# Project Scheduling in Complex Business Environments

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## Introduction

Project scheduling is a common management problem for modern business organizations to deal with on a daily basis, to arrange, control and optimize their business processes. Schedule quality has a direct impact on the business competitiveness. Unfortunately, it is well known that project scheduling problems are hard to be solved optimally, especially for large-scale practical problem instances. Driven by the scientific and business value, project scheduling has been widely studied by researchers from the communities of both Operations Research (OR) and Artificial Intelligence (AI), and a variety of approaches have been successfully developed and applied to solve real-world problems.

Traditionally, project scheduling is considered as a centralized and deterministic problem. However, today's manufacturing and management have entered into a more open and dynamic environment, which jeopardizes the effectiveness of traditional approaches and makes scheduling problems even harder to solve. My thesis aims at addressing several variations of the Resource-Constrained Project Scheduling Problem (RCPSP) in complex real-world environments. Till now, we have been working on solving two specific problems: 1) decentralized multi-project scheduling, and 2) proactive project scheduling under time-dependent activity duration uncertainty. We tackle the first problem by designing an efficient multi-unit combinatorial auction based approach to handle the decentralized scheduling requirement, while for the second problem, we employ a sampling based approach to exploit the probability knowledge of the uncertainties. In the remaining part of this abstract, I will give a brief introduction of these problems and our approaches.

## Decentralized Multi-Project Scheduling

Most corporations need to manage multiple projects in parallel. If all projects are controlled by a single manager, the problem of multi-project scheduling can be simply reduced to a RCPSP. However, this centralization assumption is violated quite often nowadays, since multiple self-interested decision makers with different individual objectives may be involved in the decision making process, due to the frequent intra- and inter-firm collaborations. Against this background, the Decentralized Resource-Constrained Multi-Project Scheduling Problem (DRCMPSP) has been proposed (Confessore, Giordani, and Rismondo 2007). DRCMPSP models a decentralized decision making environment, where each project is controlled by a Project Agent (PA), who need to compete for some shared global resources with limited capacities. Usually the PAs are coordinated by a Mediator Agent (MA) to find a conflict-free global resource allocation. However, PAs may be reluctant to share information of their projects (e.g. activity durations and resource requirements), since they could be rivals in the same market.

Market-based approach, especially Combinatorial Auction (CA), is an ideal paradigm for solving DRCMPSP, since it only requires PAs' high-level values on the resources, instead of low-level project details. However, existing CA based approaches, e.g. (Wellman et al. 2001; Confessore, Giordani, and Rismondo 2007), all suffer from scalability issue. Several approaches are scalable (Adhau, Mittal, and Mittal 2012; Zheng et al. 2014), but they are based on activity-level adjustment techniques, which inevitably require activity level information.

In (Song et al. 2016), we design a scalable approach for solving large DRCMPSP instances based on multi-unit CA, where PAs act as bidders, the MA acts as the auctioneer, and the selling items are the global resources in each time slot. The allocation problem of CA is well known to be NP-Complete. When apply CA to DRCMPSP, additional complexity is introduced due to the intractability for a PA to evaluate the combinations of items (multisets)[1]. To alleviate the computational burden of the agents, our approach employs an iterative auction process. In each auction round, each PA submits a bid that maximizes its utility. We show that it is sufficient for a PA to bid for a special type of multisets called cores, which is a compact resource utilization profile and can be easily generated from a feasible schedule obtained by solving a bidding problem using a fast polynomial-time algorithm we designed. Then, MA grants the bid according to the descending order of the average price heuristic (Gonen and Lehmann 2000), until no feasible allocation is available. The iterative auction process terminates when all PAs are allocated. Our approach runs in polynomial-time, and can pro-



[1]Essentially, this is because to compute an exact value of a given multiset, a bidder need to solve a RCPSP which is NP-hard.

duce solutions with lower Average Project Delay (APD), a commonly used criterion for DRCMPSP, compared to state-of-the-art approaches. In a later work, we extend the previous one in two aspects. Firstly, we theoretically prove the relation between the solutions of the auction and DRCMPSP. Secondly, we consider the bidding problem as a query to the bidders to elicit their values on certain multisets, and develop a branch-and-bound process based on these queries to find the optimal bidder granting sequence.

## Proactive Project Scheduling under Time-Dependent Duration Uncertainty

Traditional approaches for deterministic project scheduling consider the durations of activities as fixed. However, in most of the real-world environment, the activity durations are uncertain due to various reasons (e.g. unexpected disruptions, resource availability, weather conditions). Though it is possible to generate the schedule during execution in an online fashion, a proactive schedule that is generated before execution is considered very valuable in providing visibility for coordinating the execution process. Proactive project scheduling refers to a class of approaches that generate a baseline schedule by exploiting the probability knowledge about the activity duration uncertainty.

Most of the existing proactive project scheduling approaches, e.g. (Fu et al. 2012; Varakantham, Fu, and Lau 2016), are all based on the assumption that the activity duration can be modeled as a random variable that is not related to the scheduled time period of the activity. However, this assumption may be violated in many real-world scenarios. A typical example is when the activity durations are affected by the weather conditions (e.g. temperature, humidity, wind speed). Due to seasonality, the activity durations could be affected differently based on their scheduled time intervals.

Currently, we have developed a sampling based approach for proactive project scheduling under time-dependent duration uncertainty, based on the Consensus method from the literature of stochastic optimization (Hentenryck and Bent 2009). This is motivated by a real-world problem of scheduling an aero engine testing project, which involves a set of outdoor testing activities that are sensitive to the weather condition. Our assumption is that the scheduling horizon can be split into a set of periods (e.g. seasons, months, weeks) where the probability of the duration being affected by the weather is the same. Following the general paradigm of Consensus, our approach first samples a set of scenarios from the distributions. Then, for each period, a Consensus process is conducted to determine a set of activities to be scheduled in this period, along with their start and end times. Each Consensus process consists of two stages: 1) the Solving stage which solves each scenario as a deterministic problem, and 2) the Voting stage which makes the scheduling decisions according to a Consensus vote of the scenarios. Our approach runs in polynomial time, and experimental results show that the solutions are good both in quality and stability, two major criteria for evaluating proactive schedules.

In the future, I plan to develop a general sampling based approach which does not rely on the current assumption of horizon splitting, and can be applied to more complex probability models of activity duration uncertainties. This approach is based on the Sample Average Approximation (SAA) method (Kleywegt, Shapiro, and Homem-de Mello 2002), which provides a framework with converging guarantee for solving stochastic optimization problems through sampling. Also, instead of generating a start time schedule, I intend to change the solution form of the SAA based approach to the Partial Order Schedule (POS) (Policella et al. 2004) which is more flexible than start time schedule in coping with uncertainties. Currently, I have formulated the SAA optimization problem. For the future work, I will focus on designing a branch-and-bound algorithm to find the optimal POS, which provides a good approximation to the proactive scheduling problem, as guaranteed by the property of SAA.

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