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AN EXPERIMENTAL FRAMEWORK TO ANALYZE ALTERNATIVE DECISION-MAKING STRATEGIES USING SITUATIONAL SIMULATIONS IN CONSTRUCTION MANAGEMENT

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ABSTRACT

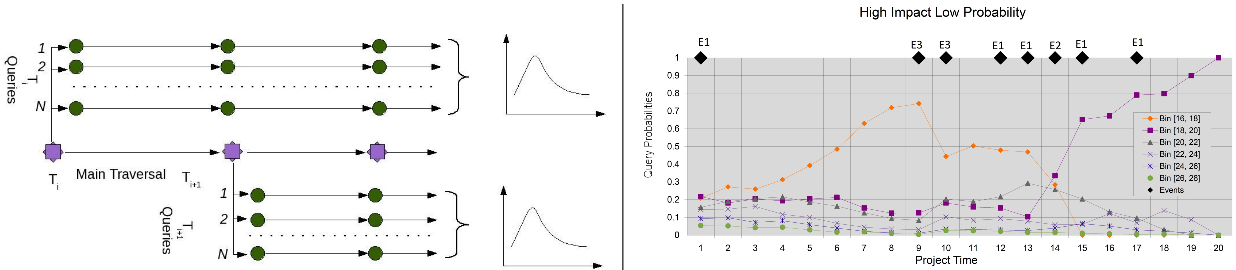
Situational simulations are dynamic, interactive, context-sensitive, adaptive environments. They further construction research by providing an interactive simulation platform that can be used to explore what-if construction scenarios and to estimate risks and contingencies. This paper extends current research to study the evolution of dynamic uncertainty in construction management projects using situational simulations as experimental testbeds. An experimental framework is proposed to explore alternative outcomes of a particular decision strategy, and also investigate the impact of alternative decision strategies under similar project scenarios. A set of preliminary experiments were conducted to illustrate the proposed framework. The significance of this research is in enhancing and informing the deliberative process during the planning and pre-planning stages of a construction project and supporting the preparation of contingency plans of action in anticipation of varying levels of project risk and uncertainty.

1 INTRODUCTION

Situational simulations are dynamic, interactive, context-sensitive, adaptive environments. In a construction management (CM) domain, the participants are exposed to diverse project management scenarios and to situations that rapidly unfold in time. Participants can react to these scenarios by making strategic decisions involving resource and activity scheduling, with the goal of completing the project at hand within schedule and under budget. The simulation allows them to explore what-if scenarios and to test the implications of their decisions in a safe environment without the fear of incurring any real losses. In brief, construction situational simulations are akin to first-person construction manager strategy games.

In general, the goals of developing CM situational simulations are: (i) to create interactive contingency planners that can be used to manage complex construction projects (Anderson et al. 2009), (ii) to formally study dynamic decision-making under uncertainty in CM crisis scenarios (Watkins et al. 2008), and (iii) to provide undergraduate students with realistic, interactive learning environments that integrate related concepts (Rojas and Mukherjee 2005a). In this paper, we merge existing research in threads (i) and (ii) above and use situational simulations as an experimental testbed to study the sensitivity of construction projects to various decision making strategies. The paper uses the case study of the steel construction project that has been used in previous studies to validate situational simulations (Daccarett and Mrozowski 2005).

The main objective of our system is to enhance project management by providing the ability to flexibly input the simulation parameters such as event probabilities, to explore "what-if" scenarios, and to assess the sensitivity of final project outcomes to alternative decisions and different risk distributions during the construction process. Such an approach can further enhance and inform the deliberative process during the planning and pre-planning stages of a construction project and help prepare contingency plans-of-action when faced with rapidly unfolding uncertainties. In summary, our objective is to study human expert level intelligent decision making. There are two general threads of research to recognize and describe expert behavior (Chi 2006). The first approach is to conduct a *retrospective study* and identify how an expert performs tasks. The second approach is to conduct a *comparative study* and measure the gap between expert and novice behavior. In this paper, we follow the second approach and recognizing the difficulty of finding normative theories for describing expert decisions (Brehmer 1992, Gonzalez et al. 2005) use simulated CM environments with various decision making strategies to facilitate such a study.



(a)
(Anderson et al. 2009)

(b)
(Anderson et al. 2009)

Figure 1: (a) Querying Schematic Diagram: Non-Interactive Mode (b) Query Output

2 BACKGROUND

Representation and reasoning about construction management information in situational simulations uses a formal, first-order logic based language enhanced with axioms of time (Rojas and Mukherjee 2005b). In later work, we extended this framework by representing the underlying structure and constraints of a construction project plan in a temporal constraint network (Anderson et al. 2007). The input to this model is an as-planned project schedule with explicit identification of significant constraints that drive the schedule, external events likely to happen during the project and associated probabilities. The representation is called TONAE (TempOral Network with Activities and Events) and it defines three classes of intervals that represent construction activities (relating the activity start time point and end time point), events (using a start time point and an end time point and relating each to the activities that are affected by the event), and constraints (relating start/end time points between activities and events). Each interval is defined by a duration upper bound and a duration lower bound indicating the allowable temporal tolerances associated with the activities (float), constraints and events. In addition, each interval is associated with a Cost Overrun Index (COI) that is indicative of the expenses/damages incurred when the duration of the specific interval exceeds the bounds. The TONAE networks advance the representation in three ways: (i) they can represent intervals as well as constraints between individual time points defining such intervals, (ii) they provide an integrated approach to express all the constraints, activities, and events using a temporal network, and (iii) they provide the ability to develop general algorithms that could be used to traverse and query the network to aid decision-making and planning.

Representation of constraints using the TONAE allows situational simulations to be used as conformant planners, i.e., systems that can automatically create contingency plans in two ways: (i) accounting for typical contingent situations (such as weather events) and (ii) automatically estimating contingencies that are difficult to foresee, by exploring combinatorial future spaces resulting from constraint violations as expressed on the TONAE. The *querying algorithm* (Anderson et al. 2009) that operates on TONAEs enumerates Monte Carlo samples of the combinatorial future spaces, estimates risk in dynamic construction scenarios as situations evolve, and classifies them by impact and probability. This approach complements traditional contingency estimation in construction (Touran 2003) which primarily uses probabilistic approaches based on pre-defined risk scenarios with limited dynamic exploration of decision outcomes. This approach further enhances existing methods by including the ability to estimate contingencies of alternative scenarios, many of which can be simulated as combinations of possible constraint violations in a dynamic environment. Specifically, epistemic events and random external events were considered. Epistemic events result from violations in construction schedule and resource constraints, while examples of external events are weather, delayed material delivery and reduced labor productivity. The contribution of the approach is that it analyzes contingencies by considering the impact of different combinations and temporal ordering of external event occurrences and constraint violations, acknowledging the difference in impact of an event at different times of the project.

Research by Anderson et al. (2009) presented the querying algorithm and illustrated its application using a steel construction case study. Figure 1a illustrates how the querying algorithm works. At each time point T_i, the algorithm samples $N = n$ (n is a very large number that provides a sufficiently accurate estimate of the future space) possible futures and develops a distribution of a final project outcome parameter such as COI or project duration. At this point, it traverses to the next time point T_{i+1}. It continues to do so for each time point without any direct strategic interaction from the planner. The distributions from each time point are collected and are illustrated for project duration. Figure 1b illustrates the probability distributions for project completion duration for different time intervals during the project. As simulated events happen, the probability distribution changes. It shows that on day 5, the probability of project completion between 16 and 18 days is 40%, the probability of project completion between 18 and 20 days is 20%, the probability of project completion between 20 and 22 days is approximately 20%, the probability of project completion between 22 and 24 days is 10% and the probability of project completion greater than 24 days is 10%. In summary, the figure illustrates how the project completion duration distributions are sensitive to simulated event occurrences.

In addition to being used as a planner and risk assessment tool, situational simulations can be used as experimental testbeds for studying decision-making in dynamic, uncertain environments specifically for assessing alternative decisions and studying their outcomes interactively through each simulation step of the construction project. Current research by Watkins et al. (2008) addresses challenges in the collection, organization and analysis of human subject data using situational simulations. A formal data collection framework was developed that can prescribe data collection protocols in a situational simulation and establishes mathematical approaches to organizing and classifying them. Preliminary results show that such data can be used to mathematically construct decision shape vectors that can be used to quantify and classify decisions.

A limitation of the application was that it was tested in the *non-interactive* mode of the situational simulation - i.e., the projections of contingency were made at the beginning of the construction project for final project outcomes without allowing researchers to test the implications of alternative decisions as the project unfolds. In this paper, we implement the querying algorithm in the *interactive* mode. In other words, we allow a decision to be entered at each time point T_i. In doing so, we integrate the ability of situational simulations to be used as a risk assessment tool and an experimental testbed for assessing alternative decisions under risk and uncertainty. Specifically, we assess how the distributions of final project cost change over the course of the construction project and the sensitivity of project performance to alternative decision-making strategies.

2.1 Experimental Testbed

The experimental testbed for this study is the Interactive Construction Decision-Making Aid (ICDMA) which is a situational simulator (Watkins, Mukherjee, and Onder 2008). We implemented the steel construction case study (Daccarett and Mrozowski 2005) within ICDMA to conduct experimental work. Anderson et al. (2009) illustrates that the query algorithm predictions for the project were reasonably close to the actual performance of the project. The case study project involved the construction of a four story steel framed office building which has 80,000 square feet of built area, and weighs approximately 400 tons of structural steel or about 10 pounds per square foot. Fabrication and erection cost $9 per square foot. A total of 964 pre-fabricated structural steel members were used in the construction. The standard bay size in the building is 30 feet by 30 feet and there are 3 bays along the width and 7 bays along the length of the building. Activity durations and constraints are expressed using the TONAE. An example of a critical constraint is: the hoisting operation for a sequence of a higher story has to start after a considerable portion of the decking operation for sequence of the immediately lower story had been completed to afford safe fall distances.

In addition, a resource-loaded schedule (32 days) representing the six sequences of steel construction was used to inform the simulation. Each sequence consisted of hoisting, bolting and connection work and decking activities, and represented the order in which sections of the frame were erected. The associated resource costs were also included for each activity. For example, each hoisting activity was associated with the specific steel members hoisted, the hoisting crew, the crane equipment used and the expected production rate of the activity. This was done for each activity in each of the six sequences. Overall, the project involved three external events and 12 temporal and resource constraints with varying probabilities of occurrence.

3 INTERACTIVE QUERYING

When querying is done in the *non-interactive* mode, the human decision-maker does not have the ability to change the course of the construction project during the simulation. The simulation samples the future space at the end of each time point and then promptly traverses the TONAE to the next time point using the as-planned schedule and cost information. If there is a critical problem - for example, when an activity cannot start because of a delayed material delivery, the simulation factors the related delay into the project. The simulation uses *delay consequence* associated with each event under consideration. It cascades the impacts caused by external events and accounts for epistemic uncertainty by checking for constraint violations - each of which in turn have a *delay consequence*. In order to extend the usefulness of the querying algorithm to events and outcomes that may cause delays that need the intervention of a planner or decision-maker to intervene in the middle of the project, it is necessary to implement querying in the *interactive* mode.

In the *interactive* mode the querying algorithm fundamentally does not change. At the end of time point T_i, it samples $N = n$ futures using a Monte Carlo simulation approach, and builds distributions of project performance parameters (COI

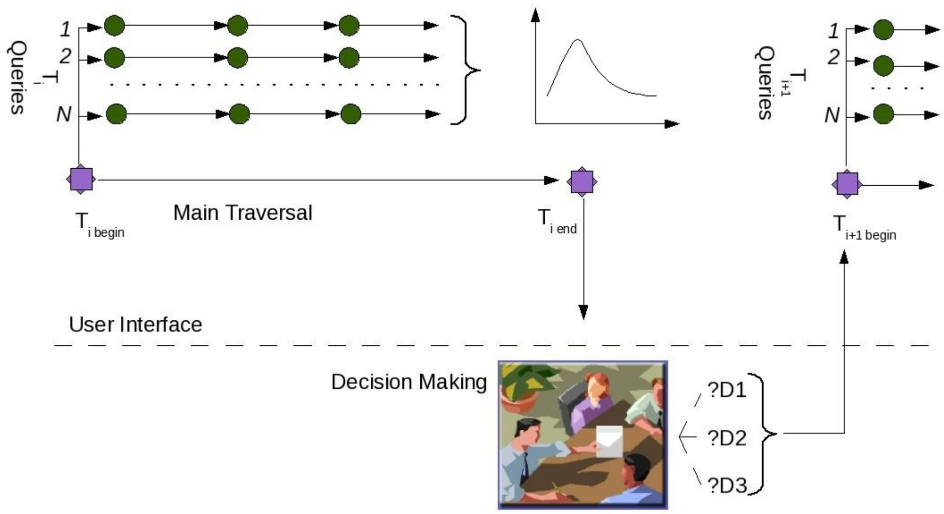


Figure 2: Querying Schematic Diagram: Interactive Mode

and/or expected remaining duration). Then instead of traversing automatically to the time point T_{i+1}, it awaits a human decision while providing the decision-maker the probability distribution information generated from querying. This provides the human decision-maker to intervene by making appropriate decisions, thus guiding the traversal to the next time point. Figure 2 illustrates the schematic for the implementation of querying in the interactive mode. $T_{i,begin}$ to $T_{i,end}$ is the discrete time point that the situational simulation simulates each turn and represents a day or week, depending on the granularity of the project being simulated. In the case of the ICDMA simulation of the steel framed office building, it is a day. At the end of this period the decision-maker is informed about the project outcome distribution - which they can use to strategically make decisions. The information is made available to the user through the ICDMA interface. ICDMA has the ability that allows decision-makers to allocate new resources (material, hire labor), to reallocate resources between activities, to change the priority of activities, and to delay activities. The interface also allows the user to input relevant decisions. The simulation uses the decisions and the project information in TONAE to traverse to the next simulation time point T_{i+1} - which is the next day in the project. This continues until the project has been successfully completed.

The interactive mode implementation of the querying algorithm within ICDMA enhances our ability to assess how uncertainty and risk in a construction project dynamically changes under differing project scenarios. It also provides us the ability to explore the sensitivity of the project to alternative decision-making strategies. In addition, this implementation also promotes the study of risk informed dynamic decision-making, because ICDMA is a simulation of a dynamic environment, and the output from the querying algorithm provides information about evolving project risk and uncertainty. The experimental work discussed in the next section explores each of the above claims.

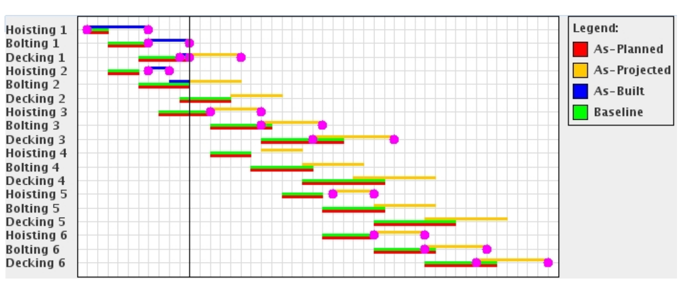


Figure 3: Starting Scenario: Schedule status at time T (schedule in days).

3.1 Experimental Design

The general experimental goals this study are as follows:

- **E1**: Record and study the nature of dynamic uncertainty as the simulated project progresses from one time point to another. The change in uncertainty may be caused by external events such as weather and/or because of specific decision strategies that may improve or worsen project performance.
- **E2**: Conduct multiple runs with the same decision strategies and different event distributions to explore alternative outcomes and the robustness of the strategy under various circumstances.
- **E3**: Investigate the impact of alternative decision strategies under similar project scenarios.

We conducted a preliminary set of experiments with the prototype framework. The experiments were limited in scope and serve the purpose of establishing an experimental framework for using situational simulations to further research in dynamic decision-making under uncertainty.

In our experimental work we considered three decision strategies. These strategies are broad outlines which help to prioritize resource and labor allocation decisions and guide individual decisions. They are:

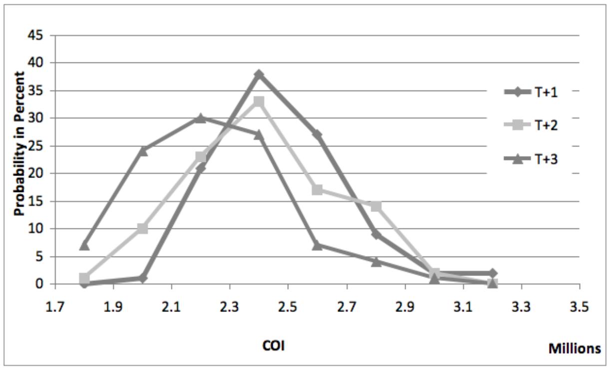
- **D1**: The decision-maker consistently aims to crash the project and unless project constraints don't allow, acquires additional labor and material to get ahead of schedule.
- **D2**: The decision-maker focuses and prioritizes critical activities and when possible re-allocates resources from non-critical activities to critical activities.
- **D3**: The decision-maker simply follows the baseline plan and does not take any aggressive measures to mitigate damages or crash the schedule. This is the control case.

The experiments were conducted by setting up a scenario in which the project was running on a delay. Figure 3 illustrates the as-planned versus the as-built schedule until that point (T) in the project. Using this scenario as a starting point we ran a total of 9 simulations. Of the 9 runs, three runs were conducted using each of the decision strategies D1, D2, and D3. Each simulation run progressed the simulation for 3 time points. Hence, for the i-th ($i = 1-9$) the simulation runs decision interventions were made 3 times: end of T, before $T+1$, end of $T+1$, before $T+2$, end of $T+2$, before $T+3$. For each decision the query probability distributions were recorded for the projected COI. Weather events (major and minor) were allowed to impact the project outcomes.

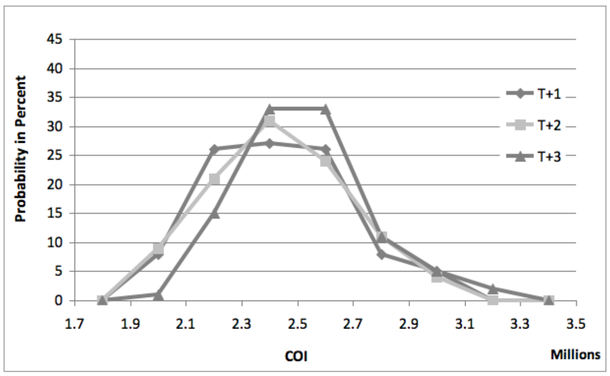
3.2 Experimental Results

In this section we discuss how the data collected, as per the discipline explained in the last section. The probability distributions from the query algorithm were collected and plotted as histograms for project cost. In the graphs, the x-axis shows the COI, an indicator of budget overrun; the y-axis shows the probability of getting a certain COI. The first two sets (Figure 4) show the outlook from three time points in the simulation. The last set (Figure 5) plots the results of three decision making strategies for comparison. The graphs were interpreted qualitatively by analyzing their positional shift and shape as follows:

- A shift to the left over time indicates worsening performance as the most likely, minimum and maximum costs of completion are increasing over time.
- A shift to the right over time indicates improving performance as the most likely, minimum and maximum costs of completion are decreasing over time.
- A wider spread and/or the development of one or more modes over time indicates increasing uncertainty in the project with the possibility of threshold events that may govern the project outcome significantly.



(a)



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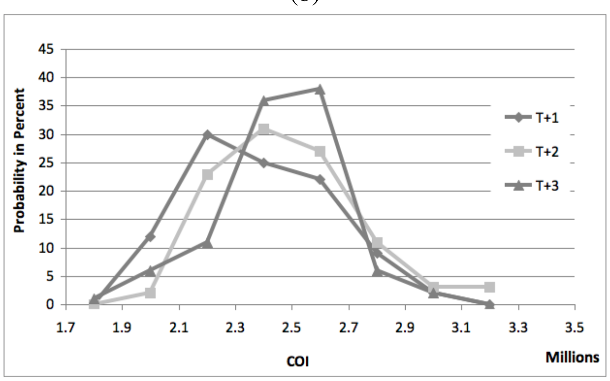
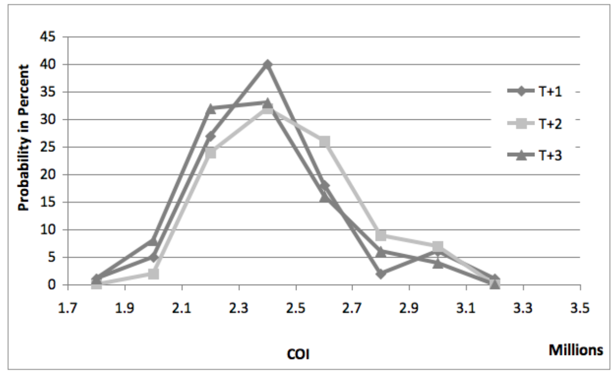
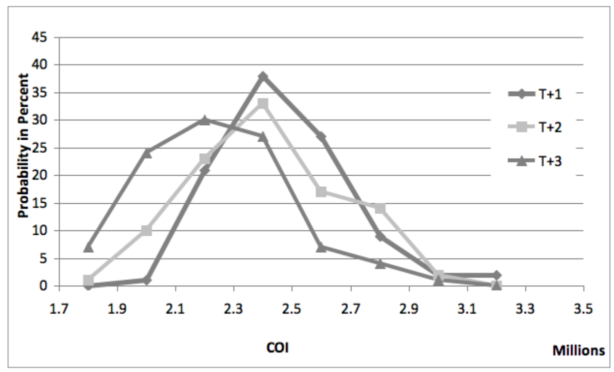


(c)

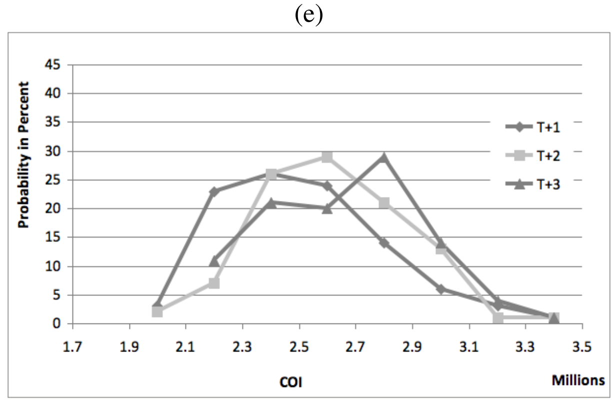
Query distributions for time point $T+1$, $T+2$ & $T+3$ for strategy: (a)D1 (b)D2 (c)D3



(d)



(e)



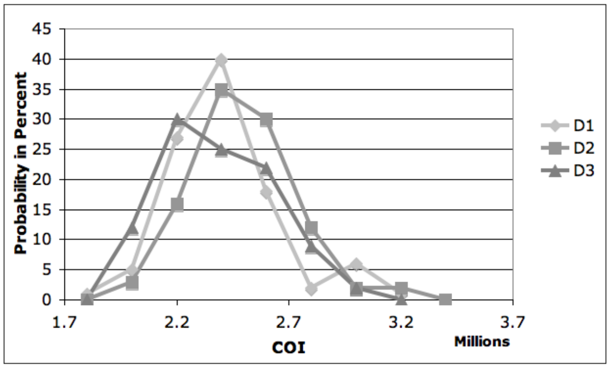
(f)

Query distributions for three different simulation runs for strategy D1

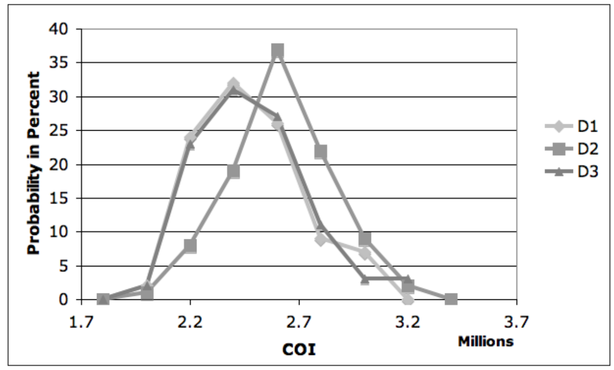
Figure 4: Query distributions

The shape analysis allows for indicators of how uncertainty in the project is changing and whether a strategy is useful or not. The experimental goals were addressed as follows:

- **E1**: Figure 4 (a, b & c.) shows how the query distributions change for each of the three decision strategies as the simulation proceeds from T to $T+3$. The three runs compared were not interrupted by any events. The projected performance when using strategy D1 improves over time. This reflects the impact of aggressively crashing the schedule. The performance when following strategy D2 and D3 both show a right shift in the plots and therefore a worsened projected performance.
- **E2**: Figure 4 (d, e & f.) shows three runs for decision strategy D1. Of the three runs, only run three had a major weather event on day $T+2$. It can be seen from the three plots that the strategy D1 in general improves projected cost performance, except in the case of run 3 when there was an external weather event that disrupts work and



(a)



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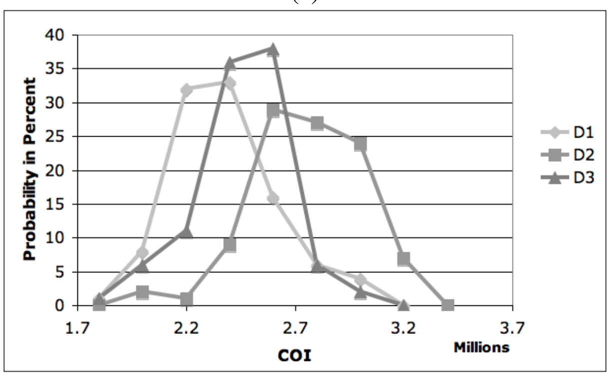


(c)

Figure 5: Comparison of three different strategies across time points (a) $T+1$ (b) $T+2$ and (c) $T+3$

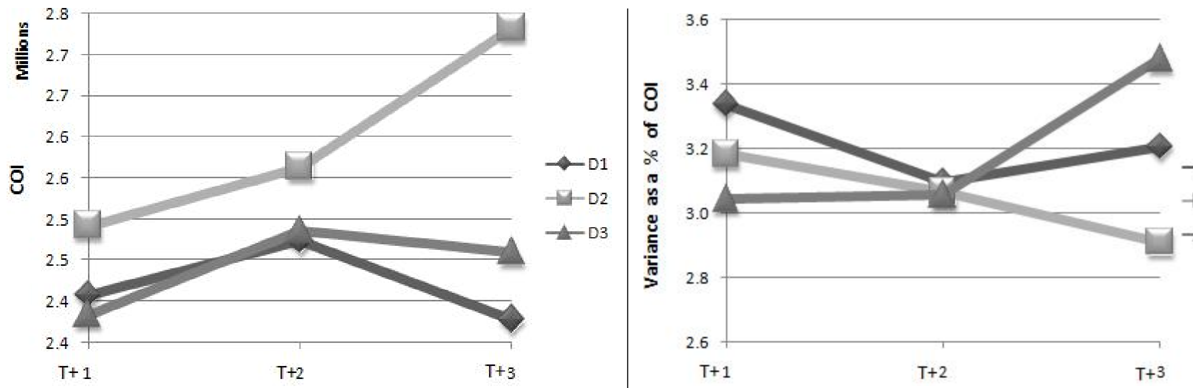
reduces productivity. In such a a situation, the query distribution gets two local maximas resulting in two competing long run outcomes.

- **E3**: Figure 5 illustrates how three different decision strategies result in three different project histories over three time points. Each of the plots illustrate the query distributions for each of the three strategies at the end of time points $T+1$, $T+2$ and $T+3$. The runs compared did not have any external events. Hence, the decision strategies can be objectively compared. It is clear from the shift in the distributions that the preferable strategies in order are D1, D3 and D2. Figure 6a illustrates the expected values of the projected COIs at the end of time points $T+1$, $T+2$ and $T+3$. It can be seen that the performance for the strategies D3 and D1 improve over three time points while that for D2 gets progressively worse. It is not unexpected that the strategy to crash the schedule is leading to superior performance projections over the three time points studied. However, it is interesting to find that the next best strategy is to stick to the as-planned schedule rather than to re-allocate resources from non-critical to critical activities. A plot of the standard deviation for each of these query distributions are illustrated in 6b.

These experiments raise more questions than answer any. For example, while an aggressive strategy to crash the schedule over the short term might look appealing, over longer time horizons, it is likely to lose its attractiveness as the time cost trade-off changes. Further investigation involving longer simulation periods will be necessary to address this issue. Similarly the change in the behavior of the standard deviations needs further investigation with a larger number of samples per run. At this time it appears that, as the uncertainties associated with a poor strategy increased the confidence of the prediction improved - this merits future investigation.

4 FUTURE WORK

We presented a framework that can show the possible futures of a project based on various decision making strategies. This paper is a preliminary step at using the querying algorithm in an interactive mode to test alternative strategies and consider alternative decisions. The preliminary analysis at this stage is based on qualitative analysis of the distribution



(a) (b)

Figure 6: Comparison of (a) Expected Values of COI Projections at the end of $T+1$, $T+2$ and $T+3$ and (b) Standard Deviation of COI Projections at the end of $T+1$, $T+2$ and $T+3$

shapes over three time periods and across three runs per decision strategy. Future work will lay the foundations for rigorous statistical comparison over multiple runs with eventual investigation of automatically having an intelligent agent try and test multiple competing scenarios. The current implementation incorporates predefined strategies that do not change as the project progresses. In other words, the depictions of the changes in the cost distribution depend on unfolding events, not on adaptive decision making. Our objective is to study and if possible replicate human expert level intelligent decision making. Therefore our future directions are threefold:

1. We plan to provide a language for defining rich strategies for decision making. For example, decisions can depend on the current state, a history of past situations, as well as the trends that were observed as a result of past decisions. In the first case, a Markov assumption is being made. In the second case, the Markov assumption is being lifted, and time points in the past are being analyzed individually. In the last case, trends rather than static situations are being analyzed.
2. Being able to provide a complex decision making strategy will allow us to conduct simulation experiments where various strategies are compared automatically. We will also try to identify the simplest strategy that produces results similar to one or more complex strategies.
3. The next step will be to conduct experiments with human decision makers and analyze the similarities and differences between automatic decision makers. This will provide insights into human mechanisms of decision making.

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