A Game Theoretic Approach to Decentralized Multi-Project Scheduling
(Extended Abstract)

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ABSTRACT

In this paper we demonstrate how decentralized multi-project scheduling problems can be solved efficiently by a group of project manager agents playing a simple sequence learning game. In the multi-project scheduling problem, multiple projects, each having a number of activities, must be scheduled. A set of local and global resources are available for carrying out the activities of the projects.

It is shown that the sequence learning game improves the best objective function value found (minimal average project delay). In fact, the combination of local reinforcement learning, the sequence learning game and a smart forward-backward implementation of the serial scheduler realizes, on average over all MPSPLIB benchmark instances, a 25% improvement on the best published results.

Categories and Subject Descriptors

I.2.1 [**Distributed Artificial Intelligence**]: Intelligent agents; I.2.8 [**Problem Solving, Control Methods, and Search**]: Scheduling

General Terms

Algorithms, Experimentation

Keywords

Multi-Project Scheduling, Reinforcement Learning, Game Theory

1. INTRODUCTION

Collaborative project management is becoming quite common in today's globally active industries. Nowadays enterprises collaborate simultaneously with different customers or partners in projects with scarce and shared resources. It helps to accelerate product development, reducing cost, and increasing quality. However, it requires careful scheduling of overlapping tasks with possibly competing resource requirements. This is exactly the focus of the decentralized resource constrained multi-project scheduling problem (DRCMPSP), which is a generalization of the familiar resource constrained project scheduling problem (RCPSP).

In the DRCMPSP, a set of n projects has to be planned simultaneously. For each project the following information is given: an earliest release date, a set of jobs or activities, precedence relations between the jobs and a set of local renewable resources. On top of these, some global renewable resources are available, which have to be shared by all projects. Each project is planned in a decentralized way by an autonomous and self-interested decision maker, that is often a project manager who has the local objective to minimize the makespan or project delay of his project. The makespan of a project is defined as the difference between the project's finishing date and the project's arrival date, while the project delay is defined as the difference between the project's makespan and the critical path duration[1]. However, the local objectives of the managers are usually in conflict with one another. Indeed, jobs of different projects may require the same shared resource at the same time. In order to enable comparing alternative solutions of a given DRCMPSP, some local and global performance criteria are defined. Commonly used criteria are the Total Makespan and the Average Project Delay. The latter will be the focus of this paper.

Multi-agent systems are frequently used as a solution mechanism for solving the DRCMPSP. In [1] a multi-agent system model, and an iterative combinatorial auction mechanism are proposed to solve the DRCMPSP. In [2] large multi-project instances are solved by integrating a metaheuristic called the centralized restart evolution strategy, with an efficient decentralized electronic negotiation mechanism. These results were further improved in [3].

Rather than letting all the project managers negotiate for each single activity to be scheduled, we let them coordinate through learning a simple sequence game managed by a trusted third party or mediator agent.

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[1]The critical path duration can be determined using the well known critical path method. It is a lower bound for the project makespan.

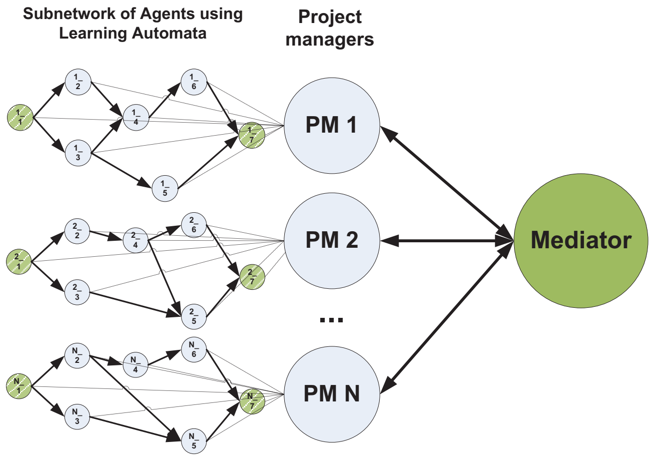

Figure 1: Multi-Agent Configuration

2. DECENTRALIZED MULTI-PROJECT SCHEDULING

The global multi-agent configuration is shown in Figure 1. A solution to the DRCMPSP is built by a serial schedule generation scheme, which is adopted from (single) project scheduling [4]. Instead of giving the serial scheduler one activity list, as is the case in project scheduling, we now pass it a sequence of activity lists, one for each project. The observation we make is that the way the different activity lists are ordered in this sequence has a non-neglectable effect on the quality of the resulting schedule[2]. Since the projects can only have a unique place in this sequence, the game we formulated is in fact a dispersion game. As such, the goal of each project manager boils down to building an efficiënt precedence feasible activity list locally, and learning a suitable place in the overall sequence of activity lists. In the method we developed, both goals are learned simultaneously and iteratively by using a global reinforcement signal, i.e. the average project delay of the schedule that was generated at the previous time step. Locally, the project managers use a network of simple reinforcement learning devices called learning automata [5] for learning an efficient activity list. This technique was previously developed in [6] for the single project version. The sequence game is played using a probabilistic version of the Basic Simple Strategy (BSS), which guarantees the players to coordinate within logarithmic time.

3. RESULTS AND DISCUSSION

To evaluate the developed approach, we use the same 140 (60+80) DRCMPSP instances as in [3], which are available from the Multi-Project Scheduling Problem Library (`http://www.mpsplib.com` last check of address: 6 October 2009). The results for these instances are shown in Table 1.

We show that a sequence learning game approach has a large positive effect on the minimization of the average project delay. In fact, the combination of local reinforcement learning, the sequence learning game and a smart forward-backward implementation of the serial scheduler improves the best known results for all the MPSPLIB problem subsets with about 25% on average. It is interesting to notice that for the very large instances (up to 20 projects with each 120 activities to be scheduled) the improvements, that we achieve with respect to the state of the art are even better (up to 47%).

[2]This may seem counter intuitive, since all projects should benefit from being scheduled first. However, projects have different release times and some projects suffer more from being scheduled late than others.

Problem subset	Best in the literature (average APD)	This paper (average APD)	Percentual Difference
MP30_2	12.4	11.2	9.7%
MP90_2	5.6	5.3	5.4%
MP120_2	60.8	49.5	18.6%
MP30_5	16.7	15.4	7.8%
MP90_5	8.9	7.8	12.4%
MP120_5	65.1	48.5	25.5%
MP30_10	84.4	52	38.4%
MP90_10	50.6	31.8	37.2%
MP120_10	143	100	30.1%
MP30_20	177.8	111.4	37.3%
MP90_20	30.4	17.6	42.1%
MP120_20	31.8	28.2	11.3%
MP90_2AC	127.8	104.3	18.4%
MP120_2AC	50.2	35.2	29.9%
MP90_5AC	287.8	244.6	15.0%
MP120_5AC	247.5	178.8	27.8%
MP90_10AC	244.9	169.4	30.8%
MP120_10AC	151	96.9	35.8%
MP90_20AC	161.8	85.4	47.2%
MP120_20AC	237.1	158.6	33.1 %

Table 1: Comparison with the best results in the literature

4. REFERENCES

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