A Swarm Based Approach for Task Allocation in Dynamic Agents Organizations

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Abstract

One of the well studied issues in multi-agent systems is the standard action-selection and sequencing problem where a goal task can be performed in different ways, by different agents. Tasks have constraints such as deadlines and characteristics such as duration, resources, etc. Agents also have different characteristics such as capacity, access to resources, motivations, etc. This class of problems has been tackled under different approaches. At the high-level coordination, the specification of the organizational issues is crucial. However, in open, dynamic environments, agents must be able to adapt to the changing organizational goals, available resources, their relationships to another agents, and so on. This problem is a key one in multi-agent systems and relates to models of learning and adaptation, such as those observed among social insects. The present paper tackles the process of generating, adapting, and changing multi-agent organization dynamically at system runtime, using a swarm inspired approach. This approach is used here mainly for task allocation with low need of pre-planning and specification, and no need of explicit coordination. The results of our approach and another quantitative one are compared here and it is shown that in dynamic domains, the agents adapt to changes in the organization, just as social insects do.

1. Introduction

The organizational structure of multi-agent systems (MAS) is one of the most significant aspect for its success [10]. The agent's organization depends on the system needs to achieve the goals, to perceive the environment and to configure the agent's activities and its interactions. One problem is to define which organization form fits those needs best.

A simple way to solve this problem is to define the organization statically, that means to find the system needs and design an appropriate organization. Once this is made off-line the advantages of a well defined organization turn into disadvantages in an unstable environment. As MAS are used in dynamic problems, static organizational structures with rigid definitions become inefficient.

MAS need to manage the problems dynamics such as variation in the number of agents, changes in environment and in the system's goals. The question is how to derive such specific organizational structure given a particular situation. Most of the works in this area focus on adapting some specific aspects of the organization or on structure generation. Each of these approaches shows good results in their specific scenarios, but they are not general solutions to the problem. Recently an approach that intends to be more general, based on the TÆMS/GPGP/DTC framework plus system self-diagnosis was proposed [8]. This is a high-level coordination framework based on specification (of the organization goals, etc.), planning, and scheduling (which we call task allocation here). This framework also shows good results but some questions about their general efficiency are still open: regarding communication issues, especially in large organizations, how efficient are the resulting organizations?

The process of generating, adapting and changing organization dynamically at system runtime in MAS is usually called self-organization. Some authors prefer to call this process *organizational adaptation* [9] or *organization self-design*. Some critics to each of this definitions can be found in [12]. In these work we use *organizational adaptation* because our approach is based in organizational self-adaptation according to the dynamic changes in organizational needs.

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This motivation for studying organizational adaptation in MAS can also be found in some biological entities such as the social insects. Social insect colonies (also called swarms) show evidences of ecological success due to their *organization* which is observed in division of labor, specialization, collective regulation, etc. [2, 3]. The needs of the colony organization change over time. These changes are associated with the phase of colony development, time of year, food availability, predation pressure, and climatic conditions. Despite this drastic variations in colony's conditions, social insects do have ecological success [16].

A social insect colony operates without any explicit coordination. An individual worker cannot assess the needs of the colony, it just has a fairly simple local information, and no one is in charge of coordination [7]. From individual workers aggregation, the colony behavior emerges without any type of explicit coordination or planning. The key feature of this emergent behavior is the plasticity in division of labor inside the colony [11]. Colonies respond to changing conditions by adjusting the ratios of individual workers engaged in the various tasks.

In this paper we propose an approach to adapt organization in MAS inspired on social insects colonies organization. Due to its domain-independence, we use TÆMS [5] to represent agents activities. TÆMS is further discussed in Section 2.1 together with GPGP, and the Design-to-Criteria (DTC) scheduler. In our approach, a TÆMS task structure is used to model the necessary activities to achieve the system goal: the task structure is read and our approach determines the allocation of the tasks. This is performed using the theoretical model of task allocation in social insect colonies discussed in Section 2.2.

In Section 3 we present our approach in detail. The target scenarios and the simulations over it are presented in Section 4. Also in Section 4, we discuss the results and the performance of the current version of our approach. Section 5 concludes with further directions for this work.

2. Organization in MAS and Social Insects

Although many approaches to organization in MAS exist, this section focuses only on organizational representation, planning and scheduling (TÆMS/GPGP/DTC framework), and on the swarm based model necessary to explain our approach.

2.1. TÆMS, GPGP, and DTC

TÆMS [5], GPGP [6], and the Design-to-Criteria (DTC) [15] have been used as a domain-independent language for description of tasks associated with agents, planning and scheduling of agent's tasks. TÆMS allows the construction of a task model in which the relation of the actions available to choice is shown, providing ways to model scenarios where tasks have deadlines and some kind of result must be reached.

Agent's activities are represented as a graph in terms of their task groups aiming at achieving agent's goals. The leaves of the graph are called executable methods, which have probability distribution on their characteristics like quality, cost, and duration. The quality of a task group depends on what is executed and when. For example, quality can be accrued by a quality accumulation function (QAF) like *sum()*, which indicates that all tasks in the structure need to be accomplished.

Besides the local effects of the execution of methods on the quality and duration of their supertasks, there exist non-local effects (NLE) such as enables, facilitates, etc. Generally speaking, a task T may enable a method M in the sense that the quality of M cannot be accrued until T is completed, i.e. the earliest start time of M is the finish time of T. Therefore enables is a hard relationship, i.e. it has to be necessarily observed.

By using these tools, it is possible to construct the task structure of a problem-solving situation. The actual structure is called an objective model of the environment, and is inaccessible to agents. However, agents have each a subjective and a conditioned model or view of it, which they use to predict other agents actions'. The subjective view contains tasks and relationships the agent believes to be the complete model of its alternatives.

NLE's which involve more than one agent are called coordination relationships. Coordination mechanisms can recognize the features of the agent's subjective view, such as redundancies and soft and hard relationships. GPGP and DTC perform analysis of the processes modeled in TÆMS, and decides on the commitments and appropriate courses of action for the agent given the constraints (deadline, resources, etc.).

2.2. Swarm-Like Organization

Theraulaz et al. [13] present a model for self-organization inspired on the plasticity of division of labor in colonies of social insects [11]. Interac-

tions among members of the colony and the individual perception of local needs result in a dynamic distribution of tasks.

This model describes the colony task distribution using the stimulus produced by tasks that need to be performed and an individual response threshold related to each task. Each individual insect has a response threshold to each task to be performed. That means, at individual level, each task has an associated stimulus (e.g. the amount of food need to be carried to the nest, if the task is to forage). The levels of the stimulus increase if tasks are not performed, or not performed by enough individuals, etc. An individual that perceives (e.g. after walking around randomly) a task stimulus higher than its associated threshold, has a higher probability to do this task. This model also includes a simple way of reinforcement learning where individual thresholds decreases when performing some task and increases when not performing. This double reinforcement process leads to the emergence of specialized individuals.

Let us assume that there are M tasks to be performed, each denoted by j, and that each of this tasks are associated with a stimulus s_j. Also assume that there are N individuals, each denoted by i, with response thresholds θ_{ij} associated with task j stimulus. An individual i engages in task j with probability:

$$T_{\theta_{ij}}(s_j) = \frac{s_j^2}{s_j^2 + \theta_{ij}^2} \quad (1)$$

where:

s_j stimulus associated with task j

θ_{ij} response threshold of individual i to task j

Each individual in the model has one response threshold to each task. Those thresholds are updated (increase or decrease) according to two different coefficients. The response threshold θ is expressed as units of intensity of stimulus.The response threshold θ_{ij} of an individual i when performing task j during time interval of duration Δt is:

$$\theta_{ij} = \theta_{ij} - \xi \Delta t_{ij} \quad (2)$$

where ξ is the learning coefficient and Δt is the time interval.

The response threshold θ_{ij} of the agent i when not performing method j during time interval of duration Δt is:

$$\theta_{ij} = \theta_{ij} + \rho \Delta t_{ij} \quad (3)$$

where ρ is the forgetting coefficient.

Each particular task in the model has one associated stimulus. The intensity of this stimulus can be associated with a pheromone concentration, a number of encounters between individuals performing the task, or any other quantitative cue sensed by individuals.

Variations in stimulus intensity can result from task performance or natural increase of task's demand. Bonabeau et al. [3] present two distinct ways to model this stimuli variation: performing a given task increases the demand for another tasks; and applying different success rates according to the task performance, changing to each specific task. The equations and results of this approaches are also presented in [3].

3. A Swarm Based Approach for Task Allocation

We use the swarm-based model to allocate insects-like agents to perform specific methods of a TÆMS task structure. This means that each agent deals with a dynamically changing TÆMS task structure and schedule its methods according to the TÆMS semantic.

Next, we discuss how the ideas of social insect organizations are used in order to allocate agents to tasks, and their application in the actual simulated scenarios.

3.1. Stimulus

As mentioned in section 2.1, a method is the element in a TÆMS task structure that represents what the agent can actually do (hereafter we call the insects tasks as methods). All methods in the TÆMS task structure have probability distributions of quality, cost, and duration. This values describes the possible results of the method execution. Therefore methods have quality (q_j), cost (c_j) and duration (d_j) and these are used to compute the stimulus s_j of a method j. The intensity of this stimulus is associated with the results of the methods execution. Each method j have one stimulus s_j:

$$s_j = \varphi * (\alpha * \hat{q_j} - \beta * \hat{c_j} - \gamma * \hat{d_j} + \beta + \gamma) + (1 - \varphi) * x_j \quad (4)$$

where:

$\hat{q_j}$ normalized expected quality of method j.

$\hat{c_j}$ normalized expected cost of method j.

$\hat{d_j}$ normalized expected duration of method j.

x_j stimulus associated with the QAF related to the method j.

$\alpha, \beta, \gamma, \varphi$ constants.

The constants are employed to set different priorities to the quality, cost and duration values (the sum of those constants should be 1). In this paper, these constants have the following values: $\alpha = \beta = \gamma = 1/3$ (in order to give quality, cost, or duration the same weight), and $\varphi = 0.5$.

The stimulus s_j for each method j is recalculated every time one method is performed by an agent (hereafter we call this an iteration). This stimulus updating is performed to model the emergent task succession discussed by Bonabeau et al. [3]. In social insects colonies, performing a given task increases the demand for another related task. For instance, creating a waste pile at the entrance of the nest generates a need for cleaning. In our approach, performing a method influences the stimulus associated with all methods of the same TÆMS task according the tasks' QAF.

Let us assume that there are M methods in the TÆMS task structure perceived by a given agent (only methods that are allowed to be performed in the current interaction). When any method k of M is performed, all methods j, related by a QAF with k, will have the x_j stimulus updated:

$$x_j = x_j + \kappa \tag{5}$$

where κ is the constant related to the QAF, as defined in Table 1.

This influence is recursive to each method of the parents tasks in the task structure tree. A constant κ associated with the QAF is used to model the influence of interrelated methods. We adopt small values for κ ($0 < \kappa \leq 1$) because the stimulus x_j is cumulative (increasing in each iteration) and takes values only between 0 and 1.

In Equation 4 we use the constant φ in order to set different priorities to the stimulus associated with the results of the methods execution (quality, cost and duration) and to the stimulus related to the emergent task succession.

QAF	κ
SeqMax, Max, SeqMin, Min	0
SeqSum, Sum	0.01
ExactlyOne	-0.01

Table 1. QAF related constants

Our approach was developed focusing on dynamic environments where the TÆMS task structure can be modified on the fly: methods can appear or disappear; the number of available agents can change; and the interrelationship among methods can also change. The latter is supported by the stimulus model presented above. However, this stimulus model does not take into account the changes in the number of agents and methods. Bonabeau et al. [3] show that emergent task succession can be achieved using fixed thresholds; however this has only limited applicability. In order to overcome these limitations of the stimulus model, our approach uses a modification of the specialization model (Section 2.2). This modification is discussed next.

3.2. Polyethism

Division of labor, in which a set of workers specialize in different set of tasks, is an important and well-studied aspect of colony behavior [11]. The age oriented specialization are called by the biologists temporal polyethism. In honey bees (*Apis mellifera*) this is the main form of division of labor. Young workers perform tasks within the hive, while older workers perform tasks outside the hive, such as foraging and colony defense.

Theraulaz et al. [13] only suggests an extension to model the temporal polyethism. His original model, without polyethism, uses two constants as learning and forgetting coefficients (Equations 2 and 3). To calculate the response thresholds with polyethism, we modify the Theraulaz et al. [13] specialization model. Our version uses two variables as coefficients of learning and forgetting based on temporal polyethism. The response threshold θ_{ij} of an individual i when performing method j is given by:

$$\theta_{ij} = \theta_{ij} - \frac{a_i}{A_i} * \frac{\mathcal{A} - m_j}{\mathcal{A}} \tag{6}$$

where:

a_i age of the agent i.

A_i maximum age of the agent i.

m_j age of the method j.

$\mathcal{A}$ age of the oldest available method.

The response threshold θ_{ij} of an individual i when *not* performing method j:

$$\theta_{ij} = \theta_{ij} + \frac{a_i}{A_i} * \frac{m_j}{\mathcal{A}} \tag{7}$$

In this specialization model, all agents start with the same θ_{ij} (usually an intermediate value). When a method is performed by an agent, the response threshold changes. For the agent to specialize in selecting a specific method, it is necessary that it selects this method some times. Thus, it is necessary to run the model for several rounds. In each round our approach produces a task allocation for the given task structure.

Given the probabilistic nature of the model, these allocations are not necessarily the same. If the task structure does not change, we consider an allocation of tasks to be the final one when it does not change after a specific number of consecutive rounds.

In equations 6 and 7, we consider the agents' age (proportional to the task deadline) and the methods' age (proportional to the oldest method's age). The age of methods and agents is computed at each iteration. A method's age increases until the method does not finish. An agent can survive a single round or stay alive during several rounds. The agents has higher thresholds regarding old methods and lower thresholds regarding new ones. Besides, a young agent has a lower threshold that an old agent regarding the same method. The idea behind this is to specialize old agents regarding a wider range of methods, and young agents regarding specific methods as it occurs in Nature.

4. Experiments

The simulations presented in this section were generated using a simulation tool developed in JAVA and using the TÆMS API.

In our approach we adopt the Bonabeu et al. tendency (Equation 1). This equation computes a probability distribution over the tendency of an agent to respond to each method's stimulus. As it is the case with social insects that inspire Bonabeu et al. models, with the use of this equation, each methods in the task structure can be performed since each has a *probability* of being carried out by an agent. Therefore, the best way to present and discuss the results is via the use of statistics: the results presented here are averages over 1,000 repetitions of each experiment.

4.1. Scenario I

We use the TÆMS task structure of Figure 1 as basis for our simulations. This task structure can represent, for instance, a typical problem of job scheduling among multi-purpose machines [4] in which the authors associate a small number of machines (2–4) with wasps. This task structure can also be related to the aircraft servicing scenario discussed in [14].

Task T_1 is the first stage of production/servicing. Jobs or aircrafts of type a, b, or c can arrive. If it is of type a, for example, then m_{1a} is allocated to an agent. This enables method m_{2a} and so on. Notice that in this scenario, there are hard relationships of type *enables* which make the task allocation little flexible.

Figure 1 shows only the duration distribution probability of each method. All methods have the same

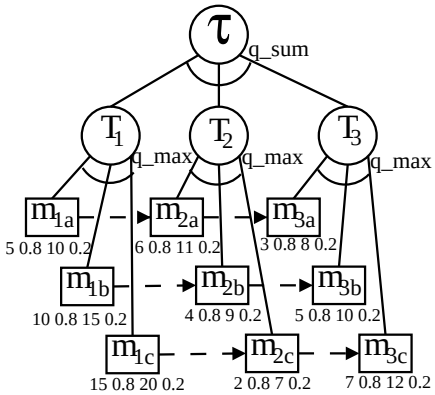

Figure 1. Objective TÆMS task structure.

cost and quality probability distribution: the cost for all methods is (0 0.8 1 0.2). The quality for all methods is (5 0.8 4 0.2). Unless said, we use deadline equal to 25.

We run DTC to compare our task allocation to the standard output produced by DTC, which is shown in Table 2. This table presents the start and end time for each method, qualities, and costs. Not shown there: the total quality is 14.35, the total cost 0.6, and the total duration 17.0.

method	start	finish	quality	cost	duration
m_{1a}	0.0	6.0	4.8	0.2	6.0
m_{2a}	6.0	13.0	4.8	0.2	7.0
m_{3a}	13.0	17.0	4.76	0.2	4.0

Table 2. DTC schedule

Although DTC deals with the probability distributions of quality, cost, and duration coming from the semantic of TÆMS , it does not handle these distributions probabilistically (e.g. using a roulette wheel). Instead it computes an average for each probability distribution. We use both, the probabilistic and the DTC approaches. The latter is useful when we compare results; the former is used otherwise.

Using our approach in a non-probabilistic variant produces the task allocation shown in Table 3. In fact, our approach produces 1000 outputs (as mentioned before), one for each repetition. The one shown in this table is the top one (more frequent) and is produced 32.7% of the time. The total quality equals to 14.4, the total cost 0.6, and the total duration 17.0. That means that our more frequent output is the one which resembles the output of DTC.

The same task structure was scheduled with prob-

abilistic treatment of the quality, cost, and duration distributions (second variant). Table 4 shows the most frequent schedule, produced 22.3% of the 1000 repetitions. The total quality equals to 15, the total cost 0.0, and the total duration 24.0. All the three methods scheduled in the first variant are also present in the second one. However, due to the probabilistic variation of the duration, sometimes more methods can be scheduled within the deadline. In total, 41.5% of the repetitions scheduled at least the 3 methods DTC did, within the deadline.

method	start	finish	quality	cost	duration
m_{1a}	0.0	6.0	4.8	0.2	6.0
m_{2a}	6.0	13.0	4.8	0.2	7.0
m_{3a}	13.0	17.0	4.8	0.2	4.0

Table 3. Top schedule (first variant)

method	start	finish	quality	cost	duration
m_{1a}	0.0	5.0	5.0	0.0	5.0
m_{2a}	5.0	11.0	5.0	0.0	6.0
m_{3a}	11.0	14.0	5.0	0.0	3.0
m_{1b}	14.0	24.0	5.0	0.0	10.0

Table 4. Top schedule (second variant)

Of course, in both variants, the overall results of our approach are not as good as the one DTC computes.

However, our approach is intended not for static environments but for dynamically evolving ones. This means that our agents can adapt to changes in the environment with no need of commitments and communication. Such environments are now presented and discussed.

4.2. Scenario II

In order to measure the performance of our approach in dynamic environments, we schedule four different TÆMS task structures appearing randomly with the same probability. The first task structure (TS_1) is the one depicted in Figure 1. The other three are variants of it: one has no enable relationships between the tasks (TS_2); one has not the task T_3 (TS_3); and the last has the deadline changed to 30 (TS_4). Beside, we have changed the quality distribution: in TS_2 it is (15 0.8 10 0.2), in TS_3 (50 0.8 40 0.2), and in TS_4 (100 0.8 90 0.2).

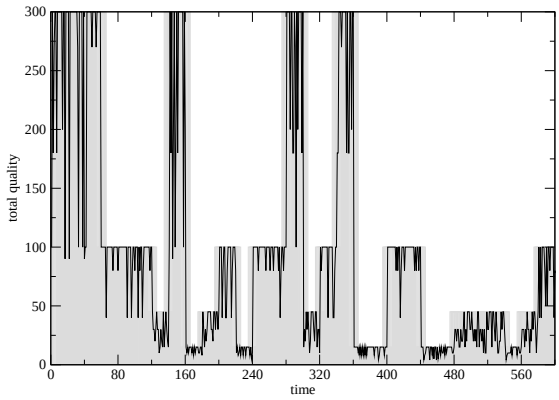

Figure 2. Change in quality over time (black line); Changes in the environment are depicted as shadow boxes.

Of course, we can only compare individual tasks structures to the DTC outputs. In our simulation, these 4 outputs appear 48% of the 1000 repetitions. However, the real power of this approach is when the environment changes dynamically.

Figure 2 shows these changes and how agents adapt to them. We change task structures randomly. In the beginning (first 50 steps), agents are still adapting. The gray shadow in the figure indicates which task structure is the actual one at a given time step. When the shadow goes up to 300, this means TS_4. Remember that the total quality is the sum over three tasks in TS_1, TS_2, and TS_4, and over two tasks in TS_3. When the shadow goes up to 100, 50, and 15, the actual task structure is TS_3, TS_2, or TS_1 respectively.

Ideally, each time a task structure changes, agents should adapt and so the quality would change instantly. Due to the time necessary for agents to adapt their stimuli, etc., there is a small delay in this process which can be seen in Figure 2 (black line does not match the shadow exactly).

Because of the probabilistic aspects of our approach (probabilistic distribution of methods' quality and probabilistic tendency to schedule a method) the black line is not constant, there is a variation in the schedules' quality for the same task structure. However, Figure 2 shows that when the task structure changes, so does the total quality associated with it.

This results show that modifying the task structure on the fly disturbs only slightly the performance of the

agents regarding the quality of the schedules produced because each time the task structure changes, agents do adapt to this situation.

4.3. Scenario III

With the same aim of the simulation described above, we now change dynamically the number of agents available to perform the task structure. In this scenario, we also employed the basis task structure of Figure 1. This time three of these task structures are subtasks of a new task group (root task) whose QAF is *sum()*. The new task group has now 3 times as many methods as the basis taks structure, i.e. 27 methods. Therefore we vary the number of agents between 1 and 27. To cope with the probabilistic nature of the problem, we perform 100 repetitions each time we vary the number of agents, totalizing 2700 repetitions.

Figure 3 shows the influence of the number of agents over the number of methods scheduled and also over the quality. Nine methods of those 27 do not have any enable NLE. As we increase the number of agents, the number of this enable-free methods performed increases. When the number of agents is equal to the number of the enable-free methods, that means 9 agents, the number of performed methods stabilizes because even if we put more agents, they cannot perform methods which are not enabled. The same reasoning applies to the quality: the best one is achieved after this stabilization, that means when the number of agents is equal to the number of enable-free methods. The highest possible quality, around 40, is reached when we have 9 agents.

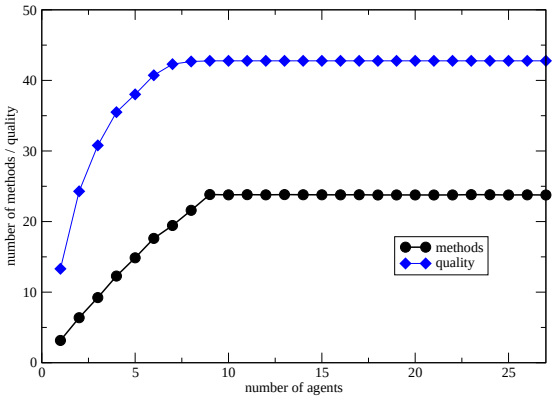

Figure 3. Number of methods and quality, for varying number of agents.

5. Conclusions

The approach presented here deals with the action-selection and sequencing problem. It aims at situations when the environment changes and so demands different organizations of tasks and agents. In other approaches, this adaptation requires a learning component, normally based on explicit coordination and/or communication.

We focus on a paradigm based on colonies of social insects, where there are plenty of evidences of ecological success, despite the apparent lack of explicit coordination. These insects adapt to the changes in the environment and to the needs of the colony using the mechanisms explained here. The key issues are the learning/forgetting specialization and the plasticity in division of labor.

Our aim is to show that such an approach can be used to allocate tasks to agents in MAS, when organizations change dynamically. As already pointed out in [2], there is no standard way of evaluating the performance of algorithms dealing with dynamic environments, because benchmark problems (e.g. travel salesman) are static problems. Therefore, we use the GPGP/DTC/TÆMS framework as comparison, although this is somehow limited to the static cases. When it comes to dynamic situations, we can only discuss the qualitative advantage of our approach. The main one is that it does not need the explicit commitments each time the number of agents changes. This is especially important when it comes to domains with large number of agents. In the scenarios we discussed here, although it takes some time for the agents to adapt, this adaptation is reached and deadlines were kept. Also, in our approach we ensure the synchronization of team members and handle teamwork redundancy. As discussed in [1], GPGP mechanisms support neither synchronization nor handle teamwork redundancy. For instance, in scenario III, more than one agent can be performing the same task but no more than one agent is able to perform the same method.

In summary, there is a tradeoff between explicit coordination leading to highly accurate outputs *versus* implicit coordination via learning and adaptation leading to more relaxed outputs (less quality, higher costs or durations in the scenarios discussed here). Our approach is certainly not the best in static situations, while it is effective in dynamic ones. The efficiency is an issue related to the specific scenarios. For instance, if, besides deadline constraints, there are also constraints

related to quality or cost, then in some cases these will not be respected.

In order to tackle these limitations, we intend to work on different parameters of the functions discussed in Section 2.2 and also study new extensions to those equations so that we can accommodate a wider range of types of agents. For instance, we might need agents with shorter life spans than others (this would imply different life probability functions), or different thresholds to the tasks in order to respond faster or slower.

We also intend to compare our results with one deadline with a large number of agents. In our approach, having such a large number of agents is straightforward since they all follow the same basic specialization/plasticity model. Even if we consider the extensions just discussed, having a large number of agents would not be a problem. What makes the comparison difficult now is the lack of such a result in the literature.

Also, resources are not explicitly modelled in our approach. We decided to do this because we are still looking for a suitable model (from the theoretical biology point of view) explaining whether or not insects have a different behavioral model for tasks and resources such as food. Handling resources and increasing the range of non-local relationships are necessary extensions in order to be able to compare other scenarios already used by the GPGP/DTC/TÆMS framework. We intend to do this next. Finally, it would be desirable to have probabilistic definitions of non-local relationships (e.g. an enables exist between T_x and T_y with probability p). In this case, this would have to be extended in TÆMS as well.

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