Construction Management Applications: Challenges in Developing Execution Control Plans

Nilufer Onder
Dept. of Computer Science
Michigan Technological University
Houghton, MI 49931
nilufer@mtu.edu

Amlan Mukherjee
Dept. of Civil and Env. Engineering
Michigan Technological University
Houghton, MI 49931
amlan@mtu.edu

Pei Tang
Dept. of Civil and Env. Engineering
Michigan Technological University
Houghton, MI 49931
ptang@mtu.edu

Abstract

The objective of automated planners is to synthesize sequences of actions (called policies in MDP frameworks) that will achieve a predetermined goal given a fully or partially observable formal representation of the domain. In contrast, the main characteristic of project management is the greater emphasis on plan execution under uncertainty as opposed to plan synthesis. This paper explains the need to transition from automated plan synthesis to plan management and identifies the challenges for the planning and scheduling communities using examples of construction projects.

Introduction

Over the past decade, following the development of powerful solutions to deterministic planning problems (Nau 2007) and the presentation of the challenges in stochastic domains (Bresina et al. 2002), the planning community has placed special emphasis on research in planning under uncertainty. Recent frameworks can deal with an overwhelming number of states or plans (Buffet and Aberdeen 2009), and can utilize complex domain models such as continuous phase distributions in generalized semi-MDPs (Younes 2005). The objective of automated planners is to synthesize sequences of actions (called policies in MDP frameworks) that will achieve a predetermined goal given a fully or partially observable formal representation of the domain. In contrast, the main characteristic of project management is the greater emphasis on plan execution as opposed to plan synthesis. The life cycle of a construction project begins with the preparation of an initial resource loaded activity schedule - or the As Planned Schedule (APS), and continues under the governance of the project design, setup, constraints, and the changes that occur during the execution of the project. The challenging problem for construction managers and the planning community is to develop plans that support the execution of an APS under the occurrence of internal feedback loops and external stochastic events.

While establishing the APS is a non trivial problem, we are not presenting it as a challenge because one can be put together using knowledge from similar previous projects. However, actions in an APS usually do not have well defined precondition or effect sets. Even when these sets are well-defined, they might be infinite. As a result, uncertainty does not manifest itself as a result of action effects, it stems from inherent variability in project parameters (such as variable crew production rates), unexpected external events (such as bad weather), and emergent phenomena that unexpectedly evolve through complex interactions between resources and project constraints. Formally speaking, the problem ceases to be a search for a plan that constitutes a valid sequence of agent actions, and instead becomes a dynamic control problem based on the satisfaction of constraints expressed in the APS. Consequently, despite various developments in planning theory, full automation of project management is still a challenging goal. The three main challenges are (1) to develop a knowledge representation scheme to represent the project, its constraints, and the sources of uncertainty; (2) to develop techniques for computing the execution time deviations from the APS; and (3) to control the project while minimizing the damaging effects of the deviations.

This paper explains the need to transition from automated plan synthesis to plan management and identifies the challenges for the planning and scheduling communities using examples of construction projects.

Background in Construction Management

The New York Times building is an interesting example that shows how a project can go in unexpected directions and how adhering to the initial plan is challenging. The New York Times is a 52-story office building which was requested to be "ultra-transparent" by the owner (Post 2007). The building features a light-gray, horizontal filigree sunscreen that masks the 650,000-sq-ft facade to the outdoor-steel exoskeleton and terra cotta sunscreen rods for energy efficiency. Even though the planning process to develop the APS spanned three years and significantly lowered expected costs using careful computer simulations, the construction project's execution was plagued with various problems. Soon after the job started, the steel fabricator closed down and the steel erector went bankrupt. The higher price given by the new contractor cost the construction managers their entire contingency funds. This is an example of an unforeseen external event that they could not have budgeted for. Moreover, the aesthetic considerations of the transparent facade slowed down the welding process. As a result of the delay, the concrete deck work crew lagged 12 to 14 floors behind the steel hoisting crew. In order to maintain labor flow and to not slow down the hoisting crew, the hoisted floors in between had to be inspected frequently for stability. This was not part of the APS and was introduced to enforce the safety rules that require stability inspections when too many floors of hoisting are completed without decking to stabilize it. This illustrates an example where the domain safety constraints regarding steel construction manifested themselves unexpectedly given the unique architectural requirements. In addition, the delays and extra expenses that started from the unusual welding requirements, and led to costly safety inspections, propagated through all the project constraints and caused multiple delays.

From a construction management point of view, advance development of plans to control crisis scenarios is a difficult problem, as the contingencies are often difficult to foresee, and even for foreseeable contingencies, the number of possible responses is immense. In response, several simulation-based frameworks have been developed to help incorporate uncertainty into the preparation of APSs. In the context of construction operations, robust discrete event simulation (DES) platforms have been used based on models that represent relationships between resources on a construction site and uncertainties in critical parameters (Martinez and Ioannou 1999; Hajjar and AbouRizk 2002). DES models help project managers understand cost-benefit tradeoffs of the assignment of resources such as equipment and labor. For example, one can determine the optimal number of trucks for an excavation operation using DES. In the strategic context, the entire scope of the construction project is modeled. Dynamic Planning Methodology (DPM) is a simulation method that uses concepts from System Dynamics and allows the examination of alternative top-down strategies on project level operational performance metrics (Pena-Mora and Li 2001). For example, it investigates the relationship between schedule pressure and uncertainty in activity durations during fast-tracking of construction projects. Both of these simulation approaches estimate expected project performance (operation duration, cost, etc.) under parameter uncertainty and variations in strategic management approaches (e.g., increasing schedule pressure). They help compare optimal control measures and examine alternative strategies, given initial conditions, and the objectives of minimizing idle time and maximizing productivity. However, they allow limited examination of the project constraints, and the interdependencies between activities. Also, the simulations are limited to an input-output paradigm that does not allow interactive assessment of alternative execution plans or development of contingency plans. Therefore, they are best used to support the development of robust APSs for projects. Using this as a point of departure, the investigation of execution plans is the next logical step.

From Plan Synthesis to Plan Management

During the execution of a construction project, at each time step (this could be a week or a day) the challenge lies in making decisions with respect to the APS. Therefore, the primary need is to develop and test strategies that optimize the deviation from the original plan. This need can be further expressed in terms of the following challenges:

1. *How to move from the precondition-action-effect based representation to an integrated representation of project specific constraints, resource allocations, and stochastic external events.* This frames the problem of execution control as one of checking for constraint satisfaction, rather than building a sequence of valid actions towards a goal. The new semantics will support reasoning about systemic constraint violations and allow inferences about the impacts of changes. For example, in the New York Times execution plan, the system should know about the safety constraints even though they are not relevant to the initial APS. For novel projects greater parametric uncertainty in activity duration also needs to be represented.
2. *How to develop algorithms that can compute deviations from the APS at the current time point (using metrics of cost and/or project duration) as well as explore the space of possible future plan realizations.* This is a problem of computing the significant deviations that pertain to the current time and to the time points in the remainder of the project. For example, in the New York Times execution plan the system should infer that the repeated delays in welding will delay the overall project and, more importantly, stability checks will be required. The timely discovery of this scenario would allow contingency planning.
3. *How to define an execution plan given semantics to represent and reason about the APS, constraints, and uncertainty information; and algorithms to characterize deviations in the APS.* Such an execution plan should provide a family of contingencies for a probabilistically characterized space of deviations. In the New York Times case, consideration of the time-cost trade-off between increasing the number of welding crews while decreasing the number of hoisting crews, versus introducing aggressive stability checking while keeping the hoisting crew on schedule, must be part of the solution.

In the next section, we present an implemented project example and point out where each challenge manifests itself.

A Benchmark Problem

Interactive Construction Decision-Making Aid (ICDMA) is akin to a first person construction manager strategy game that exposes participants to diverse project management situations that rapidly unfold in time (Watkins, Mukherjee, and Onder 2008). The participants can react to these scenarios by making strategic decisions involving resource and activity scheduling, with the goal of completing the project within schedule and under budget. We use the case of a four story steel framed office building as an example (Daccarett and Mrozowski 1999). The construction project is represented by six identical erection sequences each consisting of the following three activities: Hoisting, Bolting, and Detail work and Decking. Each activity A_i has a beginning point $A_{i,b}$ and an ending point $A_{i,e}$. After representing the activities taken from the APS, we put in the constraints that relate two time points and associate penalties with various degrees of delay. For example, for the hoisting activity of sequence 1, the following constraint:

$$\begin{aligned} 0 &: 1 \leq H_{1,e} - H_{1,b} \leq 2 \\ k^* &: 2 + k = H_{1,e} - H_{1,b} \end{aligned}$$

says that it will incur a penalty if its duration exceeds 2 days. For a delay of k days, the activity incurs a penalty which is computed by a function of k denoted by k^*. This delay represents extra costs due to longer equipment usage or increased labor hours. Examples of constraints considered in the implementation were:

- Constraint 1: In order to maintain work-flow and efficiently utilize equipment, lag time between hoisting activities for sequence i and $(i + 1)$ should be 0. This is expressed as: $\infty : H_{i+1,b} - H_{i,e} > 0$.
- Constraint 2: In order to maintain labor-flow and efficiently manage crew on site, the lag time between bolting activities for sequence i and $(i + 1)$ should be 0. This is expressed as: $\infty : B_{i+1,b} - B_{i,e} > 0$.
- Constraint 3: In order to ensure safety, the hoisting operation for a sequence of a higher storey has to start after a considerable portion of the decking operation for a sequence of the immediately lower storey had been completed to afford safe fall distances. Appropriate fall distances are maintained by ensuring that the decking operation for operation i starts before the hoisting operation for the sequence $(i + 2)$. This is expressed as: $\infty : H_{i+2,b} - D_{i,b} > 0$.

It is important to note that these constraints are project specific manifestations of construction domain constraints regarding safety and optimal resource utilization.

Disruptions in ICDMA are created when constraints are violated. These violations can result from external events or emergent uncertainty inherent to the project. An *external event* is a happening that affects the project. An event E is represented as a triple $< E_{prec}, E_e, E_{pr} >$. E_{prec} is a set of variable values that enable the occurrence of the event. E_e is the set of effects the event has on the environment. It encodes the impacts that the event will have on specific project parameters, and the variables impacted. The set of variables affected by an event can be different from the variables included in the preconditions. E_{pr} refers to the probability of event occurrence given that the enabling preconditions are satisfied. For example, a drop in labor productivity due to adverse weather can be represented as:

$$\begin{aligned} E_{prec} &= \{ \text{Weather} = \textit{Snow}, \text{Location} = \textit{outdoor} \}, \\ E_e &= \{ \text{Productivity} = 50\% \}, \\ E_{pr} &= \{ 0.75 \} \end{aligned}$$

At each time step in the simulation, ICDMA samples from the event probability distributions to determine which events will occur and what the effects will be. It uses a state based representation using a resource loaded temporal constraint network, called TONAE (Temporal Network with Activities and Events), which represents both temporal and resource constraints (Anderson, Mukherjee, and Onder 2009). At the

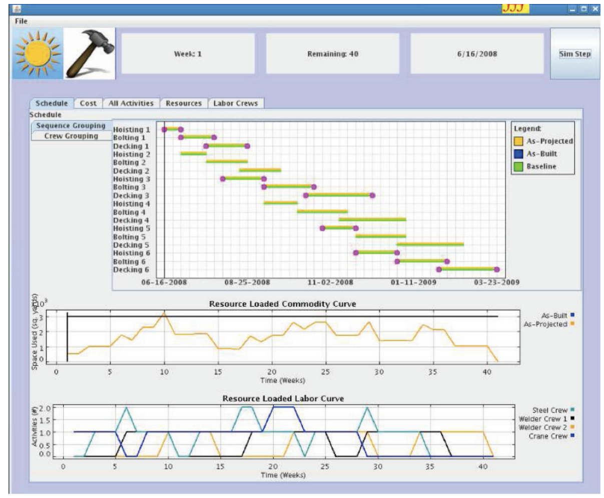

Figure 1: ICDMA at t=0

start of the project all constraints are satisfied and the APS is the state of the system at time $t = 0$ - represented as S_0 (Fig 1). ICDMA uses continuous time advancement, which is different from the DES frameworks advancing time from one discrete event to the next. Thus each time point constitutes a control point in the simulation. This is critical because stochastic external events are equally likely to happen at any point in the project.

Currently TONAE does not represent the adaptive and emergent uncertainties that arise from spatio-temporal interactions between dynamic relationships among construction labor crews, decision outcomes, and equipment on site. For example, inappropriate positioning of a crane can jeopardize safety and lead to lost productivity from congestion on site. Project specific causes that set such feedback loops in motion, and balance or reinforce them when control measures are executed, must also be investigated. Therefore, a representational challenge is to explicitly represent emergent uncertainty and consider the influence of the dynamic evolution of project constraints on the execution control plan.

In order to meet the representational challenges (**challenge 1**), all the constraints that might be relevant to the activities in the APS must also be represented. We need a rich representation including temporal constraints, safety constraints, and resource constraints such as equipment and space. The adaptive and emergent behaviors arising from interactions between individual construction components and site peculiarities also must be modeled explicitly.

The difference between the APS and the as simulated metric at time t is represented as $\triangle_t$. ICDMA can compute the deviations in terms of remaining schedule duration and extra cost incurred. It can create bins possible futures with respect to probabilities or costs but does not perform further analysis (**challenge 2**).

ICDMA does not have mechanisms to develop responses to project deviations instead decisions are obtained from the user. A decision is an assignment or re-assignment of real numbers to resource and schedule variables (e.g., if 5 more units of labor is hired then the relevant variable is updated).

The decision set consists of all reassignments and is formulated as D_t when made at the end of time point t.

At the end of each simulation run we generate the following data sets:

- A sequence of system states for each time point during the length of the simulated project: $\{S_t\}$. The TONAE is the state of the system at any given time.
- A sequence of decisions taken by the user: $\{D_t\}$.
- A sequence of deviations at each time step: $\{\triangle_t\}$.
- A sequence of query distributions recorded at the end of each time point in the simulation: $\{Q_t\}$. This is an impact distribution of a sample of possible future states that S_t can transition to.

Hence for each time point for a given run the following situation vector can be recorded as: $\mathcal{S}_t = [S_t, Q_t, \triangle_t, D_t]$. The decision-making agent arrives at the decision D_t by observing S_t and Q_t, with the objective of minimizing $\triangle_t$. The decision D_t in conjunction with the stochastic occurrence of an external event is used to update the state of TONAE to trigger the transition of the system from S_t to S_{t+1}. The decision D_t made by the agent is driven by high-level philosophies which we refer to as strategies. Examples of such strategies include a *crash strategy* where the user increases resources to decrease project duration, and a *reassign strategy* where the activities on the critical path are prioritized.

The challenges related to generating contingency responses (**challenge 3**) are as follows:

- Given a set of k strategies or policies $\{P_0, P_1, P_2 ... P_k\}$, and N simulation runs with each strategy (total of kN runs) and the sequences of situation vectors recorded for each run $\{\mathcal{S}_t^1, \mathcal{S}_t^2 ... \mathcal{S}_t^k\}$, how do we establish formal methodologies and approaches to represent and reason about the efficiency of a strategy?
- The decision-making agent can be a human or an artificial agent. The advantages of using a human agent is that each decision will take into consideration judgement and understanding of domain/problem specific knowledge. However, for large values of N it becomes impractical and error prone to have a human agent. Therefore, can an automated agent be devised that will (i) run the simulation given a particular strategy, (ii) possibly learn from human agent runs to increase its planning efficiency?

Conclusion

In this paper, we explained the need for knowledge-rich environments to deal with execution time contingencies in project management. While the examples and cases were drawn from construction projects, we believe that the desiderata are widely applicable to other dynamic project environments which have soft and hard constraints, variability in activity parameters, and external events affecting the course of the project.

Good user interfaces are also essential for effective project management, but are beyond the scope of this paper. One interesting issue is the development of powerful user interfaces for entering information about stochastic domains. Recently, such interfaces for deterministic domains have been presented in the context of the International Competition on Knowledge Engineering for Planning and Scheduling (Barták, Fratini, and McCluskey 2009).

Acknowledgments

This work was supported by the NSF grant SES 0624118 and its REU supplement to Amlan Mukherjee. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect views of the National Science Foundation. We thank anonymous reviewers for their helpful suggestions.

References

Anderson, G. R.; Mukherjee, A.; and Onder, N. 2009. Traversing and querying constraint driven temporal networks to estimate construction contingencies. *Automation in Construction* 18(6):798–813.

Barták, R.; Fratini, S.; and McCluskey, L., eds. 2009. *Proceedings of the Third International Competition on Knowledge Engineering for Planning and Scheduling*. AAAI Press.

Bresina, J.; Dearden, R.; Meuleau, N.; Ramakrishnan, S.; Smith, D.; and Washington, R. 2002. Planning under continuous time and resource uncertainty: A challenge for AI. In *Proceedings of the Eighteenth Conference on Uncertainty in Artificial Intelligence (UAI-02)*, 77–84.

Buffet, O., and Aberdeen, D. 2009. The factored policy-gradient planner. *Artificial Intelligence* 173:722–747.

Daccarett, V., and Mrozowski, T. 1999. AISC digital library: Construction management of steel construction. Available via http://www.aisc.org/content.aspx?id=21250 [accessed 10/26/2009].

Hajjar, D., and AbouRizk, S. 2002. Unified modeling methodology for construction simulation. *Journal of Construction Engineering and Management* 128(2):174–185.

Martinez, J., and Ioannou, P. 1999. General-purpose system for effective construction simulation. *Journal of Construction Engineering and Management* 125(4):265–276.

Nau, D. S. 2007. Current trends in automated planning. *AI Magazine* 28(4):43–58.

Pena-Mora, F., and Li, M. 2001. Dynamic planning and control methodology for design/build fast-track construction projects. *Journal of Construction Engineering and Management* 127(1):1–17.

Post, N. M. 2007. High-profile manhattan tower is veteran builders last hurrah. *Engineering News Record*.

Watkins, M.; Mukherjee, A.; and Onder, N. 2008. Using situational simulations to collect and analyze dynamic construction management decision-making data. In *Proceedings of the 40th Winter Simulation Conference (WSC-08)*, 2377–2386.

Younes, H. L. S. 2005. Planning and execution with phase transitions. In *Proceedings of the Twentieth National Conference on Artificial Intelligence (AAAI-05)*, 1030–1035.