Proactive Project Scheduling in an R&D Department

A Bi-Objective Genetic Algorithm

Canan Capa
Mechanical and Industrial Engineering
Concordia University
Montreal, Canada
c_capa@encs.concordia.ca

Gunduz Ulusoy
Manufacturing Systems Engineering
Sabanci University
Istanbul, Turkey
gunduz@sabanciuniv.edu

***Abstract*—In this paper, we present part of a study on stochastic, dynamic project scheduling in an R&D Department of a leading home appliances company in Turkey. The problem under consideration is the preemptive resource constrained multi-project scheduling problem with generalized precedence relations in a stochastic and dynamic environment. The model consists of three phases. Phase I of the model provides a systematic approach to assess uncertainty resulting in activity deviation distributions. In Phase II, proactive project scheduling is accomplished through two different scheduling approaches, which employ a bi-objective genetic algorithm. Phase III is the reactive project scheduling phase aiming at rescheduling the disrupted project activities. Here, we will limit our presentation to Phase II – the proactive project scheduling phase. The procedure is demonstrated through an implementation with real data covering 37 R&D projects. Computational study is performed to compare the two different scheduling approaches called single and multi-project scheduling approaches, as well as two different chromosome evaluation heuristics. Results are presented and discussed.**

Keywords: Proactive project scheduling, multi-objective genetic algorithm, R&D

I. Introduction

In the last decades we observe a proliferation among others of research and development (R&D), engineering services, IT services and software development, infrastructure projects on a global scale, which increases the emphasis on project based management – particularly multi-project management. It is suggested that up to 90 %, by value, of all projects occur in a multi-project context [1,2]. For example, R&D organizations [3] and large construction companies regularly execute multi-project scheduling procedures [4].

During project execution, especially in a multi-project environment unforeseen events arise that disrupt project plans resulting in deviations of project plans and budgets due to missed due dates and deadlines, resource idleness, higher work-in-process inventory and increased system nervousness. Most of the studies in project scheduling literature assume complete information about the problem and develop scheduling methodologies for the static and deterministic project scheduling problem (see Hartman and Briskorn [5]). However, uncertainty is inherent in all project management environments. In reality, the situation is dynamic in the sense that new projects arrive continuously and stochastic in terms of inter-arrival times and work content. Furthermore, during project execution, especially in a multi-project environment project activities are subject to uncertainty that can take many different forms. Activity duration estimates may be off, resources may break down, work may be interrupted due to extreme weather conditions, new unanticipated activities may be identified, etc. All these types of uncertainties may result in a disrupted schedule, which leads in general to the deterioration of the performance measures. Thus, the need to protect a schedule from the adverse effects of possible disruptions emerges. This protection is necessary because a change in the starting times of activities could lead to infeasibilities at the organizational level or penalties in the form of higher subcontracting costs or material acquisition and inventory costs. Therefore, project schedules should also include solution robustness to cope with the uncertainties such that actually realized activity start times during project execution will not differ much from the baseline schedule.

Constructing solution robust schedules requires proactive scheduling techniques. With the risk information on hand, proactive scheduling aims at the construction of a protected baseline schedule that anticipates possible future disruptions by exploiting statistical knowledge of uncertainties that have been detected and analyzed in the project planning phase. The literature on proactive project scheduling is relatively scarce. The objective of minimizing the total weighted instability of the schedules from a given deadline is considered in [6]. Herroelen and Leus [7] develop mathematical models for the generation of stable baseline schedules. Van de Vonder et al. [8] propose resource flow dependent float factor heuristic as a time buffering technique to produce robust schedules relying completely on the activity weights. Lambrechts et al. [9] focus on disruptions caused by stochastic resource availabilities and aim at generating stable baseline schedules. Van de Vonder et al. [10] introduce multiple algorithms to include time buffers in a given schedule while a predefined project due date remains respected. The impact of unexpected resource breakdowns on activity durations is determined analytically and an approach for inserting explicit idle time into project schedules is developed in order to protect them from possible resource unavailability and presented in [11]. In addition to these proactive strategies, there are some risk-integrated procedures. Shatteman et al. [12] develop a methodology that relies on a computer supported risk management system that allows to identify, analyze and quantify the major risk factors and derive the probability of their occurrence and their impact on the duration of the project activities. Creemers et al. [13] propose a quantitative approach that allows addressing the risk response process in a scientifically sound manner and shows that a risk-driven approach is more efficient than an activity-based approach when it comes to analyzing risks. Herroelen [14] proposes a methodology that integrates quantitative risk analysis with reliable proactive/reactive project scheduling procedures.

We consider the preemptive resource constrained multi-project scheduling problem (RCMPSP) with generalized precedence relations in a stochastic and dynamic environment and develop a three- phase model incorporating data mining and project scheduling techniques to schedule the projects in the R&D Department of a leading home appliances company in Turkey. Phase I of the model, uncertainty assessment phase, provides a systematic approach to assess uncertainty by identifying the most important sources of uncertainty, measuring the impacts of these factors to resource usage deviation levels of projects and their activities and generating activity deviation distributions by using the most important data mining techniques: feature subset selection, clustering and classification. Phase II, proactive project scheduling phase, proposes two different scheduling approaches both of which employ a bi-objective genetic algorithm (GA). Phase III, the reactive project scheduling phase, aims at rescheduling the disrupted project activities. Basic framework of the three-phase approach is given in Figure 1.

In this paper, our focus is limited to Phase II of the three-phase approach. In Section II, the problem and the problem environment are explained. In Section III, we present the solution methodology and in Section IV we present the main results obtained by the implementation of the proposed proactive project scheduling approach with real data. Finally, in Section V we conclude and provide suggestions for future work.

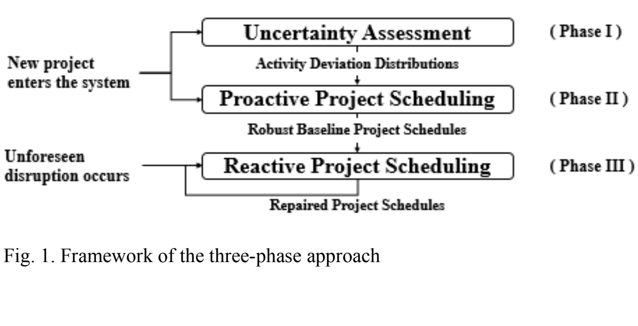

Fig. 1. Framework of the three-phase approach

II. PROBLEM DEFINITION AND ENVIRONMENT

The problem on hand is proactive scheduling of the R&D projects with a priori assigned resources in a stochastic and dynamic environment present in the R&D Department of a leading home appliances company in Turkey. The problem environment under consideration contains multiple projects consisting of activities using multi-skilled renewable resources. Projects are managed with a *stage-gate* approach and most of them are research-based projects. The department is organized in technology departments and these technology departments are comprised of technology families each of which works on a different technology field. Each technology family has a technology family leader who is responsible for all the resources that work under the corresponding technology family.

A project consists of a number of events and activities that have to be performed in accordance with a set of precedence and resource constraints. Activities require two types of renewable resources: human resource and equipment. Equipment includes machines, mechanisms and laboratories. Non-renewable resources are not considered since in this problem setting they do not constitute a limitation. The problem environment under consideration contains multiple projects using multi-skilled renewable resources. The resource requirement of activities and hence, the durations of activities are uncertain. The project network is of activity-on-node (AON) type with Finish-to-Start (FS) and Start-to-Start (SS) precedence relations with zero or positive time lags. No precedence relation is assumed between projects. The problem on hand can be considered an extension of the RCMPSP with generalized precedence relations and multi-skilled resources to include preemption, stochastic activity duration and resource availabilities and dynamic arrival of projects. The objective is generating solution robust baseline project schedules and minimizing the completion time for the overall project makespan. Solution robustness is a measure of the difference between realized schedule and baseline schedule. In our case, we use total sum of absolute deviations *(TSAD)* for solution robustness. *TSAD* is sum of the absolute deviations between actual starting times and starting times realized in a set of K simulations over all activities.

The problem environment differentiates from those in the literature in that a resource is required for the duration of its usage within an activity rather than for the whole deterministic or stochastic duration of the activity requiring that particular resource. Resources can work on more than one activity in a time period (say, a week) and the duration of the usage of the resources can differ over the periods that the activity is executed. Additionally, the concept of preemption of a resource employed by an activity is also introduced.

III. SOLUTION METHODOLOGY

The main purpose of this study is generating robust baseline schedules for the projects of the R&D department by considering the uncertainty in the resource usages of projects and their activities. In this section, after briefly explaining

Phase I, the uncertainty assessment phase, we present a bi-objective GA that uses the output of the Phase I, and two scheduling approaches each using the bi-objective GA. These scheduling approaches are called the single and multi-project scheduling approaches. The aim of these approaches is to generate non-dominated solution robust project schedules with the minimum makespan for the completion of all projects scheduled. Solution robustness is measured with *TSAD* of the schedule through *K* number of possible schedule realizations in both approaches. The single and multi-project scheduling approaches differ in that the single project scheduling approach considers the remaining part of the schedules of the already active projects as fixed and schedules only the newly arrived project using the currently available resources, whereas the multi-project scheduling approach, schedules all the active projects in the system anew together with the newly arrived project. Since the two scheduling approaches differ in the way they adopt for the scope of scheduling, the definitions of *TSAD* and makespan, thus, the objectives considered in the bi-objective GA also differ although they both try to minimize *TSAD* and makespan. Note that in the proactive project scheduling approaches, a set of non-dominated robust project schedules are generated. From these non-dominated robust schedules, the decision maker can choose the schedule that best fits the current project management environment in the system. Proposed bi-objective GA is an adopted version of NSGA-II suggested in [14], which uses an explicit diversity generation procedure along with an elite-preservation procedure. An individual is represented by a precedence feasible activity list. We make use of one-point crossover and swap mutation operators. Population management is the same as of NSGA-II. However, our bi-objective GA differs in the schedule generation scheme and chromosome evaluation procedures.

A. *Uncertainty Assessment*

Uncertainty assessment is an essential step in proactive scheduling. Since the activities require working hours from resources, the main source of uncertainty in the activity durations is the uncertainty of resource usages of the activities. Therefore, to assess the uncertainty, we investigate the deviations of resource usages of projects and their activities. Uncertainty assessment phase suggests assessing the uncertainty of projects and their activities by classifying the projects with respect to their percentage resource usage deviations, then classifying the activities with respect to their percentage resource usage deviations, thus constructing a resource usage deviation assignment procedure for the prediction of the percentage resource usage deviation levels of the activities of a newly arrived project. Final output of this phase is deviation distributions for the activities of projects. It should be noted that, this phase is not problem-specific, i.e., can be implemented for any stochastic project scheduling problem. This phase of the proposed model is comprised of three steps: (i) Deviation Analysis of Projects, (ii) Project Deviation Class Prediction and (iii) Activity Deviation Prediction.

Step I of uncertainty assessment phase establishes classification models based on real data regarding the completed projects of the R&D Department. The input of this step consists of various features that are thought to be relevant for determining the percentage resource usage deviations of the projects and the values that these features take for each project in sample project set. In this step, first, with the application of feature subset selection algorithms, the most important features are determined, then clustering is applied to the percentage resource usage deviation of projects (numeric output) to generate actual nominal class labels of the projects. Clustering is needed since most of the classification algorithms work on nominal output rather than numeric output Afterwards; these nominal and numeric output values of the projects are used in the learning stage of classification model construction. For each feature subset and output combination, a classification model is constructed. Since this learning process depends on the sample project data, to decrease the bias on the selected sample project set Step I of the uncertainty assessment phase is reinitialized with an update in the sample project set whenever a project is completed in the system.

Step II of the uncertainty assessment phase predicts the deviation class of a newly arrived project based on its input features. In this step, instead of selecting the classification model that performs best on the given data, we propose to use all prediction results of different classification models obtained with WEKA and produce probabilistic predictions for the percentage resource usage deviation levels of the projects. Thus, we provide probabilistic membership of the projects to the predetermined percentage resource usage deviation classes. This approach is more robust than selecting a single classification model and making deterministic predictions, since providing a probabilistic prediction precludes the missing of the actual deviation class of projects and tolerates the error caused by model selection. Moreover, in reality, instead of making a class prediction, giving a closeness value to each deviation class is more understandable by the project managers. Thus, it makes sense both in terms of convenience of perception and correctness. With this step in the planning phase, that is to say before the project actually starts, predicting its resource deviation level can be possible, and the needed precautions can be taken. Since relationships between important features on the prediction of deviation classes are already identified to have a better understanding of the system in Step I, Step II, as a side contribution, enables project managers to make fine-tuning on the important feature values of the newly arrived project in order to bring the project's deviation at a desired level.

Using the project deviation class prediction, in Step III, we develop a model to predict the percentage resource deviation of the activities of this newly arrived project. The aim of Step III of the uncertainty assessment phase is to obtain percentage resource usage deviation distributions for each project deviation class - activity class combination to be used in the bi-objective GA. Therefore, Step III of the uncertainty assessment phase starts with the classification of all the project activities, thus forming a number of activity subsets. Forming a distribution requires sufficient number of replications. Since we deal with R&D projects and the activities of R&D projects are usually unique and the work content is characteristic among all activities, to obtain sufficiently large amount of data for a valid distribution of percentage resource usage deviation from the mean requirement, such an aggregation and classification is compulsory. For each activity class of a newly arrived project, using the percentage resource deviation information of already completed activities in the corresponding activity class and the deviation class prediction of this newly arrived project, we obtain the adjusted frequency information for each predetermined deviation intervals. The adjusted frequency information for an interval is obtained by summing the multiplications of activity numbers in each project deviation class with the probability of the membership of the newly arrived project to that project deviation class. After obtaining these adjusted frequency distributions, probabilities of an activity having a deviation level in each range is calculated and piecewise linear percentage resource usage deviation distributions of each activity class in the newly arrived project is formed. These distributions are used to assign percentage resource usage deviation level to the to-be-scheduled activities in the proactive project scheduling approach.

B. Bi-objective Genetic Algorithm

Proposed bi-objective GA is an adopted version of NSGA-II suggested by Deb et al. (2002), which uses an explicit diversity generation procedure along with an elite-preservation procedure. The GA framework of the procedure starts with the computation of an initial population. A chromosome is composed of a precedence feasible activity sequence list of the activities of the project network. The number of chromosomes in the population is referred to as N, which is assumed to be an even integer. After each chromosome is decoded as a schedule and each chromosome is evaluated. The population is then sorted based on the non-domination levels and each chromosome is assigned a fitness value equal to its non-domination level (1 is the best level, 2 is the next-best level, and so on) with respect to its objective function values. Thus, the aim is minimization of the fitness. After that, crowding distance of a chromosome is calculated and the population is partitioned into pairs of chromosomes using *binary tournament selection* as parent selection mechanism. To each resulting pair of chromosomes, we apply one-point crossover operator to produce two new (daughter d and son s) chromosomes. Subsequently, we apply *swap mutation* operator to the genotypes of the newly produced children. Since elitism is introduced by comparing current population with previously found best non-dominated chromosomes, the procedure is different after the initial generation. After computing the fitness of each child chromosome, we add the children to the current population. Then the population is sorted into different non-domination levels (frontiers) along with crowding distance calculation and the reduction process to reduce the population to its former size *POP* is applied. Thus, we obtain the next generation to which we again apply the crossover operator and so on. This process is repeated for a pre-specified number of generations, which is denoted as *Total Generations*.

In the following subsections, details of schedule generation and chromosome evaluation mechanisms are presented.

Schedule Generation

Since the work of resources on activities are preemptive, a schedule is represented with the lists of resource, activity, week and amount (r,a,t,k) quadruple. Each (r,a,t,k) quadruple shows that resource r works on activity a at time instant t for k working hours. Our resource schedule generation scheme starts with scheduling the resources of the first activity in the chromosome. Note that, resource order for scheduling is not important since all orders give the same work schedule for that activity. Considering the earliest precedence feasible starting time of activities and starting at the first available time instant, resources are scheduled until they reach their required usage hours. After all the resources of the first activity in the chromosome are scheduled, starting and ending time of that activity is determined by simply checking the work schedules of the resources that activity requires. Then, the earliest starting time of the successor activities are updated. This procedure is repeated until all the activities in the chromosome are scheduled.

Chromosome Evaluation

For a given order of activities both the overall makespan and solution robustness are assessed through a set of K realizations mimicking the implementation phase, where a realization corresponds to a sample instance obtained by a simulation run using the activities' percentage resource requirement deviation distributions, which is determined calling Phase I of the three-phase approach. For this purpose, two alternative chromosome evaluation heuristics with the objective of quality robustness represented with makespan and solution robustness expressed in terms of *TSAD* value of the robust activity starting times from their counterparts in all K realizations, are considered: chromosome evaluation heuristic I (*CEH-I*), and chromosome evaluation heuristic II (*CEH-II*). *CEH-I* solves a *TSAD* minimization model by LP. Using the activity starting times realized in simulations, this *TSAD* minimization model aims at finding robust start times that minimizes the *TSAD* value of the scheduled activities. Note that resulting activity start times might be completely different than the activity starting times in K realizations and they might be resource-infeasible. Thus, using the resulting robust starting times, first, feasibility of these starting times is checked and if infeasible, the schedule is fixed with deferring the infeasible activities. On the other hand, in *CEH-II, K* realizations are sorted in their non-domination levels using the corresponding makespan and *TSAD* values and among the schedules that have a rank of 1, the schedule having minimum *TSAD* is selected as the robust schedule of the chromosome. The makespan and the *TSAD* values of the resulting schedule are used as performance measures of the chromosome. Note that the *TSAD* in the multi-project scheduling approach includes the deviations of the starting times of the existing activities as well.

IV. Implementation With Real Data

For the implementation, 37 completed R&D projects are used as test instances to compare the performances of the two proactive project scheduling approaches developed. All codes are written in Microsoft Visual Studio C# and CPLEX 12.5 is used as the MILP solver. All tests are performed on a computer with a 3.20 GHz Intel(R) Core(TM) i7 CPU 960 processor and 8 GB of RAM. The best combination of the parameters to be used in the bi-objective GA is determined through extensive experimentation. In the following sections, the results of the scheduling approaches obtained by using the crossover rate of 0.95, mutation rate of 0.05, population size of 50 and the number of generations and the number of schedule realizations for a chromosome are taken as 50, and 100, respectively.

A. Data

All 37 projects are the projects initiated between 2007 and 2011. Project networks are of AON type FS and SS precedence relations with zero and positive time lags. There is no precedence relation between projects. The two types of renewable resources are: Human resource and equipment. The projects in the project set require a total of 91 different equipment type resources and 183 different human resources. Activities require from one human resource to a total of more than 11 human resources and equipment. While the weekly capacity of human resources is 45 working hours, these capacity values differ from 9 working hours to 672 working hours for the resources in the equipment category.

B. Results

The results obtained by the use of *CEH-I* and *CEH-II* in the bi-objective GA are compared with respect to CPU time, diversity of the solutions and solution quality. Although, we do not present the detailed results in these terms, we provide the main conclusions arrived at through the analysis of these results. Table 1 presents the number of non-dominated solutions obtained and the CPU time required in the implementation of the method with each type of chromosome evaluation scheme. It is observed that the CPU time required to schedule the projects is less for almost all projects when *CEH-II* is used instead of *CEH-I*, since fitness of a chromosome is calculated using an already generated schedule in *CEH-II*. Thus, it seems sorting the schedules generated in the simulation with respect to their non-domination level requires less computational time than solving the *TSAD* minimization model and generating a new schedule using the output of the *TSAD* minimization model. It is also seen that when *CEH-I* is used, less number of non-dominated schedules are obtained for each project and it tends to find schedules with less *TSAD* while *CEH-II* tends to find schedules with smaller makespan values.

TABLE I. Comparison of CEH-I and CEH-II

Project ID	CEH-I		CEH-II	
	Number of Non-dominated Schedules	CPU Time (minutes)	Number of Non-dominated Schedules	CPU Time (minutes)
1	1	15.46	4	13.29
2	2	8.92	11	7.06
3	3	22.65	1	21.7
4	4	25.89	9	23.63
5	1	21.41	3	19.63
6	3	10.74	11	9.25
7	6	16.14	15	15.68
8	1	26.32	3	24.85
9	3	21.72	6	18.53
10	1	32.98	1	28.74
11	4	23.68	5	23.06
12	2	21.4	5	16.99
13	2	11.63	10	10.32
14	2	11.71	7	9.51
15	1	15.89	2	15.35
16	5	24.12	14	22.12
17	1	6.4	8	5.96
18	1	17.48	3	15.16
19	2	17.66	9	16.62
20	1	30.77	15	27.86
21	4	17.48	10	15.01
22	3	8.88	9	6.42
23	1	12.23	2	9.56
24	3	17.11	7	14.71
25	3	13.33	9	11.29
26	2	14.73	8	13.39
27	5	13.53	9	10.64
28	3	6.3	9	5.35
29	1	13.43	6	11.94
30	3	11.1	13	11.09
31	2	9.43	9	10.19
32	3	15.76	8	17.32
33	5	10.22	10	11.07
34	2	12.04	7	11.01
35	2	15.63	3	15.7
36	3	9.08	5	10.7
37	3	14.49	10	14.72

When we compared the results of the single and multi-project scheduling approaches, we saw that for most of the projects, single project scheduling approach gives better completion times. On the other hand, if we think all the projects as a composite project, the completion time of this composite project obtained with multi-project scheduling approaches approximately 5 months earlier using *CEH-I* and approximately 6 months earlier using *CEH-II*. Hence, if completing the composite project is more important than completing the projects individually, multi-project scheduling approach is better. On the other hand, a disadvantage of multi-project scheduling is that it re-schedules all the active activities with a new project initiation, so an activity is scheduled more than once even if there is no disruption affecting that activity. This re-scheduling increases system nervousness and demotivates the resources that work on the activities. An additional disadvantage is that the multi-project scheduling approach needs more CPU time than the single project scheduling approach.

V. Conclusions and Future Work

In this paper, we presented the proactive project scheduling phase of the three-phase approach developed for robust project scheduling. To the extent of our knowledge, this study is the first study considering multiple objectives on proactive project scheduling literature for the problem of the preemptive version of the RCMPSP with generalized precedence relations. To obtain robust baseline schedules, in the proactive project scheduling phase, we suggested two scheduling approaches each using a bi-objective GA with two different chromosome evaluation heuristics. Solution robustness is assured with *TSAD* minimization after a pre-specified number of schedule realizations are obtained for a chromosome. The other objective is the minimization of the makespan over all projects. The proactive project scheduling approaches are implemented on the real data from the R&D Department of a leading home appliances company in Turkey. Although we have used these two objectives, some other objectives could be used or added to the model as well. A further extension of our work could be considering the concepts of activity flexibility, project flexibility, activity priority and project priority while scheduling the projects.

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Biography

Canan Capa is a Ph.D Candidate in Industrial Engineering Program, Concordia University, Canada. She earned B.S. in Industrial Engineering from TOBB University of Economics and Technology, Turkey and M.S. in Industrial Engineering from Sabanci University, Turkey. She is currently working on air traffic flow management problems. Her research interests include data mining, project scheduling and air transportation.

Gündüz Ulusoy received his BS in mechanical engineering from Robert College, Istanbul in 1970; MS in mechanical engineering from University of Rochester in 1972 and PhD in operations research from Virginia Tech in 1975. He is currently Professor in the Faculty of Engineering and Natural Sciences, Sabancı University, Istanbul, Turkey. He has published research articles in Interfaces, Operations Research, JORS, EJOR, IJPE, IJPR, IIE Transactions, IJOPM, JOM, Computers & OR and NRL. He was an Associate Editor of the EJOR (1981-2000), served as a Contributing Editor to the International Abstracts in OR (1978-1992). He served as Guest Editor in Annals of OR, European Journal of Operational Research, Optimization Letters, Industrial Engineering Journal (in Turkish), and Industry and Higher Education and several Conference Proceedings. His current research focuses on technology and manufacturing strategies and on scheduling and evolutionary algorithms in production and project management.