theory. In *Proceedings of the Sixth International Symposium on Micromachine and Human Science*, Nagoya, Japan, 39-43.

59. Eberhart RC, Shi Y (2001) Particle swarm optimization: developments, applications and resources. In Proceedings of the IEEE Congress on Evolutionary Computation (CEC), Seoul, Korea
60. Eberhart RC, Simpson PK, Dobbins RW (1996) Computational Intelligence PC Tools, Boston, MA: Academic Press Professional
61. Farooq M (2006) From the Wisdom of the Hive to Intelligent Routing in Telecommunication Networks: A Step towards Intelligent Network Management through Natural Engineering, PhD Thesis, University of Dortmund, Germany.
62. Focardi S, Deneubourg JL, Chelazzi G (1989). Clustering in intertidal gastropods and chitons: models and field observations, *Mémoire de la Société Vaudoise des Sciences Naturelles*, 18(3) 1-15.
63. Forsyth P, Wren A (1997) An Ant System for Bus Driver Scheduling. Presented at the 7th International Workshop on Computer-Aided Scheduling of Public Transport, Boston.
64. von Frisch K (1967) The Dance Language and Orientation of Bees. Harvard University Press, Cambridge.
65. Gagné C, Price WL, Gravel M (2002) Comparing an ACO algorithm with other heuristics for the single machine scheduling problem with sequencedependent setup times. *Journal of Operation Research Society*, 53, 895-906.
66. Gambardella LM, Dorigo M (1995) Ant-Q: A Reinforcement Learning Approach to the Traveling Salesman Problem. In Proceedings of ML-95, Twelfth International Conference on Machine Learning, Tahoe City, CA, A. Prieditis and S. Russell (Eds.), Morgan Kaufmann, 252-260.
67. Gambardella LM, Dorigo M (1996) Solving Symmetric and Asymmetric TSPs by Ant Colonies. In Proceedings of IEEE International Conference on Evolutionary Computation, IEEE-EC 96, Nagoya, Japan, IEEE Press, 622-627.
68. Gambardella LM, Dorigo M (1997) HAS-SOP: An Hybrid Ant System for the Sequential Ordering Problem. Technical Report No. IDSIA 97-11, IDSIA, Lugano, Switzerland.
69. Gambardella LM, Taillard E, Dorigo M (1999) Ant Colonies for the Quadratic Assignment Problem. *Journal of the Operational Research Society*, 50, 167-176.
70. Gordon D, Collective Intelligence in Social Insects, AI-depot essay, available online at: <http://ai-depot.com/Essay/SocialInsects.html>
71. Goss S, Deneubourg JL, Pasteels JM (1985) Modelling ant foraging systems; the influence of memory and the ants' size. In *The Living State-II*. Ed. R.K. Mishra. World Scientific Publishing Co., Singapore, 24-46.
72. Goss S, Aron S, Deneubourg JL, Pasteels JM (1989) Self-organized shortcuts in the argentine ant. *Naturwissenschaften*, 76, 579-581.
73. Goss S, Deneubourg JL, Pasteels JM, Josens G (1989) A model of noncooperative foraging in social insects. *The American Naturalist*, 134, 273-287.
74. Goss S, Fresneau D, Deneubourg JL, Lachaud JP Valenzuela-Gonzalez J (1989) Individual foraging in the ant *Pachycondyla apicalis*, *Oecologia*, 80, 65-69.
75. Goss S, Beckers R, Deneubourg JL, Aron S, Pasteels JM (1990) How trail laying and trail following can solve foraging problems for ant colonies. In *Behavioural Mechanisms of Food Selection*, Ed. R.N. Hughes. NATO ASI Series, G 20, Springer-Verlag, Berlin, 661-678.
76. Grasse, PP (1959) La reconstruction du nid et les coordinations interindividuelles chez *bellicositermes natalensis* et *cubitermes* sp. La theorie de la stigmergie: essai d'interpretation du comportement des termites constructeurs. *Insects Sociaux*, 6, 41-81.
77. Guérin S (1997) Optimization Multi-Agents en Environnement Dynamique: Application au Routage Dans les Réseaux de Telecommunications, DEA, Univ. Rennes I, Ecole Nat. Supér. Télécommun. Bretagne, , Bretagne, France.

78. Heusse M, Snyers D, Guérin S, Kuntz P (1998) Adaptive Agent-Driven Routing and Load Balancing in Communication Networks, ENST Bretagne, Brest, France, Tech. Rep. RR-98 001-IASC.
79. Hogue C (1987) Cultural entomology, *Annual Review of Entomology*, 32
80. <http://institute.advancedarchitecture.org/Research/Ants/Optimization>
81. <http://www.lingolex.com/ants.htm>
82. <http://www.insecta-inspecta.com>
83. <http://institute.advancedarchitecture.org/Research/Ants/Optimization>
84. Jaffé K, Deneubourg JL (1992) On foraging, recruitment systems and optimum number of scouts in eusocial colonies. *Insectes Sociaux*, 39, 201-213.
85. Karpenko O, Shi J, Dai Y (2005) Prediction of MHC class II binders using the ant colony search strategy. *Artificial Intelligence in Medicine*, 35(1-2), 147-156.
86. Kennedy J, Eberhart RC (1995) Particle Swarm Optimization. In *Proceedings of IEEE International Conference on Neural Networks*, Perth, Australia, IEEE Service Center, Piscataway, NJ, Vol.IV, 1942-1948
87. Kennedy J (1997) Minds and cultures: Particle swarm implications. *Socially Intelligent Agents. Papers from the 1997 AAAI Fall Symposium*. Technical Report FS-97-02, Menlo Park, CA: AAAI Press, 67-72
88. Kennedy J (1998) The Behavior of Particles, In *Proceedings of 7th Annual Conference on Evolutionary Programming*, San Diego, USA.
89. Kennedy J (1997) The Particle Swarm: Social Adaptation of Knowledge. In *Proceedings of IEEE International Conference on Evolutionary Computation*, Indianapolis, Indiana, IEEE Service Center, Piscataway, NJ, 303-308
90. Kennedy J (1992) Thinking is social: Experiments with the adaptive culture model. *Journal of Conflict Resolution*, 42, 56-76
91. Kennedy J, Eberhart R (2001) *Swarm Intelligence*, Morgan Kaufmann Academic Press
92. Kuntz P, Snyers D (1994) Emergent Colonization and Graph Partitioning. IN *Proceedings of the Third International Conference on Simulation of Adaptive Behavior: From Animals to Animats 3*, MIT Press, Cambridge, MA.
93. Kuntz P, Layzell P, Snyers D (1997) A Colony of Ant-like Agents for Partitioning in VLSI Technology. In *Proceedings of the Fourth European Conference on Artificial Life*, P. Husbands and I. Harvey, (Eds.), MIT Press, 417-424.
94. Maeterlinck M (1930) *The life of the white ant*, Dodd, Mead & Co.
95. Maniezzo V, Colomi A, Dorigo M (1994). The Ant System Applied to the Quadratic Assignment Problem. Technical Report IRIDIA/94-28, Université Libre de Bruxelles, Belgium.
96. Maniezzo V, Muzio L, Colomi A, Dorigo M (1994). Il sistema formiche applicato al problema dell'assegnamento quadratico. Technical Report No. 94-058, Politecnico di Milano, Italy.
97. Maniezzo V (1998). Exact and approximate nondeterministic tree-search procedures for the quadratic assignment problem. Research Report CSR 98-1, Scienze dell'Informazione, Università di Bologna, Sede di Cesena, Italy.
98. Maniezzo V, Colomi A (1999). The Ant System Applied to the Quadratic Assignment Problem. *IEEE Transactions on Knowledge and Data Engineering*.
99. Maniezzo V, Carbonaro A (2001), Ant Colony Optimization: an overview, in C.Ribeiro (eds.) *Essays and Surveys in Metaheuristics*, Kluwer, 21-44.
100. Merkle D, Middendorf M, Schmeck H (2002) Ant colony optimization for resource-constrained project scheduling. *IEEE Transaction on Evolutionary Computation*, 6(4), 333-46.

101. Michel R, Middendorf M (1998) An island model based ant system with lookahead for the shortest supersequence problem. In: Eiben AE, Bäck T, Schoenauer M, Schwefel H-P, editors. Proceedings of PPSN-V, fifth International Conference on Parallel Problem Solving from Nature, Lecture Notes in Comput Science, Berlin, Springer, 692-701.
102. Moss JD, Johnson CG (2003) An ant colony algorithm for multiple sequence alignment in bioinformatics. In: Pearson DW, Steele NC, Albrecht RF, editors. Artificial neural networks and genetic algorithms, Berlin Springer, 182-186.
103. Passino KM (2005), Biomimicry for Optimization, Control, and Automation, Springer-Verlag, London, UK.
104. Pasteels JM, Verhaeghe JC, Deneubourg JL (1982). The adaptive value of probabilistic behavior during food recruitment in ants : experimental and theoretical approaches. In Biology of Social Insects. Eds M.D. Breed, C.D. Michener AND H.E. Evans, Westview Press, Boulder, Co, 297-301.
105. Pasteels JM, Deneubourg JL, Verhaeghe JC, Boevé JL, Quinet Y (1986). Orientation along terrestrial trails by ants. In Mechanisms in insect olfaction. Eds T.L. Payne, M.C. Birch AND C.E.J. Kennedy, Oxford University Press, Oxford, 131-138.
106. Pasteels JM, Deneubourg JL, Goss S (1987). Transmission and amplification of information in a changing environment: The case of insect societies. In Law of Nature and Human conduct, Eds I. Prigogine and M. Sanglier, Gordes, Bruxelles, 129-156.
107. Pasteels, JM Deneubourg, JL, Goss S (1987) Self-organization mechanisms in ant societies (I) : trail recruitment to newly discovered food sources. In From individual to collective behavior in social insects, Eds J.M. Pasteels and J.L. Deneubourg. Experientia Supplementum, 54, Birkhäuser, Bâle, 155-175.
108. Pasteels JM, Roisin Y, Deneubourg JL, Goss S (1987) How efficient collective behaviour emerges in societies of unspecialized foragers: the example of *Tetramorium caespitum*. In Chemistry and Biology of Social Insects, Eds J. Eder and H. Rembold. Verlag Peperny, Munich, 513-514.
109. Perretto M, Lopes HS (2005) Reconstruction of phylogenetic trees using the ant colony optimization paradigm. Genetics and Molecular Research, 4(3), 581-589.
110. Preface to the book "the Soul of a White Ant" published in 1937, available online at http://journeytoforever.org/farm_library/Marais1/whiteantToC.html
111. Saffre F, Deneubourg JL (2002) Swarming strategies for cooperative species. Journal of Theoretical Biology, 214, 441-451.
112. Schatz B, Chameron S, Beugnon G, Collett TS (1999) The use of path integration to guide route learning in ants, Nature, 399(6738), 769-777.
113. Schoonderwoerd R, Holland O, Bruten J, Rothkrantz L (1996) Antbased load balancing in telecommunications networks, Adaptive Behavior, 5(2), 169-207.
114. Schoonderwoerd R, Holland O, Bruten J Ant-like agents for load balancing in telecommunications networks, In Proceedings of Agents, Marina del Rey, CA, 209-216.
115. Schoonderwoerd R, Holland O (1999) Minimal agents for communications networks routing: The social insect paradigm. In Software Agents for Future Communication Systems, A. L. G. Hayzeldean and J. Bingham, Eds. New York: Springer-Verlag.
116. Seeley TD, Towne WF (1992) Tactics of dance choice in honey bees: Do foragers compare dances? Behav. Ecol. Sociobiol. 30, 59-69.
117. Sim KM, Sun WH (2003) Ant Colony Optimization for Routing & Load-Balancing: Survey and New Directions. IEEE Transaction on Systems, Man and Cybernetics, Part A, 33(5), 560-572.
118. Sim KM, Sun WH (2002) Multiple ant-colony optimization for network routing, In Proceedings of 1st International Symposium on Cyberworld, Tokyo, Japan, November, 277-281.

119. Sim KM, Sun WH (2001) A comparative study of ant-based optimization for dynamic routing. In Proceedings of Conference on Active Media Technology, Lecture Notes Computer Science, Hong Kong, 153-164.
120. Shouse B (2002) Getting the Behavior of Social Insects to Compute. *Science*, 295, 2357.
121. Shmygelska A, Aguirre-Hernández R, Hoos HH (2002) An ant colony optimization algorithm for the 2D HP protein folding problem. In: Dorigo M, Di Caro G, Sampels M, editors, Ant algorithms-Proceedings of ANTS2002-Third international workshop. Lecture Notes in Computer Science, 40-52.
122. Shmygelska A, Hoos HH (2005) An ant colony optimisation algorithm for the 2D and 3D hydrophobic polar protein folding problem. *BMC Bioinformatics*, 6(30), 1-22.
123. Sleigh C (2003) *Ant*, Reaktion Books Ltd.
124. Socha K, Sampels M, Manfrin M (2003) Ant algorithms for the university course timetabling problem with regard to the state-of-the-art. In: Cagnoni S, Romero Cardalda JJ, Corne DW, Gottlieb J, Guillot A, Hart E, Johnson CG, Marchiori E, Meyer A, Middendorf M, Raidl GR, editors. Applications of evolutionary computing, proceedings of EvoWorkshops 2003. Lecture Notes in Computer Science, Berlin Springer, 334-345.
125. Solnon C (2002) Ant can solve constraint satisfaction problems. *IEEE Transaction on Evolutionary Computation* 6(4), 347-57.
126. Stützle T, Hoos H (1997) The MAX-MIN Ant System and Local Search for the Traveling Salesman Problem. Proceedings of ICEC'97 - 1997 IEEE 4th International Conference on Evolutionary Computation, IEEE Press, 308-313.
127. Stützle T, Hoos H (1997) The MAX-MIN Ant System and local Search for Combinatorial Optimization Problems: Towards Adaptive Tools for Global Optimization. 2nd Metaheuristics International Conference (MIC-97), Sophia-Antipolis, France, 21-24.
128. Stützle T, Dorigo M (1999) ACO Algorithms for the Traveling Salesman Problem. In K. Miettinen, M. Makela, P. Neittaanmaki, J. Periaux, editors, *Evolutionary Algorithms in Engineering and Computer Science*, Wiley.
129. Stützle T, Dorigo M (1999) ACO Algorithms for the Quadratic Assignment Problem. In D. Corne, M. Dorigo and F. Glover, editors, *New Ideas in Optimization*, McGraw-Hill.
130. Stutzle T, Hoos HH (2000) MAX-MIN ant system, *Future Generation Computer Systems Journal*, 16(8), 889-914.
131. Subramanian D, Druschel P, Chen J (1997) Ants and reinforcement learning: A case study in routing in dynamic networks, In Proceedings of International Joint Conference on Artificial Intelligence IJCAI-97, Palo Alto, CA, 832-838.
132. Taillard E, Gambardella LM (1997) An Ant Approach for Structured Quadratic Assignment Problems. 2nd Metaheuristics International Conference (MIC-97), Sophia-Antipolis, France.
133. Theraulaz G, Goss S, Gervet J, Deneubourg JL (1990). Self-organisation of behavioural profiles and task assignment based on local individual rules in the eusocial wasp *Polistes dominulus* Christ. In : *Social Insects and the Environment*, Eds. G.K. Veeresh, B. Mallik & C.A. Viraktamath. Oxford & IBH, New Delhi, 535-537.
134. Theraulaz G, Deneubourg JL (1994) Swarm Intelligence in social insects and the emergence of cultural swarm patterns. In *The Ethological roots of Culture*, Eds R.A. Gardner, A.B. Chiarelli, B.T. Gardner & F.X. Ploojd. Kluwer Academic Publishers, Dordrecht, 1- 19.
135. Theraulaz G, Bonabeau E, Deneubourg JL (1995) Self-organization of hierarchies in animal societies: The case of primitively eusocial wasp *Polistes dominulus* Christ. *Journal of Theoretical Biology*, 174, 313-323.
136. Toksari, MD (2005) Ant colony optimization for finding the global minimum. *Applied Mathematics and Computation*.

137. Truscio R, Stranger than fiction, available on-line at: <http://home.att.net/~B-P.TRUSCIO/STRANGER.htm>
138. Verhaeghe JC, Deneubourg JL (1983) Experimental study and modelling of food recruitment in the ant *Tetramorium impurum* (Hym. Form.) *Insectes Sociaux*, 30, 347-360.
139. Wedde HF, Farooq M, Zhang Y (2004) BeeHive: An Efficient Fault Tolerant Routing Algorithm under High Loads Inspired by Honey Bee Behavior. In Proceedings of the Fourth International Workshop on Ant Colony and Swarm Intelligence (ANTS 2004), Brussels, Belgium, Lecture Notes in Computer Science, 83-94.
140. Wedde HF, Farooq M (2005) A Performance Evaluation Framework for Nature Inspired Routing Algorithms. In Proceedings of EvoWorkshops 2005, Lausanne, Switzerland, Lecture Notes in Computer Science, 136-146.
141. Wedde HF, Farooq M (2005) BeeHive: Routing Algorithms Inspired by Honey Bee Behavior. *Kunstliche Intelligenz. Schwerpunkt: Swarm Intelligence*, 18-24.
142. Wedde HF, Farooq M (2005) BeeHive: New Ideas for Developing Routing Algorithms Inspired by Honey Bee Behavior In *Handbook of Bioinspired Algorithms and Applications*, Albert Zomaya and Stephan Olariu, Ed. Chapman & Hall/CRC Computer and Information Science, 321-339.
143. Wedde HF, Farooq M, BeeHive: An Efficient, Scalable, Adaptive, Faulttolerant and Dynamic Routing Algorithm Inspired from the Wisdom of the Hive. Technical Report 801, Department of Computer Science, University of Dortmund.
144. Wedde HF, Farooq M (2005) The Wisdom of the Hive Applied to Mobile Ad-Hoc Networks. In Proceedings IEEE Swarm Intelligence Symposium (SIS 2005), Pasadena, California, USA , 341-348.
145. Wedde HF, Timm C, Farooq M (2006) BeeHiveGuard: A Step Towards Secure Nature Inspired Routing Algorithms. In Rothlauf et al., editors, Proceedings of the EvoWorkshops 2006, Lecture Notes in Computer Science, Budapest, 2006
146. Wagner IA, Linderbaum M, Bruckstein AM (2000) ANTS: Agents, networks, trees, and subgraphs, *Future Generation ComputerSystems Journal*, M. Dorigo, G. D. Di Caro, and T. Stutzle, Eds. Amsterdam, The Netherlands: North Holland, 16, 915-926.
147. <http://en.wikipedia.org>