Cooperative Task Scheduling Among Time-Bounded Agents

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Abstract. The paper describes an approach to the cooperative execution of tasks that can benefit from the application of multiple methods. Agents have alternative methods for task solving, ranging from approximate ones to others that are more precise but also more resource (time) demanding. Tasks have temporal constraints (deadlines). Agents are resource-limited and operate under time constraints. Agents go into a negotiation process in order to choose a combination of methods which maximizes the utility of the result. Agents (with their chosen methods) will be used in sequential levels to progressively improve the quality of a task solution.

1 Introduction

Resource Bounded reasoning are strategies that handle situation were the optimal behavior are computationally or economically out of reach. These strategies can trade-off between the solution quality and the computational resources rather than to compute an optimal solution. Currently, the most popular forms of resources bounded reasoning are progressive reasoning [2] [3], anytime algorithms (Dean and Boddy, 1988; Zilberstein and Russel 1996) and multiple methods [1], where centralized controls were proposed.

The motivation of Progressive reasoning is to adapt the quality of the solution to the available time. It is based on a multilevel technique, which convert an approximate solution to a more precise one. An important propriety of progressive reasoning is a decrease improvement of the quality. Effectively, the improvement done at level *i* is greater than the improvement done at level *i-1*. A level can be skipped if its execution leads to a non-respect of response time of the task.

Multiple methods also known as *design-to-time* is an approach to real time problem solving in situation where multiple methods exist for many tasks that the system need to solve. Design-to-time involves designing solution to a problem that uses all available resources to maximize the solution quality within the available time.

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Our proposition is the combination of these two approaches in a multi-agents architecture to respond to hard temporal constraints tasks. Task execution is distributed among hierarchical agent. The hierarchy represents different level of details of task solution. Furthermore, each agent is equipped with alternative methods that make trade-offs solution quality versus time. Agents have to coalesce for task scheduling to maximize the quality of task response with respect to its deadline.
Agents operating in open and dynamic environments must be able to address deadlines and resources limitation in their problem solving. In open environments, requests for service can arrive at any time, thus making it difficult to fully plan and predict the agent's future workload. In real applications, deadlines or other time constraints are present on the agent's problem solving [1] [4]. Resource limitations may also stem from agents having multiples tasks to perform and having bounded resources in which to perform them. Furthermore agents require mutual temporal information so that they can plan downstream from the interaction.
We address in this paper a cooperative task scheduling. The coordination is anytime: it finds quickly an approximate solution named minimal solution and refines it incrementally while the maximum time allocated to the negotiation allows it. There is no central control. This approach is suited to problems that require the result to be expressed at varying levels of details. An application of our application is a flexible information retrieval system (Zilberstein and Mouaddib, 1997).
The rest of the paper is organized as follow: we start, in section 2, by presenting the architecture of our system. In section 3 we present the problem and the methodology we propose. Section 4 the algorithm illustrating the methodology. In section 5, we analyse our proposition. We finish in section 6 by a conclusion and perspectives of our work.

2 System architecture

The system is composed of a set of agents, let Gamma= $\{\alpha_1,\alpha_2,...,\alpha_n\}$ be this set. Agents will treat arriving tasks progressively in order to improve its solution quality. Hence agents are organized in levels, which aim the progressive treatment of tasks, which allows the maximization of response utility.

Each agent α_i (except for agent of the first level "i=1"and the agent of the last level "i=n") has two direct neighbours by default: the low level neighbour α_{i-1} and the up level neighbour α_{i+1}.

Indirect neighbour agents of low level of agent α_i are α_k ($1 \leq k < i-1$). Indirect agents of up level of agent α_i are α_k ($i+1 < k \leq n$). In a coalition C for the treatment of a specific task an agent α_i has a unique low level neighbour agent from which it get an entry, and a unique up level neighbour agent to which it communicates results.

Each agent of Gamma has a set of alternative methods for the improvement of task solution quality. Let $M_{\alpha i} = \{M^1_{\alpha i}, M^2_{\alpha i}, ..., M^{n_{\alpha i}}_{\alpha i}\}$ be the set of alternative methods of agent α_i.

Two alternative methods M_{α}^{i} and M_{α}^{i-1}, of the same agent α, applied on an entry of quality q will give two responses with different quality $q_{\alpha}^{'i}$ and $q_{\alpha}^{'i-1}$. These same methods will necessitate different times $\delta_{\alpha,q}^{i}$ and $\delta_{\alpha,q}^{i-1}$ where $q_{\alpha}^{'i} > q_{\alpha}^{'i-1}$ and $\delta_{\alpha,q}^{i} > \delta_{\alpha,q}^{i-1}$.

The use of rough approximation by one method negatively affects the performance of a method that uses its result.

Each agent maintains the distribution of probability of every local technique. The duration of a local technique of an agent depends on first the local technique used by low-level neighbour agent and second, on which agent has communicated the entry. Table 1 shows an example. These estimations are obtained empirically.

Table 1. Example of agent acquaintance: the method 1 of agent α_i takes 20 unit of time with the probability of 0.6 and 30 unit of time with the probability of 0.4 when entries come from agent α_{i-1}. This same method takes 60 units of time with the probability of 0.7 and 75 units of time with the probability of 0.3 when entries come from agent α_{i-2} …

	α_{i-1}		α_{i-2}		…	α_1	
α_i	Pr	Dur	Pr	Dur		Pr	Dur
$M_{\alpha_i}^{1}$	0.6	20	0.7	60		0.75	120
	0.4	30	0.3	75		0.2	140
$M_{\alpha_i}^{2}$	0.7	35					
	0.3	40					
…							
$M_{\alpha_i}^{n_{\alpha i}}$	0.6	53					
	0.4	60					

3 Methodology outline

The aim is to find, for an arriving task, among agents the ones which compromise the deadline of the task and hence, will be discarded and for other agents which methods will be used so that to maximize solution quality of the task. To decide which method to use for the treatment of a given task, an agent cannot do it individually, because, in one side, the strategy is global, and in the other side, no agent knows the temporal constraints of other agents. From this fact, agents must decide together by entering in negotiation cycles. These later will allow agents to opt for a combination of methods, which increases (as better as possible) the utility of the response. The utility of the response to the task is zero if the response is produced after its deadline.

For hard temporal constraints task, the time allocated to the schedule must be limited in advance otherwise agents will constantly schedule and not perform their commitments.

We want an anytime task scheduling which has always a response at a hand when interrupted (because of expiration of the maximum time allocated to the schedule). To guaranty such behaviour we propose two-steps scheduling: the first step finds a minimal solution, which concerns only the more approximated methods of each agent of the set Gamma. This will reduce the search area of methods and hence minimize the search time.

After this, and in second time, agents try to improve, incrementally, the minimal solution by changing all or part of approximate methods with more precise ones. This process finishes when the maximal time allocated to the schedule process is expired or when more improvement leads to the violation of task deadline. The aim is to have always a solution at a hand under time pressure.

4 Preliminaries Definitions

4.1 Coalition Cost

The cost of a coalition for a task *Wj* is the necessary computational resource to respond to the task *W*j. The cost of a coalition varies with respect to the resource-consumption by previously formed coalitions for already arriving tasks not yet executed. The cost of coalition allows verifying whether or no there is task deadline violation.

4.2 Utility Function

We define an utility function of an agent α_i to a task *Wj* by $g_{\alpha_i}(W_j,t)$. It is corresponding to the utility to respond to a task *Wj* at a time t by an agent α_i. It represents the inverse of the time window between the expected time the task is ready to receive improvement by the agent α_i and the expected time the agent α_i delivers its response to the task *Wj.*

4.3 Agents Interaction

Agents communicate via a communication protocol, which is based on two primitives: *Send/Receive(Sender,Receiver,<Message>).*
There are three types of messages:
Invitation-to-participate message: this type of message is an invitation of the sender to the receiver to look at the possibility to participate for the treatment of the task Wj. This message vehicles temporal information such the cost of the coalition *Ccomp{Coalition}* formed until the sender, the expected time the sender delivers its result for the task Wj the value of the minimal utility, *Umin,* until the sender, the agent which owns the minimal utility *arg(Umin)* and task identification Wj
Invitation-to-Opt-out message: this type of message is an invitation of the sender to the receiver to opt out because of its minimal utility until now. The parameter of this message is *task identification.*
NewNeighbor message: this type of message is an updating message which permits to the receiver to know its new up level neighbour after the sender has opted out. Parameters of this message are: n*ew neighbour identification and task identification*.
NoNeighborUp message: only the agent of the last level sends this type of message when it must opt out due to its minimal utility. The parameter of this message is task

identification. The receiver of this message deduces that it has no neighbour up for the treatment of the task referenced in the message and that it is the last agent in the coalition formed for the treatment of the referenced task.

5 The algorithm

In this section, we present the two steps of cooperative task scheduling:

5.1 Step I: the minimal solution

In this step agents try to evaluate together the cost of the coalition so that there is no violation.
Agents reason about their temporal constraints using worst-case performance of their planned methods. We distinguish two main situations: the first is the design of the coalition by estimating its cost; the second concerns the detection of a violation of task deadline. Hence, one agent must opt out. We adopt a utility driven selection, where agent with the more little utility is invited to opt out from the current negotiation and hence from the treatment of the task. We address in the following these two situations.

Forward coalition formation for the minimal solution:

When a new task *Wj* asks for service, agent of the first level initiates the search of the minimal solution. It estimates its contribution with respect to its workload corresponding to resources consumption by previous commitments, and predicts the time *End-Time(*α_1*,Wj)* at which it delivers its part of *Wj* solution by using worst-case performance of its more approximated method *Wj* and worst-case performance of already planned methods for waiting tasks (during passed task scheduling). Also it estimates the cost of the coalition $\{\alpha_1\}$ *Ccomp*$\{\alpha_1\}$for the task Wj. This information will be communicated to its neighbor of up level by default using an invitation to participate message:

Invitation-to- participate (
Sender: α_1,
Receiver: $\alpha 2$,
Temporal information: Ccomp$\{\alpha_1\}$*,ET(*α_1*,Wj),*
Umin: ∞,
Arg(Unim): α_1,
Task identification: Wj
);

The utility of agent α_1 is always equal to ∞ for its mandatory role.

Each agent of the intermediate level α_i receives from an agent of low-level temporal information from which it expects its proper response time for *Wj (End-Time(*α_i*,Wj))* using worst case performance of its more approximated method for *Wj* and worst-case performance of already planned methods for waiting tasks (during passed task scheduling). It updates the cost of the new coalition by adding its temporal constraints to

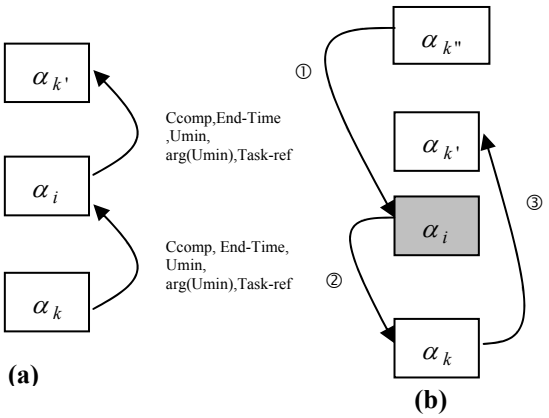
the cost received. Also it estimates its utility for the task *Wj,* compares it to the one received and updates the value of the minimal utility and its owner, if necessary. If the new cost of the coalition doesn't violate task deadline, it saves locally all expected temporal information and sends them to the next agent in the hierarchy (if exists). This process is iterated until agent αn and the coalition is progressively formed.

Expectation of task deadline violation

When at a level of an agent α_i a violation of task deadline is expected (the expected coalition cost violates the deadline of the task Wj), agent α_i has to identify among agents of low level the agent with minimal utility for the treatment of the new task. Recall this information is available in the *invitation-to-participate* message.
When informed (by an *invitation-to-opt-out* message), the agent with minimal utility $\alpha u_{\min}$ cooperates, for coherent behavior of the schedule, by linking its current low-level neighbor for the referenced task with its current neighbor of up-level by sending an updating message. Only at this time the agent with minimal utility $\alpha u_{\min}$ opts out.
The agent receiving the updating about its new neighbor of up-level for the referenced task has to resume the process of the coalition formation by sending its temporal constraints, saved for such event, to its new up-level neighbor agent for the referenced task. This later must re-estimate its temporal constraints with respect to those received: End-Time, coalition cost and the identity of low level neighbor (the sender). The figure 1 presents the minimal solution principal.
At the end of the first step each agent maintained for the treatment of the new task must know its neighbors (up and low levels) the expected Ready Time of the task results (for more improvement) at its level and the expect time it delivers its results (End Time) for the task to its neighbor of up level, if exists.

5.2 Step II: Improvement of Minimal Solution

In the second step the aim is the improvement of the minimal solution. We distinguish more then one collective behaviours depending on the cost of the coalition reached in the first step and the remaining time of the negotiation. We have to fix thresholds under which there is no need to improve the minimal solution (no sufficient time negotiation or the cost of coalition meets approximately the task deadline).



(a) Before task deadline violation: Update of the coalition cost, the expected End Time and the value of the minimal utility and its owner

(b) Expectation of task deadline violation at a level of $\alpha_{k''}$ with arg(Umin)= α_i

① receive an invitation to opt out message

② send to low level neighbour α_k the identity of its new up level neighbour $\alpha_{k'}$

③ the coalition formation is resumed from the agent α_k

Fig. 1. Minimal Solution Principal

If results of the first step allow improvement, all agents retained in the first step with their more approximated methods try to propose a more precise method which can be inter changed with the latest chosen method so that there is no task deadline violation. We propose an incremental improvement. Each cycle retrieves among all propositions in terms of duration and quality outcome. The strategy of each agent is to increase its chance to have its proposition retained. Hence its choice will be focused, among possible interchanges, on the one, which increase quality outcome with a short duration. When an agent is retained for its proposition, it is informed, the cost of the coalition is updated. This will be iterated until the time of the negotiation expires or the cost of the coalition meets task deadline.

6 Termination and Complexity

6.1 Termination

The termination of the first step is guaranteed, because of the limited number of agents corresponding to the limited number of levels in one hand, and an agent, which opts out for the treatment of the task Wj cannot join the coalition again in other hand. In second step, when the improvement is adopted, the minimal solution is improved incrementally. One method is interchanged by cycle. The maximum number of cycles

in worst case is $\prod_{\alpha_i \in Gamma} |M_{\alpha i}|$, where $|M_{\alpha i}|$ is the cardinality of the set $M_{\alpha i}$. The termination of the second step is also guaranteed because of limited number of methods at the level of each agent.

6.2 Complexity

In the first step we can have backtracking when a violation of the task deadline is expected. The worst case backtracking is the one where the evaluation of coalition cost has progressed until the last agent then the violation of task deadline is detected and the agent with the minimal utility is situated at the bottom of the hierarchy. Example: for n=5, the evaluation of coalition cost is done from agent 1 to agent 5, at the last level the violation is expected, the agent with the minimal utility is situated at the bottom of the hierarchy which corresponds to agent of level 2 (agent of the first level is the mandatory agent). The complexity of a worst case backtracking for *n* agents is *O(n)*. For *(n-1)* possible backtrackings the complexity of the first step in worst case is $O(n^2)$.

The second step leads to $\prod_{\alpha_i \in Gamma} |M_{\alpha i}|$ cycles in worst case. The number of exchanged messages in each cycle is *O(n),* in the whole step II the number of exchanged messages is $O(\prod_{\alpha_i \in Gamma} |M_{\alpha i}| * n)$.

7 Conclusion

We present an agent approach for the maximization of task utility response. Agents are cooperative. Each agent is given a set of alternative methods from the more approximate one to the more precise. The treatment of tasks is done progressively from agent of level 1 to agent of level *k*. The architecture of our system is then structured in levels. To respect task deadline, one or more levels, represented by agents, can be skipped except the first level represented by the mandatory agent α_1.

The target system is flexible and can adapt itself to the load of each agent for responding to tasks in delays. Responses will be of quality less or better depending on the methods that has been used.

Works on agent coordination under time constraints in dynamic environment using progressive reasoning paradigm were already been proposed like PGPP [6] [7], PGFS [5].

In these approaches agents are self-interested and share a common environment. Each agent decomposes its goal in PLPs and controls them. In our proposition agents have a limited rationality. Our approach is an “agentification” of reasoning level where each agent is equipped with multiple methods. Agents interactions lie on communicating their temporal information so that they can plan downstream.

Our approach tries to maximize utility of responses to tasks; the quality of the response depends on the quality of treatments given to tasks performed by agents.

These treatments consist in progressive improvement of the quality of task solution. The progressive treatment of each task is distributed among agents; this remains central in each agent in PGPP and PGFS.
In this paper we did not address the execution of the task and hence we don't address how agent react when the *End Time* of an executed method is earlier than expected. Recall that agents plan using the worst-case performance of their methods, this leads to not use resource efficiently even if the expected cost of the coalition will always respect the task deadline in worst-case. Furthermore our cooperative task scheduling relays on uncertain information. To deal with unexpected situation we need additions to the scheduling algorithm and monitoring of method performance. Particularly, when an agent opt out for the treatment of a given task, because of its minimal utility, which relay on uncertain information. When it detects that it has over estimated its response time, we want to give it the possibility to repair by asking to join the coalition with its new temporal constraints.
Another solution to explore is to distribute each method among agents. We have one method by agent. At this moment, the problem is resumed to make two types of coalitions, the first one is selective which choose one agent among a set of agents which have similar methods but different in their performances. The other type is associative, it concerns agents already selected in the first step.

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