Solving a real-life robust multi-skill resource-constrained multi-project scheduling problem

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1 Introduction

In this work, a robust real-life multi-skill resource-constrained multi-project scheduling problem is modeled and solved. The problem is motivated by the scheduling problem faced by the ten heavy maintenance centers of SNCF, the French national railway company, where trains are renovated and modernized and different components, such as electronic cards, bogies, axles and rotors, are repaired. Several rolling stock units are maintained simultaneously, and each unit is considered as a project. To complete each project, a set of activities that require resources with different skills must be performed. Different types of resources (maintenance operators and machines) with different characteristics and constraints are taken into account (see [5]). In the context of heavy maintenance, many operations are performed by human operators and estimating the required workload is not easy. Moreover, uncertain tasks, with a known probability to be required or not, should also be considered. Ignoring these uncertainties may lead to schedules of poor quality under real conditions [2].

To build robust schedules, involving hundreds of projects and thousands of operations, scenarios with a limited budget of uncertainty (see [1]) are embedded into the memetic algorithm proposed in [5]. The objective is to maximize the probability of meeting the customer deadlines.

2 Uncertainties and generation of scenarios

To generate robust schedules, we first start by defining scenarios based on historical data analyses. For uncertain tasks, we compute the probability of having to perform the task or not. In each scenario, an uncertain task has either a workload equal to zero with a probability of p_1, or a non-zero workload with a probability of p_2 (where $p_1 + p_2 = 1$). Similarly, to handle poor workload estimation, we define several realization modes for a given task. Each mode has a different workload and an associated probability of occurrence.

As many uncertainties are observed, the generation of all possible scenarios is computationally intractable. Using the worst scenarios to determine a robust schedule is (in most of the cases) very pessimistic and over-conservative [2]. Furthermore, the chances that all activities take their worst modes are nearly zero. Generating a subset Ω of random scenarios using the probabilities associated to each mode and each task could be a potential solution. However, this leads to the same issue as when generating all scenarios. In fact, a huge number of scenarios must be generated to effectively capture uncertainties, and computing a robust solution with a lot of scenarios poses significant computational challenges. Considering that our primary objective is to tackle large industrial instances, we limit ourselves to a subset of scenarios with a specified uncertainty budget [1]. To better represent reality, distinct uncertainty budgets $\Gamma_{r,k,t}$ are defined and computed using historical data for each resource r, skill k and period t. By increasing the budget of uncertainty, the approach tends to be more conservative and, for large enough $\Gamma_{r,k,t}$, it is similar to considering worst-case scenarios. More precisely, $\Gamma_{r,k,t}$ defines the following uncertainty polytope : $\Theta_{r,k,t} = \{\phi_{a,r,k}, a \in A/ES_a = t, \sum_{a\in A}(\phi_{a,r,k} - \bar{\phi}_{a,r,k}) <= \Gamma_{r,k,t}\}$, where $\phi_{a,r,k}$ (respectively $\bar{\phi}_{a,r,k}$) is the chosen (respectively deterministic) workload for activity $a \in A$, resource r and skill k, and ES_a is the earliest starting time of activity a. Note that, to generate scenarios, the scheduling horizon H is divided into months. The general idea is to model the variation of the task workload in a typical month, transitioning from the planned values to those observed in historical data.

3 Solution approach

To address this large industrial problem, an efficient memetic algorithm (MA) was implemented for the deterministic problem. The proposed MA combines a genetic algorithm (GA) for diversification and a simulated annealing algorithm (SA) used for local search [5]. The same algorithm was adapted to compute a robust schedule that maximizes the probability of meeting the rolling stock due dates. Given a set of scenarios Ω and a sequence S (representing an assignment and a sequence of tasks), this probability is defined as the tardiness service level (following [3] and [4]) and can be written : $\alpha(S, \Omega, e) = \mathbb{P}(T_e(S, \Omega) = 0)$ for rolling stock unit e. As we deal with several projects (i.e rolling stock units), and since the projects do not have the same priority, the weighted sum of the tardiness service level of the rolling stock units is maximized : $\alpha(S, \Omega, \mathcal{E}) = \sum_{e\in\mathcal{E}} w_e \mathbb{P}(T_e(S, \Omega) = 0)$, where w_e is the weight of project $e \in \mathcal{E}$.

The initial solutions are computed using the deterministic data and the original memetic algorithm. Then, the service level of each initial solution is evaluated and further improved using the memetic algorithm. Preliminary results show that schedules with a very good service level can be computed in few iterations, even if the service level of the initial solutions is very poor.

4 Conclusions

An original robust multi-skill resource-constrained multi-project scheduling problem is addressed. Different uncertainties are considered and modelled using scenarios defined with a budget of uncertainty and real data. An adaptation of a memetic algorithm proposed for the deterministic problem is proposed to determine robust schedules. Computational experiments are being conducted, the results of which will be discussed at the conference.

Références

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