Coordination for Swarm Intelligence: A Systematic Literature Review

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1 Introduction

Swarm intelligence is concerned with the design of intelligent multi-agent systems by taking inspiration from the collective behavior of social insects such as ants, termites, bees, and wasps, as well as from other animal societies such as flocks of birds or schools of fish. Colonies of social insects have fascinated researchers for many years. Swarm intelligence studies the collective behavior of systems composed of many individuals interacting locally with each other and with their environment. Even though the single members of these colonies are non-sophisticated individuals, they are able to achieve complex tasks in cooperation. Coordinated colony behavior emerges from relatively simple actions or interactions between the colonies' individual members. Swarms are systems that consist of many individuals that are organized and coordinated by principles of decentralized control, indirect communication, and self-organization.

Researchers in computer science have developed swarm-based systems in response to the observed success and efficiency of swarms in nature to solve difficult problems. Therefore, optimization techniques inspired by swarm intelligence have become increasingly popular during the last decade. They are characterized by a decentralized way of working that mimics the behavior of swarms.

Moreover, studies on the behaviour of social insects like ants or termites lead to nature-inspired coordination models where the key concept is stigmergy, which refers to a set of coordination mechanisms mediated by the environment.

Our goal is to report a systematic literature review (SLR) that identifies the state-of-the-art in coordination for Swarm Intelligence and assesses and discusses the collected and reported findings. In particular, coordination mechanisms, algorithms derived by these mechanisms and coordination models for Multi-Agent Systems will be analyzed.

This work is organized as follows. Section 2 describes our method of systematic review. Section 3 reports the results of the systematic review, answers the research questions, and the results are discussed. Finally, Section 4 conclusions are presented.

2 Method

This Systematic Literature Review (SLR) summerizes the state-of-the-art of Coordination for Swarm Intelligence. The SLR is based on the Kitchenham and Charters [1] guidelines, so it is performed in three main phases: planning, conducting and reporting the review. This section reports the protocol followed to perform the review and reduce the chances of researcher bias. The protocol includes identifying the research questions, defining the search strategy, determining the study selection criteria, assessing the quality of Primary Studies (PSs), and performing the corresponding data extraction and analysis.

2.1 Research questions

The research questions addressed by this study are:

RQ1. What are the Coordination Mechanisms for Swarm Intelligence considered in PSs?

RQ2. What are the main algorithms derived from Coordination Mechanisms for Swarm Intelligence?

RQ3. What are the Coordination Models based on Swarm Intelligence in Multi-Agent Systems?

To achieve the goal of this SLR we searched the literature for the corresponding PSs.

2.2 Search process

In order to obtain a comprehensive list of PSs, we performed a search in some of the most relevant digital libraries identified by Brereton et al [2]:

- IEEExplore
- ACM Digital Library
- Google Scholar
- Science Direct

In order to make a more exhaustive research we considered two other relevant sources: SCOPUS and Springer.

We constructed the search string based on the following rules:

- The main terms extracted from research questions.
- Synonyms and alternative spelling for each of the questions elements.
- The use of Boolean AND to connect the major research terms and Boolean OR to connect alternative spellings and synonyms of the major terms.

Stages	Number of articles included (+) or removed (-)	Total number of articles
Stage 1: Identifying potentially relevant articles	+1218	1218
Stage 2: Excluding articles based on titles and abstracts	-1058	160
Stage 3: Excluding duplicate articles	-40	120
Stage 4: Excluding articles based on full text	-92	28
Stage 5: Including pilot search-based articles	+13	41

Table 1: Stages of the paper selection process

Stage	IEEExplore	ACM	Google Scholar	Science Direct	SCOPUS	Springer	Total
1	124	22	350	33	339	350	1218
2	20	3	54	7	39	37	160
3	20	3	37	7	16	37	120
4	2	0	6	1	0	19	28

Table 2: Number of articles found in the selected digital libraries

Research strings used for each source is given in **Appendix A**. We followed the conventional practice of performing the automatic search within the titles, abstracts and keywords of the articles included in the digital libraries. Our search considered all years through the beginning of 2019. Moreover we considered only articles in English or Italian. The search and PS selection process was performed in five stages, as listed in **Table 1**. For each article, we recorded in an Excel spreadsheet the title, authors and year of the pubblication of the article, and the list of libraries in which the article was found. In this way it was possible to identify and discard any duplicates. Through this method we found 23432 articles (IEEExplore: 124, ACM: 22, Google Scholar: 19400, Science Direct: 33, SCOPUS: 339, Springer: 3514), however we decided to include only the first 350 articles in search results on Google Scholar and Springer, ordered by relevance. After this screening we selected 1218 articles. The distribution of these articles among the digital libraries is listed in **Table 2**.

2.3 Study selection

The next step is to screen the paper obtained from online databases. Screening is done using inclusion and exclusion criteria to answer the research questions. This screening was based on excluding studies that were obviously irrelevant, or duplicates.

To select PSs from the potentially relevant studies, we applied the following inclusion and exclusion criteria.

Inclusion:

- Full paper (not a PowerPoint presentation or extended abstract).
- Articles published in peer-reviewed journals or conference proceedings.
- Sources talking about coordination mechanisms for swarm intelligence, or swarm intelligence algorithms derived from coordination mechanisms, or coordination models for swarm intelligence.

Exclusion:

- Papers talking about swarm intelligence or coordination without deeping the subject.
- Novel algorithms created starting from classic swarm intelligence algorithms.
- Duplicate reports of the same study (when several reports of a study exist in different journals the most complete version of the study was included in the review).

We decided to screen the collected articles in three stages (Stage 2, Stage 3 and Stage 4 reported in **Tables 1 and 2**).

In Stage 2, we screened titles and abstracts of the papers.

In Stage 3 we excluded duplicate articles.

In Stage 4 we screened the full text of the selected papers to determine whether the inclusion and exclusion criteria was applicable.

Starting from 1218 articles, in Stage 2 we decided to exclude 1058 articles based on titles and abstracts.

In Stage 3, we excluded more 40 papers that were duplicates.

In Stage 4, the remaining 120 papers were then subject to a more detailed assessment based on their full text. In this phase we excluded more 92 articles.

Finally, in Stage 5, we added 13 relevant articles that we selected from collected papers references.

The final list of PSs includes 41 articles (**Table 3**).

2.4 Quality assessment

We followed the guidelines suggested by Kitchenham and Charters [1] to construct the quality checklist given in **Table 4**. The checklist was applied to assess the quality of each of the PSs considered.

Each question is evaluated as ”Yes”, ”Partially”, or ”No” with a corresponding score of 1, 0.5, or 0, respectively.

The results of the quality analysis show that all studies scored 1.5 or more, and only two studies scored less than or equal to 2. Fifteen studies scored 4 (S1, S2, S6, S7, S16, S17, S22, S23, S24, S27, S29, S30, S33, S35, S37) and six studies scored 3.5 (S4, S11, S13, S14, S28, S31).

Results of quality assessments are given in **Table 5**.

ID	Reference	Year
S1	Karaboga et al [3]	2014
S2	Da San Martino et al [4]	2006
S3	Cheng et al [5]	2018
S4	Karaboga and Akay [6]	2009
S5	Garg et al [7]	2009
S6	Nayyar and Singh [8]	2016
S7	Michelakos et al [9]	2011
S8	Kaswan et al [10]	2015
S9	Liao et al [11]	2013
S10	Neshat et al [12]	2014
S11	Suarez and Iglesias [13]	2017
S12	Ma et al [14]	2017
S13	Martens et al [15]	2010
S14	Fausto et al [16]	2017
S15	Dipple et al [17]	2014
S16	Diwold et al [18]	2011
S17	Omicini [19]	2012
S18	Chu et al [20]	2011
S19	Poli et al [21]	2007
S20	Gorodetskii [22]	2012
S21	Heylighen [23]	2015
S22	Merkle and Middendorf [24]	2008
S23	Grosan and Abraham [25]	2011
S24	Blum and Li [26]	2008
S25	Liu and Passino [27]	2000
S26	Garnier et al [28]	2007
S27	Yang [29]	2010
S28	Karaboga and Basturk [30]	2007
S29	Karaboga [31]	2005
S30	Dorigo [32]	2006
S31	Dorigo and Blum [33]	2005
S32	Dorigo and Di Caro [34]	1999
S33	Dorigo et al [35]	1996
S34	Reynolds [36]	1987
S35	Kennedy and Eberhart [37]	1995
S36	Bonabeau et al [38]	1997
S37	Roth and Wicker [39]	2005
S38	Tolksdorf and Menezes 2003 [40]	2003
S39	Leonardi et al [41]	2002
S40	Tolksdorf and Menezes 2004 [42]	2004
S41	Mamei and Zambonelli [43]	2005

Table 3: Mapping between the identifiers and references of the PSs

ID	Question
Q1	Are the aims clearly stated?
Q2	Are the coordination mechanisms adequately described?
Q3	Are the swarm intelligence algorithms adequately defined?
Q4	Are coordination models adequately described?
Q5	Is at least one study question answered?

Table 4: Quality checklist

ID	Q1	Q2	Q3	Q4	Q5	Total score
S1	Y	Y	Y	N	Y	4
S2	Y	Y	Y	N	Y	4
S3	Y	N	Y	N	Y	3
S4	Y	Y	P	N	Y	3.5
S5	N	P	P	N	P	1.5
S6	Y	Y	Y	N	Y	4
S7	Y	Y	Y	N	Y	4
S8	Y	Y	N	N	Y	3
S9	Y	N	Y	N	Y	3
S10	Y	N	Y	N	Y	3
S11	Y	P	Y	N	Y	3.5
S12	Y	N	Y	N	Y	3
S13	Y	P	Y	N	Y	3.5
S14	Y	P	Y	N	Y	3.5
S15	Y	P	N	N	P	2
S16	Y	Y	Y	N	Y	4
S17	Y	Y	N	Y	Y	4
S18	Y	N	Y	N	Y	3
S19	Y	N	Y	N	Y	3
S20	Y	Y	N	N	Y	3
S21	Y	Y	N	N	Y	3
S22	Y	Y	Y	N	Y	4
S23	Y	Y	Y	N	Y	4
S24	Y	Y	Y	N	Y	4
S25	Y	Y	N	N	Y	3
S26	Y	Y	N	N	Y	3
S27	Y	Y	Y	N	Y	4
S28	Y	P	Y	N	Y	3.5
S29	Y	Y	Y	N	Y	4
S30	Y	Y	Y	N	Y	4
S31	Y	P	Y	N	Y	3.5
S32	Y	N	Y	N	Y	3
S33	Y	Y	Y	N	Y	4
S34	Y	Y	N	N	Y	3
S35	Y	Y	Y	N	Y	4
S36	Y	Y	N	N	Y	3
S37	Y	Y	Y	N	Y	4
S38	Y	N	N	Y	Y	3
S39	Y	N	N	Y	Y	3
S40	Y	N	N	Y	Y	3
S41	Y	N	N	Y	Y	3

Table 5: Quality assessment results

2.5 Data collection and analisys

The data extracted from each study were:

- Full reference (title, authors, journal/conference name, year, volume, and page numbers).
- Main topic.
- Coordination mechanisms considered.
- Swarm intelligence algorithms considered.
- Coordination models for MAS considered.

Each of us extracted the data and checked the extraction of the other one. When there was a disagreement, we discussed the issues until we reached agreement.

The data was tabulated to show:

- All the coordination mechanisms for swarm intelligence (addressing RQ1).
- All the swarm intelligence algorithms inspired by coordination mechanisms (addressing RQ2).
- All the coordination models for MAS (addressing RQ3).
- The number of primary study for each coordination mechanism, algorithm and model.

The data extracted from each study are shown in **Table 6** .

3 Results and Discussion

This section summarizes the results of the study. We discuss the answers to our research questions.

3.1 RQ1. What are the Coordination Mechanisms for Swarm Intelligence considered in PSs?

The PSs consider 12 Coordination Mechanisms based on insects or other animals. Fourteen of the PSs (S5, S6, S7, S13, S14, S20, S22, S23, S24, S26, S30, S31, S33, S36) are about the foraging behaviour of ants, in particular they describes how ants use pheromone in order to coordinate themselves. Six of the PSs (S13, S20, S23, S25, S34, S35) are about the flocking of birds and schooling of fish, while seven papers (S1, S4, S8, S22, S28, S29, S36) talk about the foraging behaviour of honey bee and how bees make a dance called waggle dance to inform other bees about direction and quality of the food source. Four of the PSs (S15, S20, S36, S37) are about the nest building behaviour in termites. Three of the PSs (S11, S14, S27) are about the echolocation of microbats and three (S4, S16, S26) are about the nest site selection mechanism in honey bees. The other mechanisms described in PSs are ants collective prey retrival (S2), glowing of fireflies (S14), hunting method of whales (S14), web weaving in social spiders (S20), nest building in wasp (S26) and in weaver ant (S26). Five of the PSs (S6, S15, S17, S27, S26) are about stigmergy. Seven out of fourty-one PSs (S3, S9, S10, S12, S18, S19, S32) don't talk about any coordination mechanism.

The results above show that researcers are more interested in the foraging behaviour of ants and bees, the flocking of birds and the nest building behaviour in termites.

3.1.1 Stigmergy

The French entomologist Grassé coined the term "stigmergy" in the 1950's [44] to describe a broad class of multi-agent coordination mechanisms that rely on information exchange through a shared environment.

As stated in S6, S15, S17, S21 and S26, Grassé noted that in termite societies *"The coordination of tasks and the regulation of constructions are not directly dependent from the workers, but from constructions themselves."* and introduced the notion of stigmergy as the fundamental coordination mechanism in termite societies.

In S6, Nayyar and Singh define stigmergy as an indirect communication in Self-Organizing systems, that is a communication where different individuals contact indirectly when any one of them modifies the environment and the other responds to the new environment at a later time.

In S15 Dipple et al. make an analysis of literature documenting the numerous theoretical and experimental papers that have focused on stigmergy. In this paper Dipple et al. cover the origins of the term stigmergy along with discussing how ant algorithms have inspired new research. They cover how stigmergy works and why it provides such a trustworthy solution to coordination within insect and human environments. Moreover they present their abstract model of stigmergy.

In S17 Omicini surveys the most relevant nature-inspired coordination models in the literature, focussing in particular on tuple-based models. He states that stigmergy is one of the early Nature-Inspired models of coordination and that, nowadays, the term "stigmergy" generally refers to a set of nature-inspired coordination mechanisms mediated by the environment. In his paper Omicini highlights the role of the environment and the stochastic behaviour in stigmergic coordination.

When talking about stigmergy these papers refer to termites, ants and wasps coordination mechanisms. All this papers agree on claim that Grassé research about termites and ants behaviour are particularly significant in stigmergic coordination studies.

3.1.2 Foraging behaviour of ants

Ant colonies is probably the most widely known and studied example of stigmergic coordination in insect societies. Foraging ant behavior is a phenomenon by which ant colonies find the shortest path between food source and nest. Ants communicate not directly with each other, but rather indirectly through their environment.

In papers S5, S6, S7, S13, S14, S20, S22, S23, S24, S26, S30, S31, S33 and S36 foraging behaviour of ants is described.

This coordination mechanism is based on a chemical substance called "Pheromone". In search of food, ants roam randomly in the environment. On location of the food source, ant's first return back to their nest by laying a trail of chemical substance called "Pheromone" in their path. Pheromone lays the foundation for communication medium for other ants to follow the way and go to the food source. When other ants follow the path, the quantity of pheromone increases on that particular path. Paths with higher pheromone levels are more likely to be chosen and thus reinforced. On the other hand, the pheromone trail intensity of paths that are not chosen is decreased by evaporation, reducing its attractive strength.

3.1.3 Nest building in termites

The nest building mechanism of termites is described in papers S15, S20, S36 and S37.

As with ants, termites also use the pheromone to coordinate. Individuals create small clusters of pebble and mark it with pheromone. They carry those pebbles randomly, but prefer to travel to the places with stronger concentration of the pheromone. At each step, the individuals decide stochastically whether to deposit the pebble or carry it on. The probability of the pebble to be deposited is the greater the stronger the pheromone concentration. The larger the pile, the more pheromone it is likely to have, and thus a termite is more biased to move towards it and potentially add to the pile. As pheromone decays on lesser piles, termites will be less likely to visit them again, this helps large piles grow by preventing small piles from continuing to attract termites.

As stated by Gorodetskii in S21, this mechanism is classified as a stigmergy mechanism because it is based on indirect interactions. It is widely used in cooperative robotics, in particular, to coordinate the robot cooperation in assembling various structures.

3.1.4 Flocking of birds, schooling of fishes

Flocking of birds and schooling of fishes are two very similar behaviours, this beacuse they are based practically on the same rules. These rules are described in papers S13, S20, S23, S25, S34 and S35.

S13, S25, S34 and S35 state that natural flocks seem to consist of three behaviours: avoid collisions with nearby flockmates, match velocity with nearby flockmates, and attempt to stay close to nearby flockmates. In S23, Grosan and Abraham add two more principles: every bird in flock has the same behavior model, so the flock moves without a leader, and the motion of each bird is only influenced by its nearest flock mates.

Moreover in S13, S23 and S34 the advantages to join a flock are explained: increased effectiveness in searching for food, better predator avoidance and evasion, and improved mating opportunities.

In S34, Reynolds created a ”boid” model, which is a distributed behavioral model, to simulate on a computer the motion of a flock of birds. This model is described in S25, too.

3.1.5 Foraging behaviour of honey bee

Foraging behavior of honey bees is one of the most studied swarm intelligence coordination mechanims in literature. It is described in papers S1, S4, S8, S22, S28, S29 and S36.

After unloading the nectar, the forager bee which has found a rich source performs special movements called ”waggle dance” on the dancing area of the comb in order to share her information about the food source such as how plentiful it is, its direction and distance, and recruits the other bees for exploiting that rich source. Since information about all the current rich sources is available to an onlooker on the dance floor, probably she watches numerous dances and decides to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulated about the more profitable sources. The forager bee dances on different areas of the comb in order to recruit more bees and goes on to collect nectar from her source.

3.1.6 Echolocation of microbats

In papers S11, S14 and S27 the coordination behaviour of microbats is described.

These papers state that, in nature, most bats are equipped with a type of biologic sonar known as echolocation. The echolocation consists of two steps: the emission of loud frequency-modulated sound pulses and the reception (listening) of the echoing sounds that bounce back from surrounding objects, which essentially allows building a three-dimensional scenario of the immediate environment. Typically, bats use this specialized sonar system to assist themselves in several tasks, such as prey detection, obstacle evasion or even locating their roosting places.

3.1.7 Ants collective prey retrival

In S2, Da San Martino et al. describe the collective prey retrival behavior of ants.

When an ant finds a prey, it tries to carry it. If the prey does not move, the ant starts recruiting nest mates. First, it releases a secretion in the air in order to attract nearby ants. If the number of recruited ants is not enough to move the prey, the ant goes back to the nest leaving a pheromone trail on the ground. Such trail will lead other ants to the prey. The recruitment phase stops as soon as the group is able to move the prey. While moving toward the nest, coordination among the ants occurs through the prey itself. The change of the force applied by a single ant modifies the stimuli perceived by the other ants. Such coordination strategy is an example of stigmergy.

3.1.8 Glowing of fireflies

In S14 a swarm intelligence coordination mechanism inspired by the light-emitting behavior observed in fireflies is described.

Here Fausto et al. state that fireflies are able to interact with each other through its characteristic bioluminescent glowing. The attractiveness of each firefly is considered to be proportional to its light intensity. Furthermore, fireflies are only attracted toward brighter individuals; this is, that for any two flashing fireflies, the less bright one will be attracted toward the brighter one. Also, the attractiveness “perceived” by a particular firefly toward any other individual source decreases as the distance that separates them increases.

3.1.9 Hunting method of whales

In S14, Franco et al. illustrate the hunting method of whales known as bubble-net feeding.

In such a hunting method, a group of whales coordinate their efforts to encircle a group of small prey by swimming in a spiraling fashion around their quarry. While moving beneath the surface in such a distinctive pattern, each whale starts to exhale a burst of bubbles from their blowhole to form encircling bubble barrier (also referred as bubble-net), which prevents prey from escaping. As prey gets corralled into a tighter circle, one whale sounds a feeding call to the other whales, at which point all individuals simultaneously swim to the surface with their mouths open to feed on the trapped prey.

3.1.10 Nest site selection in honey bee

In S4, S16 and S26 the nest site selection behaviour of honey bee is described.

When a scout bee finds a suitable places to build a new hive, it comes back to the other bees where it recruits some other scouts by performing a waggle dance. Once a site is visited by a sufficient number of scout bees, these latter advertise the rest of the cluster that it is time to warm up their flight muscles and to prepare for the liftoff toward the new nest site.

3.1.11 Web weaving in social spiders

In S20, Gorodetskii describes the web weaving behaviour of social spiders.

The web weaving activity is based on connecting two ground spots with a dragline, where a ground point is a place where the web is fastened. The individuals first roam randomly weaving a dragline between two random spots. When a dragline is fastened at a point, it forms the new shortest path between two spots. Later, the individuals are attracted by already existing draglines and prefer walking upon one of them rather than on the ground. This enhances the chance of having a dragline beginning where an already existing dragline ends.

This mechanism has found practical applications in self-organizing MASs, for example, as a means for rapidly looking through distributed data in P2P networks and for network routing.

3.1.12 Nest building in wasp

In S26, Garnier et al. describe the nest building behaviour of wasp.

In this paper they state that building activities are driven by the local configuration of cells detected by the wasps on the nest. Indeed, the architecture, by itself, provides enough information and constraints to ensure the coordination of the wasp building activity. To decide where to build a new cell, wasps use the information provided by the local arrangement of cells on the outer circumference of the comb. They perceive these configurations of cells with their antennae. Wasps have a greater probability to add new cells to a corner area where three adjacent walls are already present, while the probability to start a new row, by adding a cell on the side of an existing row, is very low.

3.1.13 Nest building in weaver ant

In S26 the nest building behaviour of weaver ants is described.

The nest construction requires the repetition of two stages: assembling two leaves and gluing them. In the first stage, workers line up in a row along the margin of a leaf and pull together to bring closer the two leaves. If the gap between the two leaves is longer than a single ant, workers form a chain with their own bodies. Then, they pull together as one individual to bring them closer. In the second stage, when the leaves have been put in place, other workers carry mature larvae and use the silk they produce to glue the leaves together.

3.2 RQ2. What are the main algorithms derived from Coordination Mechanisms for Swarm Intelligence?

The PSs consider 12 main algorithms derived from coordination mechanisms listed in RQ1. Several swarm algorithms have been developed by a combination of deterministic rules and randomness, mimicking the behavior of insect or animal groups in nature. Such methods include the social behavior of bird flocking and fish schooling such as the Particle Swarm Optimization (PSO) algorithm (S3, S5, S12, S13, S14, S19, S22, S23, S24, S35), the cooperative behavior of bee colonies such as the Artificial Bee Colony (ABC) technique (S1, S4, S8, S9, S12, S14, S18, S28, S29), the social foraging behavior of ants such as the Ant Colony Optimiation (ACO) (S5, S6, S7, S13, S14, S18, S22, S23, S24, S30, S31, S32) and Ant System (AS) (S6, S7, S13, S18, S24, S30, S33), the mating behavior of firefly insects such as the Firefly Algorithm (FA) (S12, S14) and the echolocation of microbats such as the Bat Algorithm (S11, S14, S27). The other algorithm described by this PSs are Artificial Fish Swarm Algorithm (AFSA) (S10), Social Spider Optimization (SSO) (S14), Whale Optimization Algorithm (WOA) (S14), Bee Nest Site Selection (BNSS) (S16), Termite (S37) and Democratic Collective Transportation (DCT) (S2)

As can be seen from the research results above, in swarm intelligence, the most successful initiative is Ant Colony Optimisation. Some of the other most popular techniques are PSO and ABC.

3.2.1 Ant System & Ant Colony Optimization

The ant colony optimization (ACO) algorithm is one of the most well-known nature-inspired metaheuristics. The ACO approach was first proposed by Marco Dorigo in 1992 under the name of Ant Systems (AS) and draws inspiration in the natural behavior of ants [S14].

In S6, S7, S13, S18, S24, S30 and S33 the first Ant System algorithm is described, and papers S5, S6, S7, S13, S14, S18, S22, S23, S24, S30, S31 and S32 overview ACO, and some of them make a description of the most popular variants of ACO and give examples of their application (S7, S13, S22, S24, S30, S31, S32).

In S33, Dorigo et al. describe how the initial algorithm researched was the Ant System (AS) foraging algorithm that describes how ants will lay down pheromone to find the most optimal path. In this paper, the AS algorithm has successfully been applied to the Travelling Salesman Problems.

This ant-inspired approach has given rise to a whole set of meta-heuristics collectively known as Ant Colony Optimization (ACO) algorithms. In S7, Michelakos et al. state that since the first publishing of the Ant System algorithm by Dorigo several versions of the ACO strategy have been proposed, but they all follow the same basic ideas:

- search performed by a population of ants
- incremental construction of solutions
- probabilistic choice of solution components based on stigmergic information
- no direct communication between the ants

In S6, Nayyar et al. state that ACO is used to solve various discrete problems in different areas of science and other engineering disciplines. Since its evolution, ACO has attracted lots of researchers to take up its algorithms and apply to solve various complex problems and has been proved the best technique to get optimized results.

3.2.2 Particle Swarm Optimization

The particle swarm optimization algorithm is still attracted many researchers' attention over nearly a quarter century. Particle swarm optimization (PSO) was invented by Eberhart and Kennedy in 1995. It is a population-based stochastic algorithm modeled on social behaviors observed in flocking birds [S3].

In S3, S5, S12, S13, S14, S18, S19, S22, S23, S24 and S35, PSO is described. Moreover, papers S3, S18, S19, S22 and S24 list popular PSO variants and improvements, and S3, S13, S19 and S24 give examples of usages and applications.

In S35, Eberhart and Kennedy introduce for the first time PSO as a method for optimization of continuous nonlinear functions. The method was discovered through simulation of a simplified social model. In this paper they introduce the particle swarm optimization concept in terms of its precursors, briefly reviewing the stages of its development from social simulation to optimizer. Then they discuss the implementation and results.

The swarm of birds in PSO is typically modelled by particles in multidimensional space that have a position and a velocity. These particles fly through hyperspace and have two essential reasoning capabilities: their memory of their own best position and knowledge of the global or their neighborhood's best, where "best" simply meaning the position with the smallest objective value. Members of a swarm communicate good positions to each other and adjust their own position and velocity based on these good positions. So a particle to make a suitable change in its position and velocity uses three informations: a global best, the neighborhood best that the particle obtains by communicating with a subset of the swarm and the local best.

In S22 the advantages of PSO are listed.

Due to its simplicity and easy implementation, the PSO method and its variations, has been extensively studied and applied into a wide variety of engineering areas and, as a result, has become one the most popular swarm intelligence approaches currently available for solving complex optimization problems. [S14]

3.2.3 Artificial Bee Colony

As stated in S9, the Artificial Bee Colony (ABC) algorithm is a representative of a number of swarm intelligence algorithms that are inspired by some type of behavior observed in real bee colonies. It was introduced by Karaboga, who applied it to continuous optimization problems and, as declared by Karaboga et al. in S1, it is now one of the most widely studied on and applied to solve the real worlds problems.

In papers S1, S4, S8, S9, S12, S14, S18, S28 and S29, ABC is described. ABC variants and its applications are analyzed in papers S1, S4, S8, S9 and S22. In ABC a bee colony can be thought of as a swarm whose individual agents are bees. Each bee at the low-level component works through a swarm at the global level of component to form a system. This system is characterized by the interacting collective behavior through labor division, distributed simultaneous task performance, specialized individuals and self- organization.

3.2.4 Firefly Algorithm

In S12 and S14, the Firefly Algorithm is described.

The Firefly Algorithm (FA) is a swarm intelligence approach inspired by the light-emitting behavior observed in fireflies. In the FA approach, search agents, modeled as a swarm of fireflies, are assumed to be able to interact with each other through its characteristic bioluminescent glowing. In particular, such interactions are modeled as attractions toward other conspecific individuals within the target solution space.

3.2.5 Bat Algorithm

In S11, S14 and S27, the Bat Algorithm is described.

The bat algorithm is a bio-inspired swarm intelligence algorithm proposed by Xin-She Yang in 2010 to solve optimization problems. The algorithm is based on the echolocation behavior of bats. In the BA approach, search agents are modeled as a swarm of bats whose position within the d-dimensional search space represent a possible solution for a given optimization problem.

In S27, Yang states that BA is potentially more powerful than PSO and genetic algorithms. He declares that the primary reason is that BA uses a good combination of major advantages of these algorithms in some way.

3.2.6 Artificial Fish Swarm Algorithm

In S10, Neshat et al. state that Artificial Fish-Swarm Algorithm (AFSA) is one of the best methods of optimization among the swarm intelligence algorithms. This algorithm is inspired by the collective movement of the fish and their various social behaviors. In this paper many improvements, advantages, disadvantages and application of AFSA are listed.

3.2.7 Social Spider Optimization

In S14, the Social Spider Optimization (SSO) algorithm is described.

In S14, Fausto et al. state that SSO is a swarm intelligence approach that draws inspiration into several collective behaviors observed within a colony of social spiders. An important trait about social spiders lies in their capacity to perceive vibrations transmitted through the communal web. Social spiders employ these vibrations to gain specific information, such as the size of trapped preys or the characteristics of neighboring members.

3.2.8 Whale Optimization Algorithm

In S14, the Whale Optimization Algorithm (WOA) is described.

In this paper, Fausto et al. state that WOA is a novel bio-inspired metaheuristic which draws inspiration on the predatory behavior observed in humpback whales. This whales, different to other species, distinguish themselves for employing a unique cooperative hunting maneuver known as bubble-net feeding.

3.2.9 Bee Nest-Site Selection

In S16, Diwold et al. introduce a new optimization process based on the nest-site selection behaviour in honey bees.

Diwold et al. state that nest-site selection is a processes that constitutes a decision-making process and enables a colony to identify and converge towards one best solution. The principles underlying nest-site selection seem of particular interest for dynamic optimization problems, where the problem space changes during the optimization process. They propose to use the bees' nest-site selection behavior for developing bee inspired optimization techniques. Nest-site selection involves the active discovery of potential sites by scout bees and a decision on the best site. It is a decision-making process that has a clear optimum which is in contrast to foraging which mainly regulates the distribution of foragers over available food sources.

3.2.10 Termite

In S37, Roth and Wicker present a biologically inspired algorithm called Termite, which is based on the hill building behaviour of termites. Termite addresses the problem of routing in the presence of a dynamic network topology.

3.2.11 Democratic Collective Transportation

The paper S2 presents a new agent coordination model named Democratic Collective Transportation (DCT). The model is inspired by ants collectively transporting large preys to the nest. In this model, the constraint that all agents try and move the prey toward the same destination (the nest) is removed: each agent has a desired destination. The group moves the prey toward the direction chosen by the majority of agents with no centralized control. Based on this model, an algorithm for the Image Alignment problem has been devised.

3.3 RQ3. What are the Coordination Models based on Swarm Intelligence in Multi-Agent Systems?

Stigmergic coordination has received a growing attention in the past few years. In fact, by decoupling interacting agents via the mediation of an active environment, stigmergy promotes the definition of robust and adaptive multi-agent systems. [S41]

The PSs identify three coordination models which can be used to develop Multi-Agent Systems (MAS). These coordination models are SwarmLinda (S17, S38, S40), TOTA (S17, S40, S41), Co-Fields (S17, S39).

3.3.1 SwarmLinda

Swarm intelligence is an interesting opportunity to rethink scalability of tuple spaces.

As stated in S17, SwarmLinda enhances Linda implementation with swarm intelligence to achieve many natural-system features such as scalability, adaptiveness, and fault tolerance. This is obtained by modelling tuple templates as ants and enhancing them with a probabilistic behaviour when looking for matching tuples in a distributed setting.

In S38, Tolksdorf and Menezes demonstrate that organized behavior in SwarmLinda can be implemented based on a few simple rules that mimic naturally forming multi-agents systems. Here they base the description of a SwarmLinda on the following abstractions:

- Individuals are the active entities that are able to observe their neighborhood, to move in the environment, and to change the state of the environment in which they are located.
- The environment is the context in which the individuals work and observe.
- The state is an aspect of the environment that can be observed and changed by individuals.

In S40, Menezes and Tolksdorf describe the concept of swarming as an adaptive mechanism and demonstrates how its concepts can be thought in terms of Linda, given rise to the SwarmLinda model. Finally, they present some discussion on issues related to SwarmLinda.

3.3.2 TOTA

As stated in S40, TOTA (Tuples on the Air) is a take on the use of swarm abstractions in Linda which is complementary to SwarmLinda. In TOTA tuples are propagated through a network of nodes with no fixed or predetermined location. Tuples can be coordinated to form swarms or flocks. At the base of that coordination is no global view but a completely decentralized local-sensing collection of equal peers in a network.

In S41, Mamei and Zambonelli, show how the TOTA middleware can be exploited to support a variety of stigmergy-based coordination activities. In this paper application examples are presented to show that TOTA can promote a simple programming of a variety of different types of stigmergic interactions, in a variety of operational environments. This application examples include: flocking with field, where a group of agents coordinate their movements to maintain a specific distance from each other while moving, and routing with pheromone, where agents move in an ad-hoc network spreading pheromone trails during their movements that is used to route messages to agents.

Menezes and Tolksdorf [S40] state that TOTA and SwarmLinda are very adaptable. The difference between these systems lie on the fact that SwarmLinda wants designers to be oblivious to the swarming that may happen in the system. Ideally, a SwarmLinda designer would not need to have any understanding of swarming and related concepts such as the propagation rules defined in TOTA.

In S17, Omicini states that TOTA provides an interesting blend of stigmergy and field-based coordination, being first of all a stigmergic coordination model, whose middleware is adopted for supporting and implementing the Co-fields model.

3.3.3 Co-Fields

In S39, Mamei et al. introduce Co-Fields. This paper presents a general coordination methodology in which swarm's components are simply driven by abstract computational force fields (Co-Fields), generated either by agents, or by the environment. As written in the paper, this model can provide a unifying abstraction (and thus a general framework) for a large class of swarm intelligent systems and it can also be exploited to formalize these systems in terms of dynamical systems.

The Co-Fields model provides a modeling framework to design a multi-agent system (MAS). Its primary focus is to consider and model the MAS as a "whole", in which agents achieve their goal not because of their single capabilities, but because they are part of an self-organized system that leads them to the goal achievement.

Several example of swarm systems modeled with Co-Fields are presented. They briefly survey different swarm intelligent coordination policies, like birds flocking and ant foraging, and they show how can they be modeled in terms of the Co-Fields model.

In S17, Omicini state that in the last years new models of coordination were proposed, which are inspired by the way masses and particles in our universe move and self-organise according to environmental properties represented by gravitational and electromagnetic fields. In the so-called field-based coordination models, computational force fields, generated either by the coordinated components or by the coordination middleware, propagate across the environment and drive the actions and motion of the component themselves. Co-fields is one of this coordination models, which exploit computational fields to coordinate collective intelligent behaviours, such as the many form of swarm intelligence.

4 Conclusions

This paper reports an SLR that identifies and analyzes coordination mechanisms and algorithms for Swarm Intelligence and coordination models that use Swarm Intelligence in Multi-Agent Systems. A total of 1218 potential articles were identified using automatic searching in six digital libraries. After screening the articles and performing a pilot search we selected and analyzed 41 PSs.

The results of the systematic review indicate that Swarm Intelligence based coordination is a highly active area of research. This primarily due to the essential properties of Swarm Intelligence that are decentralized control, indirect communication and self-organization. The results of the SLR show that the ants, birds and bees behaviours are of greater interest to researchers than other mechanisms, in fact, these activities are more frequently exploited for algorithms and models. In particular the concept of stigmergy and stigmergic coordination is widely studied in order to coordinate swarm of agents in multi-agent systems.

We have identified twelve main coordination mechanisms and we found that the foraging behaviour of ants, flocking of birds and foraging behaviour of honey bees are the most analized. The algorithms obtained by these behaviours, that are Ant Colony Optimization, Particle Swarm Optimization and Artificial Bee Colony respectively, are the optimization techniques most used.

In total, we have identified twelve main algorithms derived from Swarm Intelligence behaviours. The advantage of optimization techniques inspired by Swarm Intelligence over traditional techniques is their robustness and flexibility. These properties make Swarm Intelligence a successful design paradigm for algorithms that deal with increasingly complex problems.

Finally we have identified three main coordination models based on Swarm Intelligence for Multi-Agent Systems, that are SwarmLinda, TOTA and Co-Field.

ID	Main topic	Coordination Mechanism	Algorithm	Coordination Model
S1	Comprehensive survey of the advances with ABC and its applications.	Foraging behaviour of honey bees (Honey bee dance, waggle dance)	Artificial Bee Colony	
S2	A novel agent coordination model inspired by the way ants collectively transport large preys.	Ants collective prey retrival	Democratic Collective Transportation (model)	
S3	Comprehensive review of the particle swarm optimization algorithm.		Particle Swarm Optimization and variants	
S4	Survey of the algorithms based on the intelligence in bee swarms and their applications.	Foraging behaviour of honey bees (Honey bee dance, waggle dance), Nest site selection in Honey Bee	Artificial Bee Colony and others	
S5	Brief description of swarm intelligence and swarm robotics	Foraging behaviour of ants (pheromone)	Particle Swarm Optimization, Ant Colony Optimization	
S6	Review of the Ant Colony Optimization	Foraging behaviour of ants (pheromone), Stigmergy	Ant System, Ant Colony Optimization and variants	
S7	Brief presentation of ACO and data mining, and outline the various ways that these technologies could be combined	Foraging behaviour of ants (pheromone)	Ant Colony Optimization, Ant System	
S8	Overview of ABC application areas	Foraging behaviour of honey bees (Honey bee dance, waggle dance)	Artificial Bee Colony	
S9	Review of various variants of the original ABC algorithm		Artificial Bee Colony and variants	
S10	Review of AFSA algorithm and descriction of the evolution of this algorithm along with all improvements		Artificial fish swarm algorithm (AFSA) and variants	
S11	Description of the first physical and computational implementation of the bat algorithm to swarm robotics	Echolocation of microbats	Bat Algorithm	
S12	Comparison of some Swarm Intelligence algorithms		Particle Swarm Optimization, Firefly Algorithm, Artificial Bee Colony	
S13	Survey of the intersection of Swarm Intelligence and data mining	Foraging behaviour of ants (pheromone), flocking of birds	Particle Swarm Optimization, Ant Colony Optimization, Ant System	
S14	Review about nature-inspired optimization algorithms	Foraging behaviour of ants, echolocation in bats, glowing of fireflies, hunting method of whale	Ant Colony Optimization, Artificial Bee Colony, Bat Algorithm, Firefly Algorithm, Particle Swarm Optimization, Social Spider Optimization, Whale Optimization Algorithm	
S15	Analysis of influential literature documenting the numerous theoretical and experimental papers that have focused on stigmergy	Nest construction in termites, stigmergy		
S16	Use of the bees' nest-site selection behavior as the basis for developing new bee inspired optimization techniques	Nest site selection in Honey Bee	Bee Nest Site Selection	
S17	Survey the most relevant nature inspired coordination models in the literature	Stigmergy		SwarmLinda, TOTA, Co-Fields
S18	Overview and experiments of PSO, ACS, and ABC		Particle Swarm Optimization, Ant System, Artificial Bee Colony	
S19	Overview of research in particle swarms and some new directions and applications		Particle Swarm Optimization and variants	

S20	Introduction to the state of the art in the field of self organizing MASs	Foraging behaviour of ants, nest building in termites, web weaving in social spiders, flocking of birds		
S21	Classification of different varieties of stigmergy according to general aspects	Stigmergy		
S22	Optimization methods that have been developed in the field of swarm intelligence	Foraging behavoiur of ants, foraging behaviour in honey bee	Ant Colony Optimization, Particle Swarm Optimization	
S23	Theoretical foundations of swarm intelligence, focus on PSO e ACO	Flocking of birds, foraging of ants	Ant Colony Optimization, Particle Swarm Optimization	
S24	Focus on two of the most successful examples of optimization techniques inspired by swarm intelligence: ACO and PSO	Foraging of ants	Ant Colony Optimization, Ant System, Particle Swarm Optimization	
S25	Overview of swarm intelligence	Flocking of birds		
S26	Review of the main biological principles that underlie the organization of insects' colonies	Nest building in wasp, foraging in ants, house hunting in the honeybee, nest construction in the weaver ant, Stigmergy		
S27	Propose of a new metaheuristic method, the Bat Algorithm, based on the echolocation behaviour of bats	Echolocation of microbats	Bat Algorithm	
S28	ABC algorithm is used for optimizing multivariable functions and it is compared with other algorithms	Foraging of bees (waggle dance)	Artificial Bee Colony	
S29	Cosideration of a particular intelligent behaviour of a honey bee swarm, foraging behaviour, and description of a new artificial bee colony (ABC) algorithm simulating this behaviour of real honey bees for solving multidimensional and multimodal optimisation problems	Foraging behavoiur of bees (waggle dance)	Artificial Bee Colony	
S30	Overview of Ant Colony Optimization	Foraging behavoiur of ants (pheromone)	Ant System, Ant Colony Optimization and variants	
S31	Survey on theoretical results on ant colony optimization	Foraging behavoiur of ants (pheromone)	Ant Colony Optimization	
S32	Presentation of the ACO meta-heuristic		Ant Colony Optimization	
S33	Ant System as a new approach to stochastic combinatorial optimization	Foraging behavoiur of ants (pheromone)	Ant System	
S34	Presentation of a model of polarized, noncolliding aggregate motion, such as that of flocks, herds, and schools	Flocking of birds		
S35	Introduction of a method for optimization of continuous nonlinear functions: PSO	Flocking of birds	Particle Swarm Optimization	
S36	Description of self-organization in social insects	Foraging behaviour of ants (pheromone), foraging behaviour of bees (waggle dance), nest building of termites		
S37	A swarm intelligent routing algorithm named Termite has been presented and its performance evaluated	Nest building of termites	Termite	
S38	Description of how swarm intelligence can be used in the implementation of a Linda-based system called SwarmLinda.			SwarmLinda
S39	Presentation of a coordination model in which swarm's components are driven by abstract computational force fields called Co-Fields			Co-Fields

S40	Description of the ability of Linda-based systems to adapt to the predictable and unpredictable changes in distributed environments		SwarmLinda, TOTA
S41	This paper shows how the TOTA middleware can be effectively exploited to support a variety of stigmergy-based coordination activities		TOTA

Table 6: Primary study characteristics

A Search strings

A.1 Library: IEEExplore

Search String: "swarm intelligence" AND coordinat* AND (model OR models OR algorithm OR algorithms OR method OR methods OR technique OR techniques OR mechanism OR mechanisms)

A.2 Library: ACM Digital Library

Search String: "swarm intelligence" AND (coordination OR coordinated OR coordinate OR coordinating) AND (model OR algorithm OR method OR technique OR mechanism)

A.3 Library: Google Scholar

Search String: "swarm intelligence" (coordination OR coordinated OR coordinate OR coordinates OR coordinating) (model OR algorithm OR method OR technique OR mechanism)

A.4 Library: Science Direct

Search String: "swarm intelligence" AND (coordination OR coordinated OR coordinate OR coordinating)

A.5 Library: SCOPUS

Search String: "swarm intelligence" AND (coordination OR coordinated OR coordinate OR coordinates OR coordinating) AND (model OR models OR algorithm OR algorithms OR method OR methods OR technique OR techniques OR mechanism OR mechanisms)

A.6 Library: Springer

Search String: "swarm intelligence" AND coordinat* AND (model OR algorithm OR method OR technique OR mechanism)

References

[1] B. Kitchenham and S. Charters. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*. Technical Report EBSE 2007, Keele University, UK, 2007.

[2] Brereton, Pearl, Kitchenham, A. Barbara, Budgen, David, Turner, Mohamed, Mark, and Khalil. *Lessons from applying the systematic literature review process within the software engineering domain*. JSS 80, 2007.

[3] D. Karaboga, B. Gorkemli, and C. Ozturk. A comprehensive survey: artificial bee colony (abc) algorithm and applications. *Artificial Intelligence Review*, 42:21–57, 2014.

[4] G. Da San Martino, FA. Cardillo, and A. Starita. A new swarm intelligence coordination model inspired by collective prey retrieval and its application to image alignment. *Parallel Problem Solving from Nature - PPSN IX*, pages 691–700, 2006.

[5] S. Cheng, H. Lu, X. Lei, and Y. Shi. A quarter century of particle swarm optimization. *Complex & Intelligent Systems*, 4:227–239, 2018.

[6] D. Karaboga and D. Akay. A survey: algorithms simulating bee swarm intelligence. *Artificial Intelligence Review*, 31:61–85, 2009.

[7] A. Garg, P. Gill, P. Rathi, Amardeep, and K.K. Garg. An insight into swarm intelligence. *International Journal of Recent Trends in Engineering*, 2, 2009.

[8] A. Nayyar and R Singh. Ant colony optimization- computational swarm intelligence technique. *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2016.

[9] I. Michelakos, N. Mallios, E. Papageorgiou, and M. Vassilakopoulos. Ant colony optimization and data mining. *Next Generation Data Technologies for Collective Computational Intelligence*, pages 31–60, 2011.

[10] K.S. Kaswan, S. Choudhary, and K. Sharma. Applications of artificial bee colony optimization technique: Survey. *2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2015.

[11] T. Liao, D. Aydın, and T. Stützle. Artificial bee colonies for continuous optimization: Experimental analysis and improvements. *Swarm Intelligence*, 7:327—356, 2013.

[12] M. Neshat, G. Ghodrat Sepidnam, M. Mehdi Sargolzaei, and A.N. Adel Najaran Toosi. Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial and indicative applications. *2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2014.

[13] P. Suárez and A. Iglesias. Bat algorithm for coordinated exploration in swarm robotics. *International Conference on Harmony Search Algorithm*, pages 134—144, 2017.

[14] H. Ma, S. Ye, D. Simon, and M. Fei. Conceptual and numerical comparisons of swarm intelligence optimization algorithms. *Soft Computing*, 21:3081–3100, 2017.

[15] D Martens, B. Baesens, and T. Fawcett. Editorial survey: swarm intelligence for data mining. *Machine Learning*, 82:1––42, 2010.

[16] F. Fausto, A. Reyna-Orta, E. Cuevas, A.G. Andrade, and M. Perez-Cisneros. From ants to whales: metaheuristics for all tastes. *Artificial Intelligence Review*, pages 1–58, 2019.

[17] A. Dipple, K. Raymond, and M. Docherty. General theory of stigmergy: Modelling stigma semantics. *Cognitive Systems Research*, 31-32:61–92, 2014.

[18] K. Diwold, M. Beekman, and M. Middendorf. Honeybee optimisation – an overview and a new bee inspired optimisation scheme. *Handbook of Swarm Intelligence*, pages 295–327, 2011.

[19] Omicini. A. Nature-inspired coordination models: Current status and future trends. 21:3081–3100, 2012.

[20] S.C. Chu, H.C. Huang, J.F. Roddick, and J.S. Pan. Overview of algorithms for swarm intelligence. *International Conference on Computational Collective Intelligence*, pages 28–41, 2011.

[21] R. Poli, J. Kennedy, and T. Blackwell. Particle swarm optimization. *Swarm Intelligence*, 1:33–57, 2007.

[22] V.I. Gorodetskii. Self-organization and multiagent systems: I. models of multiagent self-organization. *Journal of Computer and Systems Sciences International*, 51:256–281, 2012.

[23] F. Heylighen. Stigmergy as a universal coordination mechanism: components, varieties and applications. *Human Stigmergy: Theoretical Developments and New Applications*, 2015.

[24] D. Merkle and M. Middendorf. Swarm intelligence and signal processing [dsp exploratory]. *IEEE Signal Processing Magazine*, 25:152–158, 2008.

[25] C. Grosan and A Abraham. Swarm intelligence. *Intelligent Systems*, pages 409–422, 2011.

[26] C. Blum and X. Li. Swarm intelligence in optimization. *Swarm Intelligence*, pages 43–85, 2008.

[27] Y. Liu and K.M. Passino. Swarm intelligence: Literature overview. 2000.

[28] S. Garnier, J. Gautrais, and G. Theraulaz. The biological principles of swarm intelligence. *Swarm Intelligence*, 1:3–31, 2007.

[29] X.S. Yang. A new metaheuristic bat-inspired algorithm. *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*, pages 65–74, 2010.

[30] D. Karaboga and B. Basturk. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm. *Journal of Global Optimization*, 39:459–471, 2007.

[31] D. Karaboga. An idea based on honey bee swarm for numerical optimization. *Journal of Global Optimization*, 2005.

[32] M. Dorigo. An introduction to ant colony optimization. *Approximation Algorithms and Metaheuristics*, 2006.

[33] M. Dorigo and C. Blum. Ant colony optimization theory: a survey. *Theoretical Computer Science*, 344:243–278, 2005.

[34] M. Dorigo and G. Di Caro. Ant colony optimization theory: a survey. *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99*, 1999.

[35] M. Dorigo, A. Colorni, and V. Maniezzo. Ant system: Optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 344:29–41, 1996.

[36] C.W. Reynolds. Flocks, herds, and schools: A distributed behavioral model. *SIGGRAPH '87 Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, pages 25–34, 1987.

[37] J. Kennedy and R. Eberhart. Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995.

[38] E. Bonabeau, G. Theraulaz, J.L. Deneubourg, and S. Aron. Self-organization in social insects. *Trends in Ecology & Evolution*, 12, 1997.

[39] M. Roth and S. Wicker. Termites a swarm intelligent routing algorithm for mobile wireless adhoc networks. *Stigmergic Optimization*, pages 155–184, 2005.

[40] R. Tolksdorf and R. Menezes. Using swarm intelligence in linda systems. *Engineering Societies in the Agents World IV, 4th International Workshop*, 2003.

[41] L. Leonardi, M. Mamei, and F. Zambonelli. Co-fields: Towards a unifying model for swarm intelligence. *Engineering Societies in the Agents World III: Third International Workshop*, pages 68–81, 2002.

[42] R. Tolksdorf and R. Menezes. Adaptiveness in linda-based coordination models. *International Workshop on Engineering Self-Organising Applications*, 2004.

[43] M. Mamei and F. Zambonelli. Programming stigmergic coordination with the tota middleware. *4th International Joint Conference on Autonomous Agents and Multiagent Systems*, 2005.

[44] P.P. Grassè. 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. *Insectes Sociaux*, 6:41—-80, 1959.