Scheduling and Coordination of Distributed Design Projects

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Abstract

In the era of time-based competition, companies are tending to distribute product design across regions to cut short design cycles and better penetrate local markets. This distributed design involves many uncertainties and risks, and generating good decentralized schedules and effectively coordinating distributed activities without intruding organizations' propriety information and decision-making authorities are important and challenging. This paper studies the scheduling and coordination of distributed design projects with uncertainties while managing design risks. A novel mathematical optimization model that balances modeling accuracy and computation complexity is presented, and a solution methodology that combines Lagrangian relaxation and stochastic dynamic programming is developed. Numerical results demonstrate that near optimal solutions are obtained, and uncertainties are effectively managed for problems of practical sizes.

Keywords: Scheduling optimization, Distributed design project, Coordination

1. Introduction

A short product design cycle is critical to the success of companies in the era of time-based competition. The completion of design projects is required to be on time, predictable, and with small fluctuation. The underlying design activities, however, are often interlinked and quite uncertain. Time-critical projects may also suffer the risk of failure if they cannot meet established deadlines. These uncertainties and risks often have major impact on the commitment of designers and resources and on project completion. A recent trend is for companies to distribute product design activities across regions to cut short design cycles through "round-the-clock/round-the-globe" development and to better penetrate local markets (Krause et al., 1994). This distributed design, however, involves more uncertainties and is riskier than a centralized one because of complicating factors such as location, time zone, language, and cultural differences; communication and coordination requirements; and individual organization's proprietary information and decision-making authorities. Generating good and robust schedules and effectively coordinating these activities are thus critical, especially under the concurrent engineering paradigm where the delay of a single task may have a domino effect on subsequent tasks and on other projects sharing designers and/or resources. Effectively scheduling and coordinating multiple distributed projects and managing risks, however, are extremely difficult because of the complicating factors mentioned above.

Literature Review. In project scheduling, traditional methods such as Program Evaluation and Review Technique (PERT) and Critical Path Method (CPM) ignore resource capacity. To handle finite resources, major efforts have been concentrated on developing heuristic procedures to obtain "satisfying" solutions because the problems are a generalization of the NP-hard job-shop scheduling problems where the computational requirements for obtaining an optimal solution grow exponentially as the problem size increases (Patterson, 1984). To deal with projects having probabilistic routings and repetition of activities, Graphic Evaluation and Review Technique (GERT) has been introduced. Optimal solutions are difficult to obtain for problems with precedence constraints except for a few specialized cases (Neumann, 1990). Risk analysis models and methods for project management have been presented in Cooper and Chapman (1987). Not many results have been obtained for simultaneously scheduling projects and managing risks. To manage and coordinate distributed design, Seliger et al. (1997) developed a method based on network theory by using circuits to describe the flow of information. In Luh et al. (1997a), an optimization-based method was developed for scheduling collocated design projects with uncertain number of design iterations while managing risks.

Overview of the Paper. This paper studies the scheduling and coordination of design projects while managing risks in an uncertain environment, where a decentralized corporation concurrently pursues multiple projects distributed across its divisions. The study is motivated by the development of a scheduling and coordination system for distributed helicopter design, and our goal is to obtain near optimal solutions with quantifiable quality in a computationally efficient manner. In Section 2, an optimization model that balances modeling accuracy and solution complexity is presented. In Section 3, a solution methodology that combines Lagrangian relaxation, stochastic dynamic programming, and heuristics is developed. Numerical results in Section 4 show that near optimal solutions are obtained, and uncertainties are effectively managed for problems of practical sizes.

2. Problem Formulation

The decentralized corporation considered consists of multiple *divisions*, and each division has a finite number of designers of distinct capabilities and resources of different types. For simplicity of presentation, both designers and resources are modeled as *generic resources* with given functionality. Since these resources may be distributed across locations of different time zones, they are available at different hours. Multiple design *projects* are pursued by the corporation, and Project p has a due date and is divided into *subprojects* based on overall product design strategy. Without loss of generality, it is assumed that a subproject is associated with a particular division. In the following, an integer optimization problem is formulated based on what was presented in Gou et al. (1997) for deterministic and distributed manufacturing scheduling with the following new features: simultaneous requirements of multiple types of resources by a task, time zone differences, coordination requirements, project uncertainties, and design risks.

Corporation Level. From the decentralized scheduling viewpoint, a division is responsible for scheduling resources and subprojects within its responsibility, and the corporation coordinates these schedules across divisions without intruding individual division's proprietary information and decision autonomy. This two-level structure is shown in Figure 1.

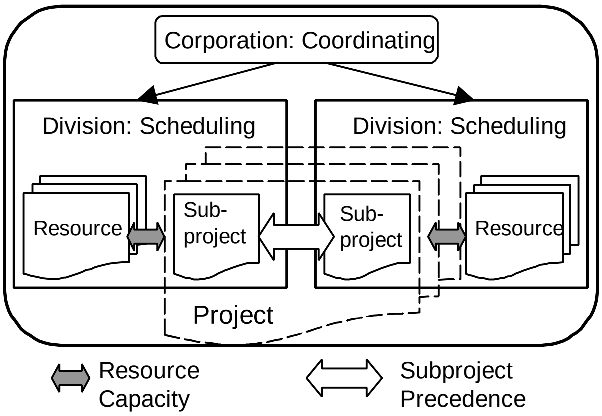

Figure 1. Decentralized Scheduling Structure

In a project, subprojects can be performed in parallel, subject to precedence constraints. As shown in Figure 2, a particular subproject may be required to be integrated with another subproject, and the design result of a particular subproject may be needed by several other subprojects. For some projects, their due dates may not be known exactly in advance because of the changing markets. These uncertain due dates and other division level uncertainties to be explained later are modeled as independent discrete random variables with given distributions. Subproject precedence constraints are corporation-wide constraints coupling various divisions together, and are difficult to handle for various realizations of random events. They are thus required to be satisfied in the expected sense to reduce solution complexity, and to reflect the common practice in coordinating distributed uncertain activities.

As mentioned earlier, some time-critical projects may fail and be dropped out of consideration if they cannot meet established deadlines. Such a risk is captured by a "failure penalty" R_p when Project p cannot be completed before a given "hard deadline." This penalty depends on the importance of the project (opportunity cost) and the status upon failure (cost foregone). The penalty R_p is thus the sum of these two costs which can often be estimated and are assumed given here.

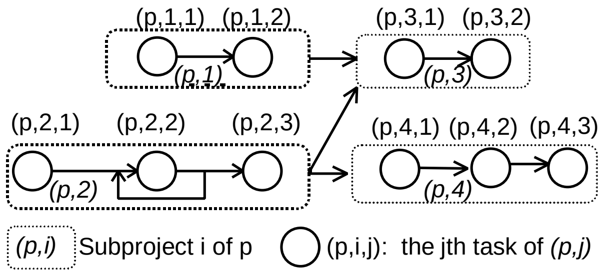

Figure 2. A Simplified Design Project p

The goal of scheduling and coordination is to meet on-time project completion with small fluctuation, discouraging starting earlier than necessary, and reducing project failures. Minimizing the variance of project completion is required for robust scheduling. Since this variance minimization is recognized to be NP-hard (Kubiak, 1993), it is indirectly handled by reducing the deviation between projects' completion and their due dates. The objective function is thus to minimize the expected total cost J, including penalties for late/early completion, starting too early, and project failures. The expectation is taken with respect to all uncertainties considered and random decision variables.

Division Level. In a division, each subproject is further broken down into a series of inter-related *tasks* (Figure 2). A task may simultaneously need resources of different types for a specified amount of time, and the total number of resource units allocated to tasks cannot exceed the resource capacity per type. The processing time may substantially vary from estimates because of the creative nature of design. Iterations of a task may also occur when the result of the task fails to meet design specifications. Task/iteration precedence constraints and processing time requirements are required to be satisfied for each possible realization of uncertainties for modeling accuracy, and division-wide coupling resource capacity constraints are required to be satisfied in the expected sense for reducing the solution complexity (Luh et al., 1997a). The communication and coordination efforts needed between interdependent tasks are captured as additional time required with lengths depending on the coordination efforts needed. With different working hours across time zones, the resources' off-duty time are explicitly modeled in the formulation. The scheduling objective function at a division is derived from the corporation objective after subproject precedence constraints are relaxed by using Lagrangian relaxation to be explained in Section 3. This objective function is to be minimized by selecting appropriate task/iteration beginning times and resources, subject to the constraints mentioned above.

Since coupling constraints can be modeled as linear equalities or inequalities and the objective functions are additive in terms of decision variables, the problem formulation is "separable" at both levels. This separable formulation is essential for Lagrangian relaxation.

3. Solution Methodology

Similar to the pricing concept of a market economy, the Lagrangian relaxation (LR) method replaces coupling subproject precedence constraints by "soft" prices (Lagrange multipliers) for precedence violations, and the original problem can be decomposed into smaller and easier division subproblems. The derived division objective function includes the corresponding project costs from the corporation level, and the costs for violating subproject precedence constraints.

Within each division, a division subproblem is further decomposed into subproject subproblems by replacing the coupling resource capacity constraints by prices (multipliers) for the use of resources at each time. After solving these subproblems by using stochastic dynamic programming to be explained later, the resource prices or multipliers are iteratively adjusted by using a conjugate subgradient method (Gou et al., 1997) based on the degree of capacity constraint violations, following again the market economy mechanism. Subproblems are then resolved using the new set of multipliers.

To solve subproject subproblems, the stochastic dynamic programming (SDP) algorithm of Luh et al. (1997a) is extended. In the SDP, a stage corresponds to one iteration of a task, and within each stage, states are possible iteration beginning times. Task and iteration precedence constraints are embedded in SDP paths for all possible realizations of random events, and state transitions are governed by probabilities and scheduling decisions. Project failure penalties are embedded within stage-wise costs so that risks are managed by appropriately trading off failure penalties vs. other costs. Time zone differences are explicitly considered where a task can only be started within the working hours of the assigned resources, and the resources' off-duty time is considered in calculating the task's completion time. The complexity of this SDP algorithm is only slightly higher than that for the deterministic centralized scheduling (Luh et al., 1997c).

After division subproblem solutions are obtained, the precedence prices (multipliers) relaxing subproject precedence constraints are iteratively updated by using the same conjugate subgradient method based on the degree of precedence constraint violations. Division subproblems are then resolved. This two-level decomposition and coordination naturally maps LR onto the decentralized scheduling structure. Without intruding divisions' proprietary information and decision-making authorities, division schedules are coordinated by modifying their objective functions according to the precedence prices.

The above optimization process is stopped after a fixed amount of computation time, a fixed number of multiplier updating iterations, or when an optimal solution has been detected. The solutions of individual subproblems, when put together, may not constitute a feasible schedule since coupling constraints have been relaxed. A feasible schedule is dynamically constructed by using a heuristics based on subproblem solutions and the realizations of random events. Rescheduling can be performed periodically or after a major random event occurs, and better results can be achieved without much extra computation time if previous multipliers are used.

It has been proved that a corporation level dual cost D is a lower bound to the optimal expected feasible cost J* (Luh et al., 1997b). The relative duality gap (J-D)/D thus provides measures of the quality of schedules obtained.

4. <u>Testing Results</u>

The method has been implemented in C++, and testing has been performed on a Pentium Pro200 personal computer. Two examples are presented to demonstrate the performance of the algorithm implemented (denoted as A1). For comparison purpose, two other algorithms (denoted as A2 and A3, respectively) are also used. In the deterministic algorithm A2, all random variables are replaced by their means, and the converted deterministic problem is solved by using the approach of Gou et al. (1997). In the centralized algorithm A3 (Luh et al., 1997a), the corporation is responsible for all divisions' scheduling. The three algorithms use the same heuristics to dispatch tasks without rescheduling.

Example 1: This example is to show the impact of complicating distributed design factors. A corporation has two divisions D1 and D2 each working eight hours per day. D1 has two resource types 1 and 2 each with a single unit, and its time zone is 12 hours earlier than that of D2 which has a single unit of type 3 resource. As summarized in Table1, three projects are to be scheduled over a six-day planning horizon from the beginning of a working day for D1. The time unit is 1 hour, and t_{pij} is the processing is abbreviated as (p,i,j). Task (1,2,1) may complete in one iteration, or it may require a second iteration with a probability P = 0.2. In projects 1 and 2, subprojects are performed sequentially, e.g., task (2,2,1) can only be started after the completion of (2,1,1). Three cases are presented in the following where it can be shown by exhaustive search that A1 generates the optimal schedules.

Table 1. Data of Example 1

Project	Due date	Task	Resource needed	t_{pij}
1	20	(1,1,1)	1	8
		(1,2,1)	3	12
		(1,2,1)	3	10
2	20	(2,1,1)	2	8
		(2,2,1)	3	14
3	30	(3,1,1)	2	4
		(3,1,2)	1	4

Case 1. Four time zone differences (0, 6, 12, and 16 hours) between D1 and D2 are considered, with results shown in Figure 3. When D1's time zone is earlier than that of D2, the expected costs J are smaller than that of zero hour difference. This is because that the second subprojects of Projects 1 and 2 are performed at D2, and design cycles can be cut short through the "round-the-clock" development. To analyze the impact of coordination requirements among distributed tasks, the problem is re-tested where these requirements are captured as 1, 3, and 5 hour coordination time, respectively, and results are shown in Figure 4. It can be seen that coordination efforts have a major impact on the project completion. In both tests, the costs of A1 are either lower than or the same as those of A2, and this will be further examined in Case 2.

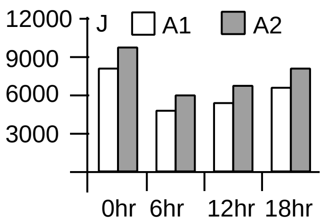

Figure 3. Expected cost for different time zone

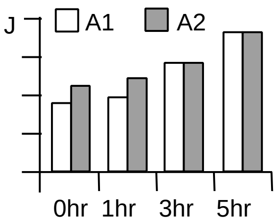

Figure 4. Expected cost for different coordination

Case 2. This case is to show that A1 can generate good schedules under various uncertainties. By changing the iteration probability P to 0.1, 0.4, and 0.6, testing results are shown in Figure 5 where results of A1 are better than or equal to those of A2. The reason is that A2 handles uncertainties based on their mean values, and cannot adequately manage the realizations of individual events.

Case 3. To show the effect of managing design risks, it is assumed that Project 1 will fail with a penalty R_1 if task (1,2,1) cannot be completed before deadline 90. With R_1=500, 5000, and 50000, the results are shown in Figure 6. Compared with A2, A1 can accurately trade off failure penalties vs. late/early completion penalties to get better schedules since it can effectively handle uncertainties.

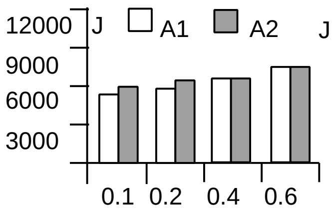

Figure 5. Expected cost for different Probability P

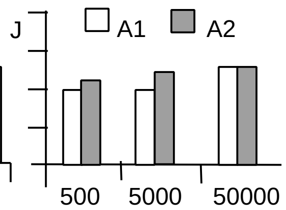

Figure 6. Expected cost for different Risk Penalty

Example 2: This example is to demonstrate that the method's ability to solve large size problems. The data was drawn from an industry partner, and uncertainties are contrived based on a preliminary analysis of the distributed helicopter design. There are 45 units of 18 type resources distributed at 3 divisions across two different time zones. Forty-seven projects are to be scheduled over a planning horizon of 160 time units, with 24 projects having uncertainties. The projects consist of 55 subprojects that are decomposed into 292 tasks, with a total of 2888 multipliers. The results after running the algorithms for 3 minutes are summarized in Table 2 with dual cost (D), expected cost (J), duality gap (Gap), and sum of project completion variances (σ^2), where J and σ^2 are estimated by 1000 Monte Carlo simulation runs.

These results show that A1 can provide better schedules than those of A2 in a computationally efficient manner. Compared with A3, A1 can generate good schedules without much loss of quality while maintaining divisions' proprietary information and decision autonomy. The computation time for A1 can be further reduced by solving individual division subproblems in parallel.

Table 2 Results of Example 2

Method	J	D	Gap	σ^2
A1	8248	7128	15.7%	688
A2	8900	7680	24.8%	1832
A3	7924	7216	9.8%	593

5. Concluding Remarks

A "separable" problem formulation and an optimization-based solution methodology are presented for scheduling and coordination of distributed design projects with uncertainties while managing design risks. A two-level Lagrangian relaxation framework is established to meet the requirements of limited information accessibility and individual decision-making autonomy. With a balance between modeling accuracy and computation complexity, the method can effectively solve problems of practical sizes in a timely fashion.

ACKNOWLEDGMENT. This research was supported by the National Science Foundation under grants DMI-9500037 and the United Technologies Research Center.

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