A Predictive-Reactive Dynamic Scheduling under Projects' Resource Constraints for Construction Equipment

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Abstract: Major portion of projects' cost is dedicated to construction equipment's costs which signify the importance of employing optimal equipment's schedules in projects. In this paper the problem of construction equipment scheduling for a company with several ongoing projects in different regions is studied. The goal is scheduling heavy construction equipment and their assignments to jobs so that the total cost for the company and disruptions in projects' schedules is minimized while considering the priorities and critical paths of the projects. A robust predictive-reactive integer model with a hybrid dynamic approach is employed in modeling the problem. Case studies showed considerable savings in cost and minimizing disruption in schedules in real time.

1 INTRODUCTION

Equipment scheduling problem is the problem of allocating jobs to equipment over time. Since availability of equipment and also jobs' schedules change during the projects, it is important to solve the resource scheduling in projects dynamically. Literature on dynamic equipment scheduling is very sparse. Changes in resources or jobs could result in dynamic characteristics of projects (Ouelhadj and Petrovic, 2009).

A considerable number of studies have been done on scheduling, but studies in construction equipment scheduling are very rare (Słowiński and Węglarz, 1989). In (Dodin and Elimam, 2008) a static mixed integer model for scheduling equipment based on tradeoffs among several costs is proposed; however, a static model is not as efficient as dynamic models in dynamic environment of projects. Cost of ownership or renting construction equipment such as cranes form main portion of project costs. So implementing an optimal resource management in construction industry is one of the main ways in reducing costs. Moreover, Ernst et al. (Ernst et al., 2004) highlights necessity of designing mathematical models for each area of application due to their unique characteristics. Here equipment scheduling in the area of construction management is studied.

2 PROBLEM STATEMENT AND METHODOLOGY

2.1 Problem Statement and Methodology

Large construction companies in the United States and all over the world conduct several concurrent projects at different sites in different locations, while having a limited number of construction equipment spread over the sites which are idle some of the time during a project. Heavy construction machines are highly costly and their ownership or rental cost constitutes a significant portion of project cost. Besides available owned equipment located in sites, a company could use the option of renting similar equipment from outside providers in different cities. Schedule of the projects with the need of a specific machine, and transportation network information is assumed to be available in real time. The goal is to solve the decision problem on using owned equipment or rentals and to assign jobs to them in order to maximize the benefit to the company. Some assumptions are made through the study. Labours are paid hourly and they do not cost when they are idle. Rentals can be left at their job location after finishing their task. Finally, rental and salvage price during usage period is determined based on prices on the start day of the task. The incorporated notation is first shown below.

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L = Set of job site locations
$i\,,j$ = Indices used for locations $(i, j \in L)$
N_j = Set of works being done in site $j \in L$
n = Index used for works
t = Index used for time (day)
t_0 = Beginning time of scheduling $(t_0 = 1)$
TL_n = Latest time possible for starting work n
TE_n = Earliest time possible for starting work n
D_n = Duration of work n (in units of time)
T_{ij} = Travel time from location i to location j
C_{ij} = Transportation cost from location i to j
R_{ij}^t = Rental price from location i for use in location j at time t (\$/day)
S_j^t = Usage cost (depreciation cost) for an owned equipment in location j at time t (\$/day)
$Q_i^{t_0}$ = Available owned equipment in i at time t_0
W_n^t = Utility value of doing work n at time t (\$)

Variables used in the model are as following.

$$x_{ij}^{tn} = \begin{cases} 1 & \text{a machine from location i assigned to work n at time t in location j} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij}^{tn} = \begin{cases} 1 & \text{a rental machine from location i assigned to work n at time t in location j} \\ 0 & \text{otherwise} \end{cases}$$

$q_i^t =$ Number of available machines with no work assigned to in location i at time t

The problem is modelled as a multi-objective model incorporating several objectives as following.

i. Maximizing utility:

$$Max. \sum_{j\in L} \sum_{n\in N_j} (\sum\nolimits_t (W_n^t \sum_{i\in L} (x_{ij}^{tn} + y_{ij}^{tn}))) \tag{1}$$

ii. Minimizing transportation cost:

$$Min. \sum_{i\in L} \sum_{j\in L} (C_{ij} \sum_{n\in N_j} \sum_t (x_{ij}^{tn} + y_{ij}^{tn})) \tag{2}$$

iii. Minimizing rental cost:

$$Min. \sum_{i\in L} \sum_{j\in L} \sum_t (R_{ij}^t \sum_{n\in N_j} (T_{ij} + D_n) y_{ij}^{tn}) \tag{3}$$

iv. Minimizing usage cost:

$$Min. \sum_{i\in L} \sum_{j\in L} \sum_t \sum_{n\in N_j} S_j^t D_n x_{ij}^{tn} \tag{4}$$

To combine all objectives, without loss of generality it is assumed that they all have same weight and importance for the company; however, knowing the trade-offs between different objectives, the decision maker can decide on the weight vector based on his utility function by studying the Pareto set of attributes (Bui and Alam, 2008). Following are the constraints in the model.

$$\sum_{i\in L} \sum\nolimits_{t=TE_n}^{TL_n} (x_{ij}^{tn} + y_{ij}^{tn}) = 1 \;\; ; \forall j \in L, \forall n \in N_j \tag{5}$$

$$\sum_{j\in L} \sum_{n\in N_j} x_{ij}^{(t+T_{ij})\ n} \le q_i^t \;\; ; \forall i \in L, \forall t \tag{6}$$

$$q_i^t = q_i^{t_0} - \sum_{t=t_0}^{t} \sum_{j\in L} \sum_{n\in N_j} x_{ij}^{(t+T_{ij})\ n} + \sum_{j\in L} \sum_{n\in N_i} \sum_{t=t_0}^{t-D_n} x_{ji}^{tn} \;\; ; \forall i \in L, \forall t \tag{7}$$

$$q_i^t \ge 0 \;\; and\ integer \;\; ; \forall i \in L, \forall t \tag{8}$$

$$x_{ij}^{tn}, y_{ij}^{tn} = \;\; Binary \; ; \forall i \in L, \forall j \in L, \forall t, \forall n \in N_j \tag{9}$$

Constraints (5) enforce exactly one piece of equipment being assigned to each job in the acceptable time period. Constraints (6) assure not sending more than available idle equipment from each location to other locations. Constraints (7) define the number of available idle equipment in each location at each time period.

To define W_n^t , value of doing a job at time t, as in (10), three factors are employed. First is cost and penalty of conducting the work at any time other than the planned schedule. This signifies the difference between critical and non-critical jobs. Second is the importance and priority of conducting a job from the perspective of managers which can be calculated using Analytic Hierarchy Process method (Saaty, 1990). Third is the linkage between different jobs due to the technical issues in a project.

$$W_n^t = \begin{cases} 0 & ; \quad t > TL_n\ or\ t < TE_n \\ \left(\frac{(\sum_{i\in P_n} B_i + B_n)}{1 + (TL_n - TE_n) * (t - TE_n)} * \frac{B_n}{\sum_{i\in P_t} B_i} \right) * \beta ; & TE_n \le t \le TL_n \end{cases} \tag{10}$$

P_n is set of all projects which project n is one of their predecessors. P_t is set of all projects which are in need of the equipment at time t. $0 \le \beta \le 1$ is the project n's importance index for the managers, and B_i is the budget assigned to project i.

The predictive-reactive scheduling has two steps. The model presented above generates a predictive schedule employing available data in the first stage. In the second stage, which can be repeated several times, the original model is adjusted in order to revise the schedule in response to real time events and changes. In this stage notations are borrowed from the first stage; however, the additional letter "P" identifies updated information and the new set of variables after rescheduling time (tp_0) in stage two; e.g. TLP_n is the updated latest starting time for work n. The multi-objective function in the second step contains additional elements as following.

i. Minimizing rental cancelation penalty:

$$Min. \sum_{j\in L}\sum_{n\in NP_j|not\ done}\sum_{t|tp_0\leq t-TT(i,j)\leq tp_0+2}\sum_{i\in L|y_{ij}^{tn}=1} 0.3R_{ij}^{t}\left(y_{ij}^{tn} - yp_{ij}^{tn}\right)\left(T_{ij}-D_n\right) \quad (11)$$

ii. Minimizing rental cancelation after equipment is sent:

$$Min. \sum_{j\in L}\sum_{n\in NP_j|not\ done}\sum_{t|t-TT(i,j)\leq tp_0}\sum_{i\in L|y_{ij}^{tn}=1} R_{ij}^{t}(y_{ij}^{tn} - yp_{ij}^{tn})(T_{ij}+D_n) \quad (12)$$

iii. Minimizing transportation cost due to job cancelation:

$$Min. \sum_{j\in L}\sum_{n\in NP_j|not\ done}\sum_{t|t-TT(i,j)\leq tp_0}\sum_{i\in L\left|(y_{ij}^{tn}+x_{ij}^{tn})\right.=1} C_{ij}((y_{ij}^{tn} + x_{ij}^{tn}) - (yp_{ij}^{tn} + xp_{ij}^{tn})) \quad (13)$$

iv. Minimizing equipment schedules' disruption due to changes in schedules:

$$Min. \sum_{j\in L}\sum_{n\in NP_j|not\ done}\sum_{t}\sum_{i\in L|(y_{ij}^{tn}+x_{ij}^{tn})=1} ((y_{ij}^{tn} + x_{ij}^{tn}) - (yp_{ij}^{tn} + xp_{ij}^{tn})) \quad (14)$$

Objective (11) minimizes 30% cancelation fee for rentals scheduled for the next 48 hours in step one which are cancelled in step two. Rental fee is assumed not to be refundable after a shipment is occurred in objective (12). Objective (14) minimizes number of disruptions in the new schedule comparing to step one's schedule. Assigning appropriate weights to different objectives and summing them up, the problem would be a multi-objective problem. An additional constraint (15), is also added to the original constraints to assure no equipment being assigned to the cancelled jobs.

$$\sum_{i\in L}\sum_{t=t_0}^{TLP_n}\left(xp_{ij}^{tn} + yp_{ij}^{tn}\right) = 0\ ;\forall j\in L, \forall n \in NP_j|DP(n) = 0 \quad (15)$$

Employing updated data into the new model a new optimal schedule will be generated in stage two.

2.2 Numerical Analysis

The proposed dynamic model is applied on several randomly generated examples with different problem sizes; however, due to space limit, some of the results are going to be discussed here. A set of cases for a company with 25 site locations, 30 jobs, and 100 day schedule is studied. Changes to the projects are detected on day 40th including addition of different number of new jobs. Projects' information and resources data are exogenous and generated randomly. Machine used in solving the problem is a desktop computer with a 2.8 GHz CPU and 1.99 GB of RAM. Xpress-IVE 7.0 is employed as the optimization software.

Project's cost for both dynamic and static models for several randomly defined cases with different number of additional jobs are compared in Figure 1. In dynamic model, rescheduling is run when changes are detected, while in static model equipment are assigned to projects on a first come first serve basis without considering optimal reduction of cancelation penalties, unnecessary transportation costs and delays in critical jobs. The figure shows that applying rescheduling has reduced costs in projects.

Figure 1: Effectiveness of rescheduling in reducing projects' costs for several cases.

An interesting result from solving the model with both binary variables and relaxed binary variables is that although model's coefficient matrix is not uni-modular, both models give the same set of solutions (Table 1). Interestingly enough, relaxing binary variables which are the majority of the variables in the problem does not improve the solution time considerably. This might be due to dependency of the node on which the algorithm is branching. Another observation is that as the problem size grows solution time increases significantly. Figure 2 illustrates sensitivity of solution time to time horizon length in a case with 25 site locations and 5 additional jobs in the second stage. Results show, for an average medium size problem, the dynamic model can be solved in a reasonable amount of time and is beneficiary to the economy of the project. However, for a large size problem development of an appropriate heuristic is inevitable.

Table 1: Objective function and solution time for main and relaxed models.

First step	# jobs		1	5	10	15	20	25	30
	Main	Solution Time(Sec.)	2.312	14.079	0.438	44.781	53.703	97.906	58.203
		Objective Value	348.549	1401.09	3633.77	4502.7	6855.02	7534.75	8768.3
	Relaxed	Solution Time(Sec.)	2.282	11.954	0.39	46.109	52.312	75.578	44.219
		Objective Value	348.549	1401.08	3633.77	4502.7	6855.02	7534.74	8768.3
Rescheduling	# jobs		6	10	15	20	25	30	35
	Main	Solution Time(Sec.)	13.813	55.531	0.641	187.437	303.234	445.813	417.047
		Objective Value	2054.33	2838.3	3588.57	4863.64	6977.71	5497.8	9542.4
	Relaxed	Solution Time(Sec.)	14.375	61.094	0.625	235.297	342.093	439.312	402.313
		Objective Value	2054.33	2838.3	3588.56	4863.64	6977.71	5497.8	9542.4

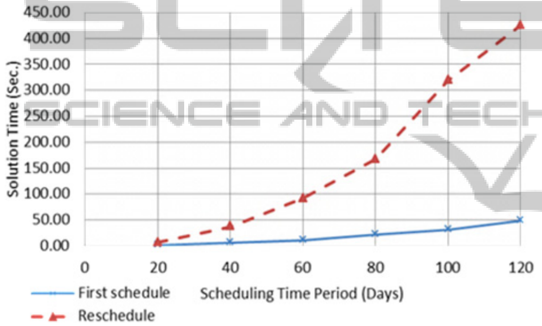

Figure 2: Increase in solution time with the increase of scheduling horizon, for 20 jobs in the first step.

3 CONCLUSIONS

In this study the problem of assigning and scheduling construction equipment to jobs of several projects over several sites of a construction company considering the priorities and critical paths of the projects is modelled as robust predictive-reactive model. In the proposed dynamic model not only the demands are satisfied and the cost is minimized, but also interruptions in the project schedules due to resource availabilities are minimized. The model is capable of solving a moderate size problem in a reasonable amount of time; however, dynamic model makes it complex for large scale problems and finding optimal solution would be challenging. Designing an appropriate heuristic for large scale problems and also considering stochastic nature of projects is remained for future work.

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