ACO Modeling: Organizational Modeling of an Ant Multi-Colonies Optimization Approach

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ABSTRACT

This paper describes the organizational modeling of the Ant Colony Optimization (ACO). It presents a modeling approach of the ACO based on Holonic Multi-Agent paradigm named HMAS (Holonic Multi-Agent Systems). The approach of modeling used is organizational and it uses four basic concepts: Capacity, Role, Interaction and Organization (CRIO). The Traditional modeling techniques fail to capture interactions between loosely coupled aspects of a complex system. However, the organizational model of the ACO has highlighted the different roles that can occur in such optimization device. The solving approach highlights two fundamental concepts from behavioral intensification and diversification. Since, it is difficult to distinguish an intensification from a diversification behavior, though these two trends are identifiable in the organizational model of the proposed ACO, a single role can combine the roles $Intensify$ and $Diversify$. So, a $Manager$ role is identified and is responsible for the coordination of research by the colonies, and the management of the pheromone memory.

General Terms:

Ant colony, Ant colony optimization (ACO), multi-agent system (MAS), sensor network

Keywords:

Ant, agent, colony, metaheuristic, multi-agent, organization, role, sensor

1. INTRODUCTION

The reactive approach argues that intelligence is a global property of the multi-agent system. This is achieved by the behavior of simple agents in interaction [26, 24, 12]. The optimization techniques from ant colonies (Ant Colony Optimization or ACO) were applied with satisfactory results to various optimization problems such as multi-agent patrolling [27, 26, 18, 19], graph coloring [6], the traveling salesman problem [9], and also the vehicle routing problem [23, 3, 2].

In order to facilitate the analysis and design of an approach to problem resolution based on ant colonies, the interest has been to a multi-agent modeling approach and in particular the organizational approach. Organizational approaches offer many advantages over agent-centered approaches including: heterogeneity of languages, modularity, multiple architectures and applications, security of applications [16, 14, 13]. The objective of this work is to use an organizational approach based on Role, Interaction, Organization and Capacity (CRIO) (cf. [15, 16]) for the analysis and design of the ACO metaheuristic.
The rest of the paper is organized as follows. Section 2 presents a state of the art on multi-agent systems and combinatorial optimization. This section also presents agent-based approaches for optimization , while distinguishing agent-oriented heuristics from agent-oriented metaheuristics. Section 3 presents the difference between real ants and virtual ants, as well as an application of the ACO. Section 4 describes an organizational approach for the design of metaheuristics. The analysis, design and agentification of the ACO metaheuristic by an organizational approach are presented in section 6. Finally, section 7 provides a conclusion of the paper.

2. MULTI-AGENT SYSTEMS AND COMBINATORIAL OPTIMIZATION

Among the numerous definitions of the term *agent*, some seem to be a consensus within the multi-agent community. To define an agent, *Ferber* [12] dentifies some key properties that apply to both natural and artificial systems. Thus, *is called agent a physical or virtual entity* [12]:

(1) *which is capable of acting in an environment,*
(2) *which can communicate directly with other agents,*
(3) *which is driven by a set of trends (in the form of individual objectives or a function of satisfaction, and even survival, it seeks to optimize),*
(4) *which has its own resources,*
(5) *which is able to perceive (but to a limited extent) its environment,*
(6) *which has only a partial representation of this environment (and possibly no),*
(7) *which has competences and provides services,*
(8) *which can eventually recur,*
(9) *whose behavior tends to meet its objectives, taking into account the resources and expertise available to it, and according to its perception, its representations and communications received.*

This definition emphasizes the ability to act of the agents, and not only to reason. Action is according to *Ferber*, a fundamental concept for multi-agent systems. It is based on the fact that agents perform actions that modify the environment and therefore their future decision-making. From this definition of the concept of agent, we consider a multi-agent system as a set of agents sharing a common environment. These agents communicate and collaborate to achieve personal or collective goals. The environment can be considered, as the area shared by the agents and representing the communication medium.
A fundamental issue raised in the design of *MAS* is according to *Ferber*: ≺≺*Should agents be designed as already intelligent entities, that is capable of solving certain problems by themselves, or should they be assimilated to very simple beings reacting directly to environmental changes?*≻≻. These two alternatives correspond to two schools of thought: cognitive and reactive.

If in the cognitive approach intelligence is attributed to individual agents, the reactive approach argues that intelligence is a global property of the multi-agent system. This is achieved by the behavior of simple agents interacting. The reactive agents have a complexity that does not go beyond that of a automaton. They have no representation of the environment nor of the other agents, and often little memory. Their actions and perceptions are purely local [26, 11]. Thus, the multiplicity of interactions and their stochastic nature make it possible to obtain, through self-organization and emergence of structures, robust and adaptive collective properties. An example of this approach is the *optimization by ant colony*. In this system, each ant has a simple behavior, but the interactions between ants realized via pheromones make it possible to gradually produce a proximate and even optimal solution . From this description, it is therefore possible to integrate agents in certain optimization processes. Among the agent-based approaches for optimization , it is possible to distinguish agent-oriented heuristics from agent-oriented metaheuristics.

2.1 Agent-oriented heuristics

Agent-oriented heuristics use the structure of the problem while agent-oriented metaheuristics use the structure of the solution space. This means that in the first type of approach, each agent is associated with a part of the problem, the combined actions of agents therefore producing a solution when viewed as a whole. In the second type of approach, it is a distributed solving process. Thus, an agent is associated with one or more solutions.
Most multi-agent systems have simple reactive agents whose interactions favor the emergence of a solution to the problem addressed. The decomposition of the problem is often natural and the rules that govern the behavior of agents are relatively simple. For example, in the heuristic for the resolution of the positioning problem [21], agents are associated with resources. This decomposition is based on the natural distribution of spatialized components of the problem, the displacement of agents being governed by a combination of forces.
Once a problem can be broken down into sub-goals associated with agents, and that we can define the behaviors and interactions between agents for achieving these sub-goals, then a multi-agent heuristic may be considered [7].
The interest of these approaches reside in their simplicity, flexibility and robustness. Simplicity is due to the fact that the rules governing the behavior of agents are relatively simple. This simplicity explains the flexibility of these approaches, that is their potential to be adapted when adding new constraints on the search space. Robustness is viewed in the sense that the system is able to adapt to dynamic changes that may occur on the instance of the problem.
However, the efficiency in terms of computational time is often obtained at the expense of the quality of the solution obtained. In these heuristics, the behavior of agents does not necessarily allow to come out with the local optima and the result is generally related to the initial configuration of agents. To address this problem, it is necessary to execute several times the heuristic, or to set up a disturbance procedure. Finally, these heuristics are specific to the types of problems treated as the agents are associated with specific components of the problem.

2.2 Agent-based approach and metaheuristics

Some metaheuristics can be presented according to the terms of the collective problem solving. We can then call them multi-agents metaheuristics. This is the case for example of the ant colony optimization and the particle swarm optimization. Indeed, these two approaches are based on a metaphor of social insects, which allows to describe them in terms of agents and interactions. In these approaches, an agent is associated with the construction or the improvement of a single solution. The interactions between agents are intended to share information about promising areas of the search space, so as to make it more efficient for exploration [7].
This cooperation between agents is implemented in two different ways. In the ant colony optimization, agents cooperate through the matrix of pheromones [27, 26, 8, 10]. This particular situation of cooperation between agents interacting indirectly is called *stigmergy* [22]. In the particle swarm optimization, the agents interact directly peer-to-peer: this is known as *coordination* [22].
The interest of the agent approach in these two metaheuristics is the ability to naturally describe their functioning, which facilitates the design. The distribution of the calculus should allow a more efficient exploration of the search space while allowing a possible parallel implementation of the algorithm. However, let's note that the ant colony optimization assumes in its original version, a shared environment in which agents evolve.
The ant colony algorithms are a class of recently proposed metaheuristics for hard optimization problems. These algorithms are based on the collective behaviors of deposit and tracking observed in ant colonies. A colony of simple agents (ants)communicate indirectly through dynamic changes in their environment (pheromone trails) and so build up a solution to a problem, based on their collective experience [27, 8, 10].

2.3 Metaheuristics for hard optimization

An optimization problem in the general sense is defined by a set of possible solutions whose quality can be described by an objective function f. We then try to find the solution s^* with the best quality $f(s^*)$. An optimization problem can present equality (or inequality) constraints on s or can be multi-objective if multiple objective functions have to be optimized.

Some optimization problems, however, remain out of reach of exact methods. A number of characteristics can indeed be problematic, such as the absence of strict convexity (multimodality), the existence of discontinuities, a non-derivative function, presence of noise, etc [17]. In such cases, the optimization problem is said hard because no accurate method is able to solve it in a reasonable time. We will then make use of heuristics and metaheuristics.
An optimization heuristic will be considered an approximate method which is simple, fast and suitable for a given problem. Its ability to optimize a problem with a minimum of information is off-

set by the fact that it offers no guarantee as to the optimality of the best solution found. For [17], from the point of view of operational research, this defect is not always a problem, especially when only an approximation of the optimal solution is being sought.

Among heuristics, some are adaptable to many different problems without major changes in the algorithm, this is referred to as *metaheuristics*. Metaheuristics are generally *iterative*: that is the same research scheme is applied several times during the optimization and *direct*: that is they do not use the information of gradient of the objective function. They take particular interest in their ability to avoid local optima by either accepting a degradation of the objective function in the course of their progress, or by using a population of points as a research method. These metaheuristics are generally inspired by analogies with reality (physics, biology, ethology, etc). Among them we can name simulated annealing, genetic algorithms, evolutionary algorithms, tabu search, ant colonies, etc. One of the challenges in the design of metaheuristics is therefore to facilitate the choice of a method and simplify its adjustment to suit a given problem. We focused particularly on metaheuristics so called *ant colonies*.

3. DESCRIPTION AND ANALYSIS OF ANT COLONIES-BASED OPTIMIZATION

Ants represent an important component of this metaheuristic. It is therefore necessary to understand its operating system.

3.1 Real ants and virtual ants

The behavior of ants is a collective behavior. Each ant's priority is the well being of the community. Each individual in the colony is a priori independent and is not supervised in one way or another. This concept is called *Heterarchy* as opposed to *Hierarchy*. Each individual is helped by the community in its development and in return it helps to the proper functioning of this one. When observing a colony of ants looking for food, one realizes that it solves problems such as the search for the shortest path. Ants solve complex problems by relatively simple mechanisms.

While walking from the nest to the food source, and vice versa (which is random at first), ants lay on the ground an fragrant substance called *pheromone*. This substance therefore creates a chemical trail, on which the ants are found. Pheromones act as path marker. Thus when the ants choose their way, they tend to select the trail that carries the highest concentration of pheromones. This allows the other ants to find the food sources found by their peers, or to find the way back to their nests. This behavior allows to find the shortest path to the food when the pheromone trails are used by the entire colony.

By similarity to real ants, virtual ants are used to solve combinatorial optimization problems. Virtual ants have a dual nature. First, they model abstract behavior of real ants, and secondly, they can be enriched with capabilities that lack real ants in order to make them more efficient than the latter. Thus, there are similarities and differences between real and virtual ants.

Similarities

On cooperation: As it is the case with real ants, a virtual colony is a set of non-synchronized entities that gather together to find a *good solution* to the considered problem. Each group of individuals should be able to find a solution whatever the quality of this solution.

On pheromone trails: These entities communicate through the mechanism of pheromones trails. This form of communication plays a great role in the behavior of ants. It makes it possible to change the way the environment is perceived by them.

On the evaporation of pheromones: This mechanism allows to forget more or less slowly what happened before. Thus it may implicitly direct the search towards new directions without too many constraints of old decisions.

On the shortest path: Virtual ants just like real ants share a common goal which is the search for the shortest path linking a starting point (or nest) to one or many destination site(s) (or source(s) of food).

On the principle of locality: Real ants do not make hops in their displacement. It can be the same for virtual ants, this depending on the structure of the environment. Thus, on the basis of local perceptions, real or virtual ants make local displacements.

On random choice: When they are in a point, real and virtual ants must decide on which adjacent point to move. This decision is made randomly and also depends on the local information located on the current point and those on adjacent points.

Differences

On the memory of the ant: Unlike real ants that have very limited memory, virtual ants memorize the history of their actions in a tabu list. Based on this list, an action already undertaken can be avoided by the ant. They can also store additional data on their performance.

On the nature of pheromones: While real ants lay down a physical information on the trail they run through, virtual ants as for them alter the information in state variables associated with the problem. Pheromones are modeled by numerical values. Thus, at each iteration, a depositing of pheromones corresponds to an increase (or incrementation) of this numerical value and an evaporation corresponds to a decrease (or decrementation).

On the quality of the solution: Virtual ants deposit a quantity of pheromone proportional to the quality of the solution they have discovered.

On the depositing of pheromone: Virtual ants can update the pheromone trails in an immediate way or not. If the pheromone's update is not immediate, it can be done by ants after completing the construction of their solution.

Additional capacities:In order to improve the performance of the system, virtual ants may be provided with artificial capabilities. These capabilities are generally related to the problem and can be:

—anticipation : an ant makes a choice based not only on the local state, but also on the following states.

—backtracking: an ant can come back to a state already visited because the decision taken in this state has been bad.

3.2 Functioning and application of an ACO

In order to better present and understand the implementation of the ACO approach, without loss of generality, a description is made in the case of an application to the problem of multi-sensor patrol. The problem of the patrol is to achieve a behavior that minimizes the visit time on the same node by agents [27, 26, 20]. According to [4], this problem consists in making move a set of agents or robots on a predefined area in such a way, informally, that every part of this area is visited by agents as often as possible.

The patrol environment being considered as a graph, the ant colony approach will consist of deploying ant colonies in this environment. The various ants of the different colonies will deposit pheromones on the nodes of the graph. This will determine the best patrol strategy by agents on the basis of nodes coverd by each member of the group. In a typical patrol, there would be no problem in determining a strategy based on registered pheromones. Since the pa-

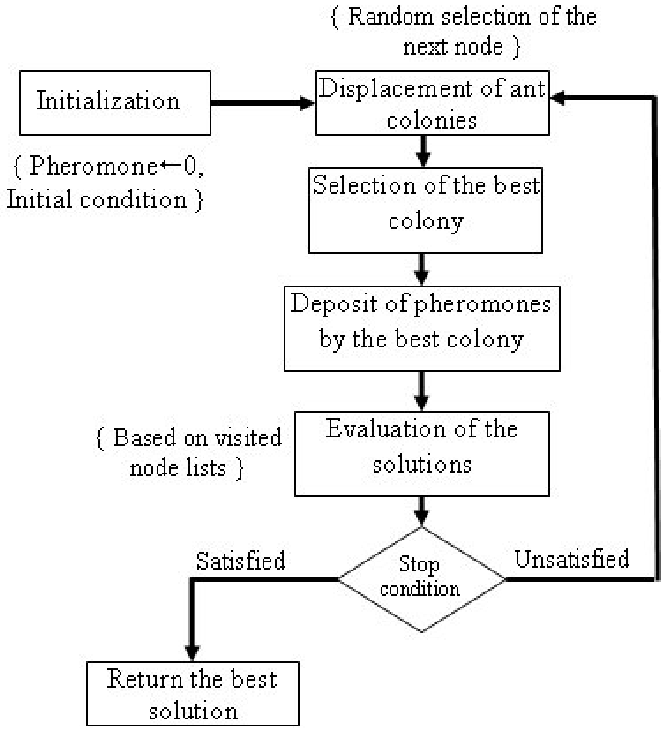

Fig. 1. Overall structure of AMCO

troller agents are mobile sensors, constraints of energy, resources, displacement and communication should be taken into account . In such a network, exist a sensor called *Sink* having more resources than all the others. Thus, the path of the *Sink* and that of other sensors should meet most often. It is therefore to determine a strategy that allows data exchange between the other sensors and the *Sink*. In our case, this will allow the *Sink* to send alerts to the control center in case one (or more) event(s) would be perceived by another sensor. The overall algorithm is divided into two phases, the first is the research phase of a satisfactory patrol strategy by the colonies, and the second phase is the actual patrol based on the results of the first phase. In the resolution, while determining a patrol strategy for each agent, the algorithm provides one (or more) agent(s) able to play the role of Sink. Thus, the Sink will have a number of meeting points with other sensors.
A strategy for an agent is defined by the list of nodes to be browsed by it. The overall strategy consists of determining the set of agent-specific strategies. This overall strategy will be considered as the solution of the patrol problem by the *ACO* approach. Unlike the classical ACO approach (cf. [17, 25, 10, 5]), we consider here a competition between several colonies. We call this approach AMCO (Ant Multi-Colony Optimization). The best colony is considered at first as one that minimizes a certain criterion. Only this colony will be capable of depositing pheromones. We present on figure 1 the scheme and overall structure of this metaheuristic. Initialization corresponds to a reset to zero of the matrix of pheromones.
After the initialization phase, we proceed subsequently to the deployment of the the various colonies. The displacement of ants of the different colonies is based on a random selection of the next node to be visited. The probability of selection of a node by the ant k of the colony l is defined by the expression of $p_{ij}^{k,l}$ below:

$$p_{ij}^{k,l}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{u \in autorised_l}[\tau_{iu}(t)]^{\alpha}[\eta_{iu}]^{\beta}} & \text{if } j \in autorised_l \\ 0 & \text{else} \end{cases}$$

where
$autorised_l = \left\{V - \sum_{i=1}^{r} tabu_{i,l}\right\}$ represents the set of unvisited nodes by the ants in the colony l, and $tabu_{i,l}$ represents the set of nodes already visited by the ant i of the colony l.
V represents the set of nodes in the graph.
$\tau_{ij}(t)$ represents the intensity of pheromones on the edge (i, j) at the cycle t.
$\eta_{ij} = 1/c_{ij}$ indicates the visibility of the node j relatively to the node i, that is the inverse of the distance c_{ij} between the nodes i and j.
α and β are considered as parameters for controlling respectively the intensity of pheromones and the visibility.

The update of the intensity of pheromones is defined by the equation 1.

$$\tau_{ij}(t+1) = \rho\, \tau_{ij}(t) + \Delta_{\tau_{ij}} \tag{1}$$

where
$1 - \rho$ is the evaporation coefficient.
$\tau_{ij}(t + 1)$ and $\tau_{ij}(t)$ represent the intensities of pheromones on the edge (i,j) at the cycle time t+1 and t, respectively.
$\Delta_{\tau_{ij}}$ is the quantity of pheromone deposited on the edge (i,j) by all the ants of the colony at this cycle.

After a displacement as above indicated with no depositing of pheromones, we proceed to a pheromone deposit by the best colony. During their tour, the set of ants of the best colony deposit a quantity of pheromone $\Delta_{\tau_{ij}}$ on the edge (i, j) of the graph. Equation 1 reflects this update of pheromones. The purpose of this depositing is to bring the other ants from other colonies to eventually follow the itinerary of the best colony.
Each colony represents a potential solution to the problem. The evaluation of the solutions are done on the basis of the objective functions.
When retrieving the best solution, each ant provides part of the solution to the problem. The assembly of the different sub-solutions allows for the solution to the original problem.

4. ORGANISATIONAL APPROACH AND METAHEURISTIC

Metaheuristics form a family of optimization algorithms aimed at solving difficult optimization problems for which there is no known classic most efficient method. Properties related to the notion of metaheuristic can be summarized as [1]:

—metaheuristics are strategies to guide the search process.
—the expected goal is the efficient exploration of the search space in order to find a solution near to the optimal.
—techniques used in metaheuristics range from simple local search to complex learning procedures.
—metaheuristics are stochastic algorithms.
—they may incorporate mechanisms to avoid being trapped in an area of the search space.
—metaheuristics are described following a level of abstraction independent of the specific problem to be addressed.

—metaheuristics can encapsulate specific information to the problem in the form of sub-heuristics controlled at a higher level.
—the most modern metaheuristics introduce mechanisms to adapt and guide research dynamically. We talk of adaptive and self-adaptive approaches.

Thus, various metaheuristics can be seen in various forms. According to [7], common and essential principles of metaheuristics are expressed by the classical concepts of intensification and diversification, on the one hand, and the concepts of research strategy and adaptation or self-adaptation of this search strategy, on the other hand. Some metaheuristics are originally presented according to a point of view of collective problem solving. We can then qualify them as multi-agent metaheuristics. This is the case for example of the optimization by ant colonies *(ACO)* or the particle swarm optimization. Metaheuristics such as ant colony optimization and particle swarm optimization can be described as falling within the field of multi-agent systems. Indeed, these two approaches are based on a social insect metaphor which can describe them in terms of agents, interactions and organizations.

Cooperation between agents is implemented in two different ways. In the ant colony optimization, agents cooperate through the pheromone matrix. This particular situation of cooperation between agents interacting indirectly is called stigmergy. Contrariwise, in the particle swarm optimization, agents interact directly peer-to-peer. This is referred to as coordination [22].
Since this work falls within the context of the ant colony optimization, it is appropriate to provide a set of analytical and conceptual tools for a better implementation of the ACO. For this, we rely on the *AMF* (Agent Metaheuritic Framework) organizational model [7] which is based on the RIO (Role-Interaction-Organization) meta-model.

4.1 Organizational model metaheuristics

In order to obtain our organizational model metaheuristic, we will use an asset that has the AMF organizational model. It considers a metaheuristic as an organization (in the sense of the RIO meta-model) which aims to explore the search space of an instance of the problem in order to find an optimal solution or near to the optimal. Within this organization, it is possible to identify trends or distinct mechanisms of intensification and diversification. Intensification allows to concentrate research in promising zones and diversification serves to discover zones of the research space not yet explored. These two trends are guided by a set of structured information on the search space. An additional mechanism managing this information is used to coordinate and equilibrate intensification and diversification. In addition, for some metaheuristics, the search strategy can be adapted dynamically as a function of the optimization context and research experiments.
From this succinct description, it is possible to identify four fundamental roles in the *Metaheuristic* organization : Intensifier, Diversifier, Guide and Strategist. The Intensifier and Diversifier roles are related to the intensification and diversification trends or mechanisms. These two concepts are defined below.

Definition: Intensifier Role
The Intensifier role aims at the intensification of research. Intensification allows to concentrate research in promising areas (of better quality) of the search space. The Intensifier role therefore operates on information on previously explored areas and uses the objective function of the problem to guide research.

Definition: Diversifier Role
The Diversifier role aims at the diversification of research. Diversification moves research in unexplored areas of the search space. The diversification of research is based on random or any function other than the objective function. The Diversifier role eventually uses information about previously explored areas in order to move away from it.

Note that in these definitions, informations corresponding to the areas of the search space (promising areas, previously explored areas, unexplored areas) can take different forms. For instance in the ant colony optimization, promising areas correspond to traces of pheromones.
As for the Guide role, it describes the coordination and the search for balance between intensification and diversification. Below is a definition corresponding to the guide role.

Definition: Guide Role
The Guide role implements an overall research strategy by coordinating Intensifier and Diversifier roles. This role is responsible for balancing the intensification and diversification trends. In addition, the Guide role selects the solution or solutions that will be the result of the optimization process. To perform these various tasks, the Guide role manages a memory from which it is possible to extract information on promising areas of the search space and possibly on explored areas. This memory is updated by combining the results of the intensification and diversification.

The Strategist role corresponds to adaptation, the latter possibly being expressed by the observation of research experiences, the evaluation of these experiences, or the modification of the research strategy. In most cases, the adaptation of the research strategy corresponds to the adjustment of the strategic parameters. This role is defined below.

Definition: Strategist
The Strategist role aims to adapt the research strategy. For this, it interacts with the Intensifier, Diversifieur and Guide roles to observe their experiences and adjust accordingly their behaviors.

The interest of the AMF organizational model is to introduce a set of quite general concepts to be common to different metaheuristics and taking the form of roles or interactions.

5. ORGANIZATIONAL MODEL OF THE ANT COLONIES OPTIMIZATION

5.1 Principle of the ant colonies optimization

The ant colonies optimization considered here is inspired from the collective behavior of ants. This behavior allows ants of different colonies to optimize the path between the food and the anthill. Each ant of a colony builds a path and lays down a trace of pheromone that will be used by the following ants of the colony. With successive deposits of pheromones and the evaporation phenomenon, ants gradually take a shorter path. In the considered ant colonies optimization, the search for new solutions is carried out by the different colonies. The memory that guides this research corresponds to a pheromone matrix. This matrix is used by the colonies to incrementally build solutions. A possible solution is a set of sub-solutions determined by each ant of the colony.
We present on Figure 2 an overview on the application of the AMCO approach. Thus, several colonies are put in competition to

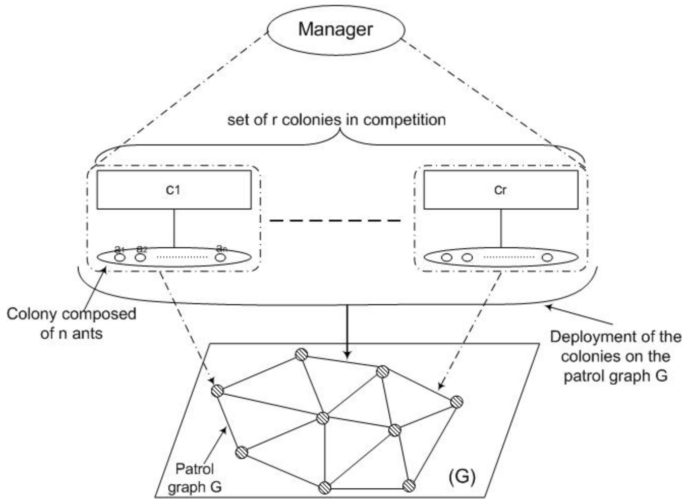

Fig. 2. Application and global view of AMCO

select the best colony whose aim will be to steer the best solution by a deposit of pheromone. The main function of the *manager* will be to coordinate all the activities of the various colonies.
With the RIO meta-model and the AMF organizational model, we have introduced concepts to organisationally model a system and thus a metaheuristic. From an organizational model, it is then possible to describe a multi-agent system where each agent is associated with a set of roles. In this section, we rely on the RIO approach and on the AMF organizational model to propose an organizational model of the AMCO metaheuristic.

5.2 Organizational model of the AMCO metaheuristic

The organizational model of Figure 3 presents the different roles that interact within the organization. These roles are involved in the whole process of optimization that is, the process of determining the set of optimal solutions.
One can identify in the model that there's a consideration for a role called strategist. Here, the strategist role is responsible for setting whether or not there's dispersion of agents in order to define the major research policies of better solutions. The Guide role coordinates the activities of the Intensifier and Diversifier roles.

5.3 Basic organization of AMCO

To get an organizational model of this metaheuristic, it is difficult to distinguish an intensification behavior from a diversification behavior, even if the two trends are identifiable. Thus, in the proposed organizational model of the ant colonies optimization, a unique role combines the $Intensifier$ and $Diversifier$ roles.
Thus, Figure 4 presents an organizational model of the optimization by ant colonies.
According to the basic organizational model of AMCO, one can have multiple instances of colonies but only one instance of the *Pheromon Manager*. The multiplicity of colonies is justified by the fact of the setting in competition and the choice of the best colony. This model brings out the interaction between the two main roles of the organization. The roles that make up this organization are described in the subsections 5.4 and 5.5.

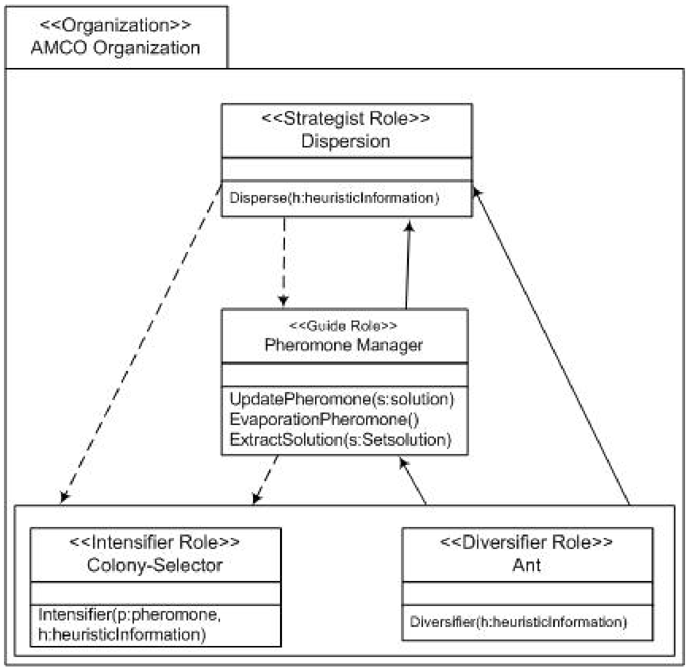

Fig. 3. An organizational model of the AMCO approach

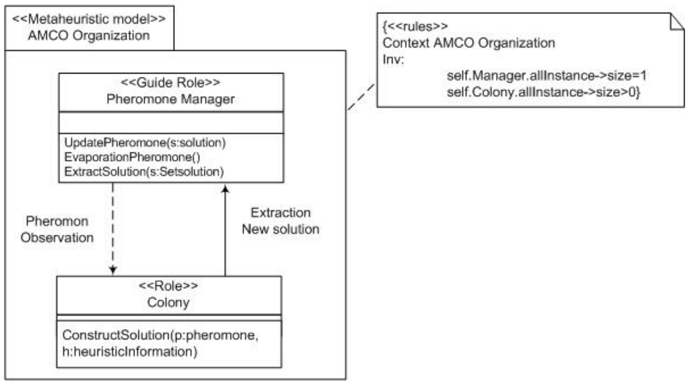

Fig. 4. Basic organizational model of AMCO

5.4 Manager role

Pheromone manager role: This role coordinates the research carried out by the colonies and manages a memory consisting of a matrix of pheromones. This matrix corresponds to a memory by reference to [28] who uses the memory in its approach to guide the research process and thereby constitutes a central element of metaheuristics.
The *Manager* role can be seen as a refinement of the Guide role. Its behavior consists of updating the pheromone matrix when a solution was obtained by a colony and to gradually evaporate the pheromone. Its objective is to implement an overall research strategy based on the Intensifier and Diversifier roles, with the aim to combine these two roles, and then to select the solution or solutions which will be the result of the optimization.

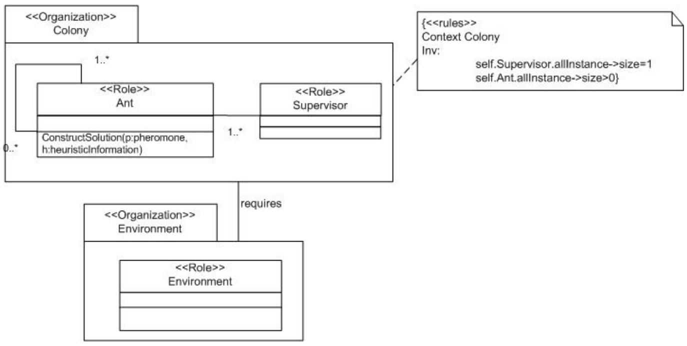

Fig. 5. Organizational model of colonies

5.5 Colony role

Colony role : The intensification and diversification are combined in the process of stochastic decision of ants of a colony. Thus, in the *AMCO* organization, the Colony role corresponds to these two trends. These trends are effectively integrated in the *Ant* role (see Figure 5), as a colony will consist of ants.
The purpose of the Colony role is to build new solutions using the pheromone matrix. Thus, this role is responsible for the exploration of areas of the search space where good quality solutions were found, while displacing research in unexplored areas of the search space.
According to [1], intensification is a research guided by the objective function while diversification is based on a random or a function other than the objective function. Thus, in *ACO*, when a solution is generated by a colony, the heuristic or random component of the choice of the edges by ants in the graph is related to diversification while the component leading to the selection of the edge with a higher pheromone rate corresponds to intensification. The pheromone rate is related to the previous evaluations of solutions. To each colony corresponds a potential solution to the problem, each ant of the colony providing a part of the solution. The extraction of the solutions is done during the execution of the *ACO* and only those that are applicable to the problem by the sensor networks are preserved.

6. AGENTIFICATION OF THE METAHEURISTIC ORGANIZATIONAL MODEL BASED ON ANT COLONIES

This is to describe the multi-agent system structure associated with the metaheuristic. For this, it is necessary to identify the different types of agents composing the multi-agent system, specify the assignment of roles to agents and describe the scheduling of roles for each type of agent. The main input data to perform this step corresponds to the refined model of the metaheuristic. The agentification will rely on this refined model and will consist in:

(1) Identifying agents
(2) Assigning roles to the agents
(3) Defining the scheduling policy of roles within the agents
(4) Defining the policy of execution of the agents

Figure 6 presents an agentification of the *AMCO* organizational model.
The instantiation of the *AMCO* organization presented on Figure 6 corresponds to a *natural* distribution of the ant colonies. In this distribution, a set of agents playing the *Colony* role interacts with a single agent associated to the *Pheromone manager* role.

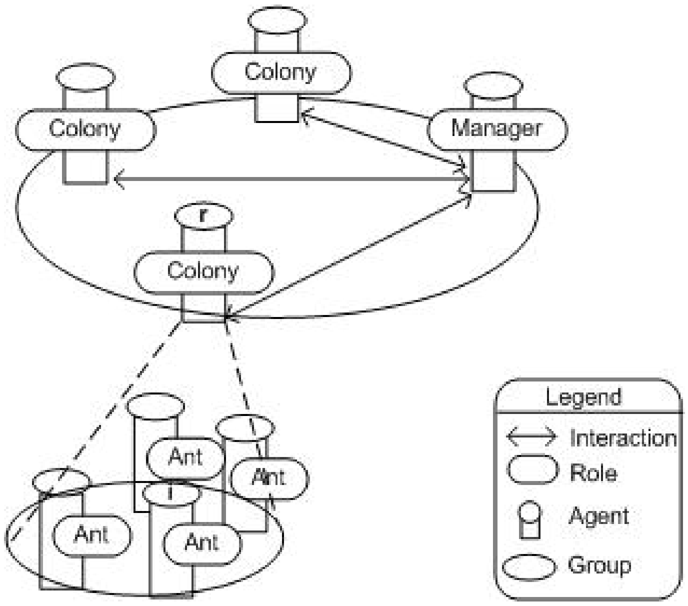

Fig. 6. Agentification of the AMCO organization

When choosing a solution component, the ant is subject:

(1) To a tendency to exploit the information of the pheromone matrix, but also
(2) To a tendency to use heuristic information.

These two trends are combined in the process of stochastic decision of the ant and correspond respectively to the intensification and diversification of research. After creating a solution, a deposit of pheromone whose intensity depends on the quality of the solution is performed. The successive deposits of pheromone combined with evaporation will lead the colonies to find better quality solutions.

7. CONCLUSION

In this paper, an organizational modeling of the optimization using ant colonies was presented. After presenting a state of the art on multi-agent systems and combinatorial optimization, the analysis and organizational modeling of the ACO made it possible to bring out the different roles. Since it is difficult to distinguish an intensification behavior from a diversification behavior, even though these two trends are identifiable in the organizational model of the ACO, it should be noted that a single role can combine the $Intensifier$ and $Diversifier$ roles. As for the $Manager$ role, it is responsible for the coordination of research carried out by the colonies, and the pheromones memory management.
Although the results presented in this paper have demonstrated the effectiveness/efficiency of the organizational approach, it could be further developed in a number of ways. In the short term, this includes working on the applications and extensions, and the related results will be reported in future papers. As a medium-term prospect, we intend to examine the simulation on several instances of the optimization problem in order to make our organizational approach a truly general purpose one.

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