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USING SITUATIONAL SIMULATIONS TO COLLECT AND ANALYZE DYNAMIC CONSTRUCTION MANAGEMENT DECISION-MAKING DATA

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ABSTRACT

In this paper we lay the foundations for studying decision-making in complex dynamic construction management scenarios using situational simulations as experimental testbeds. We draw on research conducted in dynamic decision making, construction data-mining and situational simulations to develop methods to study human decision-making data collected in ICDMA - a situational simulation of a real four story steel frame office building construction project. Specifically, we address challenges in the collection, organization and analysis of human subject data. We define a discipline driving the collection of human decision-making data, establish a semantics to organize the data and a simple mathematical syntax to represent it. We also present an analysis of preliminary experimental work and show that our method can be used to analyze patterns in complex construction decision-making. Finally, we present an agenda of research in construction decision-making using situational simulations that can be conducted using our proposed methods.

1 INTRODUCTION

Successful management of complex projects requires effective decision making. A decision-making environment which changes as a function of the sequence of decisions, independently of them, or both, is referred to as a dynamic task environment (Edwards 1962). Construction project management scenarios are examples of high stakes, dynamic task environments. For example, a delay in a particular activity related to events such as material delivery, the need for rework, lowered labor productivity, weather, or similar external circumstances can result in cascading delays that impact the final cost and schedule of the project, with impacts running into large sums of money, litigation and or liquidated damages.

Expertise in managing such environments is dependent on the ability to make critical decisions, and select appropriate management strategies to complete the project on schedule and under budget. Construction crisis scenarios can be modeled as combinations of resource and temporal constraint violations (Rojas and Mukherjee 2006). Hence, it is likely that effective decisions reflect the same model that describes the crisis scenarios they address. The hypothesis driving this research is that there are significant patterns in effective construction decisions that drive strategy selection, even when they are made in different contexts. This research is to study the dynamics of human decision-making in construction management. The contributions are twofold. First, the research will help in the development of powerful systems that assist effective construction decision-making. Second, it will add to the knowledge of decision-making in dynamic environments, by extending existing research to complex decision-making environments such as construction management.

The challenge lies in analyzing large volumes of construction decision-making data to find the anatomy of a good decision. Case studies can provide important guidelines to classify project scenarios and to investigate patterns in effective decision-making. However, they can be misleading as they narrate limited scenario specific responses, instead of

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providing general statistically significant trends. In addition, it is not possible to explore what-if scenarios to test changes in responses in a case study. (Pennell, Durham, Ozog, and Spark 1997) Data regarding construction projects can be difficult to collect. Direct observation while not impossible, is time consuming and costly. Besides, collecting data is a complex operation, if the level of detail at which data is being collected, and the level of abstraction of the model being used are not known. Existing construction databases have been studied (see discussion in Section 2.2) and can often be used to construct project histories. However, such data seldom provides information regarding decisions that shape the course of the project, and the factors that influence the anatomy of effective decisions.

The first step is to address appropriate levels of detail at which construction decision-making data need to be collected, and the level of abstraction at which such data need to be analyzed. Situational simulations (Rojas and Mukherjee 2006) allow large quantities of human-subject data to be quickly and easily obtained because it is completely digital. It is also easy to duplicate scenarios for multiple human subjects, providing the ability to conduct controlled experiments by exposing human subjects to similar scenarios. In this paper, we discuss the role of situational simulations in studying human decision-making in construction management. Specifically, we present a formal method to capture decision data from a simulated construction environment.

The significance of this work is that it furthers the knowledge of construction management decision-making, its effectiveness, and its impact on project outcomes. The broader impact of this research is in its contribution to the study of dynamic human decision-making in complex environments.

2 THEORETICAL FOUNDATIONS

The decisions and strategic responses in construction scenarios can vary significantly depending on the specific project scenarios at hand. We hypothesize that the anatomy of an effective decision is dependent on the dynamics of the relationships between resource and temporal constraints driving the project, instead of being dependent only on the project context. This is supported by notions that have been established by previous research in construction crisis management and decision-making in dynamic task environment. In this section we discuss relevant research that supports our hypothesis and research in construction data mining and situational simulations to establish the foundations for our research methodology.

2.1 Decision-making in Dynamic Environments

Existing research on decision-making in dynamic task environments has documented the characteristics of such environments and the challenges they pose to decision-makers. Some of the challenges identified are:

- Ability to take into account the rate of change of the construction environment and relate their sense of timing, to the system evolution rate (De Keyser 1990, Kerstholt 1994, Kerstholt 1995)
- Capacity for selecting strategies by appropriately updating uncertainties and identifying risks when the system is changing (moving targets) (Ford, Schmitt, Schechtman, Hults, and Doherty 1989, Payne, Bettman, and Johnson 1993) resulting in sub-optimal performance
- Sub-optimal decisions that can result from misperceptions of feedback (delayed rather than immediate) (Diehl and Sterman 1995)
- Failure to adapt to changes in the environment with a tendency to continue working on models of the environment that have ceased to exist (e.g., Lusk and Hammond's (1991) work with weather forecasters.)

Kerstholt and Raaijmakers (1997) mention that most studies so far have involved subjects who are often not familiar with the domain and have little or no adaptive expertise. Given that construction management scenarios are dynamic task environments (Sterman 1992), it is likely that the same challenges will apply to construction decision-making and elicit an organized response. Kerstholt and Raaijmakers (1997) also note that many expert decision makers in dynamic environments "are able to maintain an overview of the system under control, whereas others tend to fixate too much on single local diagnosis problems." This is one of the main differences (Bransford, Brown, and Cocking 1999, Chi 1988) identified between expert and novice approaches to problem solving. Finally, research in expert-novice cognition suggests that expert cognition and knowledge exhibits structured organization. Effective decision-making, being a product of expert cognition more often than not, it is likely to reflect a similar structure and organization. This supports the hypothesis driving this research.

Recent research in construction decision making has investigated strategic decision-making of construction managers who are given the opportunity to reason with the causal knowledge of key performance factors and indicators (Dissanayake and AbouRizk 2007). A subjective method for modeling construction performance was presented using cognitive maps to represent mental models or internal knowledge representation of construction managers. Fuzzy cognitive maps model the cause and effect relationship between concepts that present themselves in a construction project. In this method, the concepts are represented as nodes in a graph, and the links between the nodes represent the cause and effect relationship between concepts. This work is important to our own because we are modeling human decisions that drive construction projects.

Our analysis does not start with a directed graph of concepts that provides the basis for inferences. Instead, this research captures and analyzes human decision-making data, including data describing the context and environment in which the decisions are taken. The analysis method finds significant associations between the context of decisions, with consequences and the decisions, to find the most significant patterns in effective construction decision-making. Given the difficulty of capturing human subject data directly from construction sites, we use situational simulations to capture human decision-making data while human subjects explore what-if scenarios and try alternative scenarios. The models reflect relationships between decision variables and environment variables. We depart from (Dissanayake and AbouRizk 2007) by developing objective methods that identify concepts from the graphical reasoning models.

This leads us to the discussion of situational simulations and data mining methods that will provide the methodology to collect data and develop graphical reasoning models.

2.2 Construction Data Mining

Construction databases have been analyzed using data mining methods to investigate delays in construction projects. Soibelman and Kim (2002), analyzed the US Army Corps of Engineers construction database. The research effort emphasized careful data preparation, including identification of statistical outliers followed by their elimination after manually verifying their validity. The data set was subjected to feature subset selection algorithms, and a decision tree was developed from the results. This decision tree identified several important relationships in the construction data that predicted project delays. Such relationships were used as inputs to neural networks, that were trained on a subset of the original data. This approach proved to be successful at predicting delays in new data.

Soibelman and Kim's (2002) research focuses primarily on developing a framework for identifying how the project variables such as weather can be related to the occurrence of delays in the project. It does not, however, include the influence of the contexts in which decisions are made by construction managers on project delays. In our research, we consider a decision to be a function that maps the state of the construction project onto an action. In other words, when a particular state is observed, the decision maker issues a decision which affects the flow of the construction project by rescheduling activities or re-allocating resources. The impact of the action can vary significantly based on the state of the project at which the decision is taken. The same decision can have different outcomes in different contexts. Because of this, the delay observed is based not only on the observed set of environmental conditions, but also on the decision issued by the decision maker.

Our work addresses patterns in decision making across varieties of contexts. The goal is to develop a framework in which the relationship between decisions and environmental conditions can be studied.

2.3 Situational Simulations

Situational simulations provide an interactive simulation platform that can be used to explore "what-if" construction scenarios, estimate risks and contingencies, test alternative plans during construction, and facilitate the capture and analysis of decision-making data. They create temporally dynamic clinical exercises of construction project scenarios that expose users to rapidly unfolding events and the pressures of decision making. The design, development, and use of general-purpose situational simulations can be found in previously completed research (Rojas and Mukherjee 2006, Rojas and Mukherjee 2005, Rojas and Mukherjee 2003).

ICDMA (Interactive Construction Decision Making Aid) is a specific implementation of a general purpose situational simulation framework and its description can be found in previous work by authors (Anderson, Onder, and Mukherjee 2007). It simulates the construction of a steel frame building and was developed on the basis of a real construction project, the information for which is compiled and documented (Daccarett and Mrozowski 2005). The building has four stories, has $80,000$ square feet of built area, 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.

ICDMA simulates the construction project based on the as-planned schedule and costs. The human-subjects in it are construction managers. Construction managers

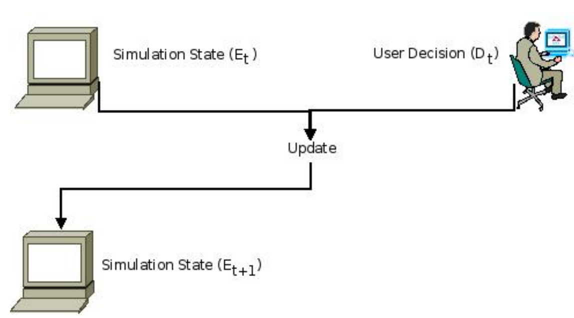

Figure 1: The process used to update the state of ICDMA

are decision-makers whose primary goal is to complete a construction project on time and under budget. The simulation presents a construction manager with a situation, and allows the manager to respond. Consequences from the decisions result in new scenarios that require the subjects to respond. This process continues until the completion of the simulated construction project (Figure 1). Upon completion, the elapsed simulation time and the costs encountered are recorded. Figure 2, illustrates the interface of ICDMA, providing the subject with information on planned and actual performance with respect to budget and schedule (Gantt Chart) and future predictions with respect to project completion time and final cost.

Throughout the simulation, human subjects (often referred to in this paper as *users*) play the role of construction managers and are presented with events that force the simulated project to deviate from its original plan. Typical subjects have various levels of experience, ranging from senior level construction engineering and management students with limited project management experience to construction managers with several years of experience. The goal of the subjects is to complete the project on schedule and under budget. They face multiple decision-making challenges in their efforts to complete the project. The challenges are generated as events in the system. There can be two kinds of events that the subject has to handle. The first kind of events are external in nature and the construction managers have no control over them. Examples of such events include failed material delivery and bad weather. External events cause delays in planned construction activities which may in turn have consequences cascading throughout the project, as a delay in one activity may delay other activities that are related to it by time and resource constraints. Such cascading delays, impacts and complex feedback from previous human subject decisions (for example a labor crew that has been assigned to more than a single activity at the same time) lead to the second type of events, namely, internal events. The manager's reaction to these crisis scenarios and the specifics of the scenarios are captured by the simulation.

The ICDMA provides us with a *micro-world* to study human decision-making (Gonzalez, Thomas, and Vanyukov 2005) in dynamic environments such as the construction project management domain. Previous decision-making research in similar domains have successfully used microworlds and Gonzalez et al. (2005) present a taxonomy of dynamic decision making. According to their classification framework, ICDMA ranks as follows:

- Dynamics: ICDMA is a highly dynamic environment as the simulation environment changes autonomously (external events and internal events) and directly in response to users' decisions. While the decisions are not taken in "real-time" the simulation runs in "pseudo real-time" requiring the users to make decisions under the pressure of time and rapidly unfolding events.
- Complexity: ICDMA shows moderate complexity as the user can currently manage resource variables - including labor crew management and material management. While the user cannot directly reschedule activities, they can control the length of the schedule indirectly through their control on productivity.
- Opaqueness: ICDMA is highly opaque to the user, as the external events are randomly and unexpectedly generated and the internal events can be apprehended by the user only if they are critically aware of the state of the simulation.
- Dynamic Complexity: ICDMA shows high dynamic complexity because user decisions often result in internal events that are similar to decision feedbacks that are de-localized in time and space.

Hence, we use the ICDMA as an experimental testbed to collect and analyze decision-making data. Data regarding the decisions made and the consequences of each decision, are collected through the course of the simulation. The following sections describe the formal methods of collection and analysis.

3 THE DATA COLLECTION FRAMEWORK: ORGANIZATION AND DISCIPLINE

Organization of the collected data should reflect the underlying structure and semantics of the domain parameters that are being measured. In this section we present a simple, but representative approach to effectively organize the data. The primary premise of the data organization is that the results of a construction project can be traced by following the activities of critical labor crews that primarily drive efficient work-flow and productivity on a project. This is supported by evidence in the literature that labor flow and work flow on a construction site are co-dependent and significantly impact productivity (Thomas, Horman, Jr., and Chen 2003). It has also been shown that variability in labor productivity can be minimized by appropriately matching the labor resource to the amount of work available to perform (Thomas 2000). Hence, we believe that activities of the primary labor crews specifically with respect to changes in work, crew size and scheduled hours will reflect the impact of the decisions.

In order to set up the simulated environments, we first divide all the activities into groups of primary activities that define the project. To each of these groups of activities we assign the relevant materials that are used and the primary labor crews that are dedicated. For example, in the construction of a steel-framed office building, which is the project simulated in ICDMA, we can classify the primary activities driving the schedule into three groups: Hoisting

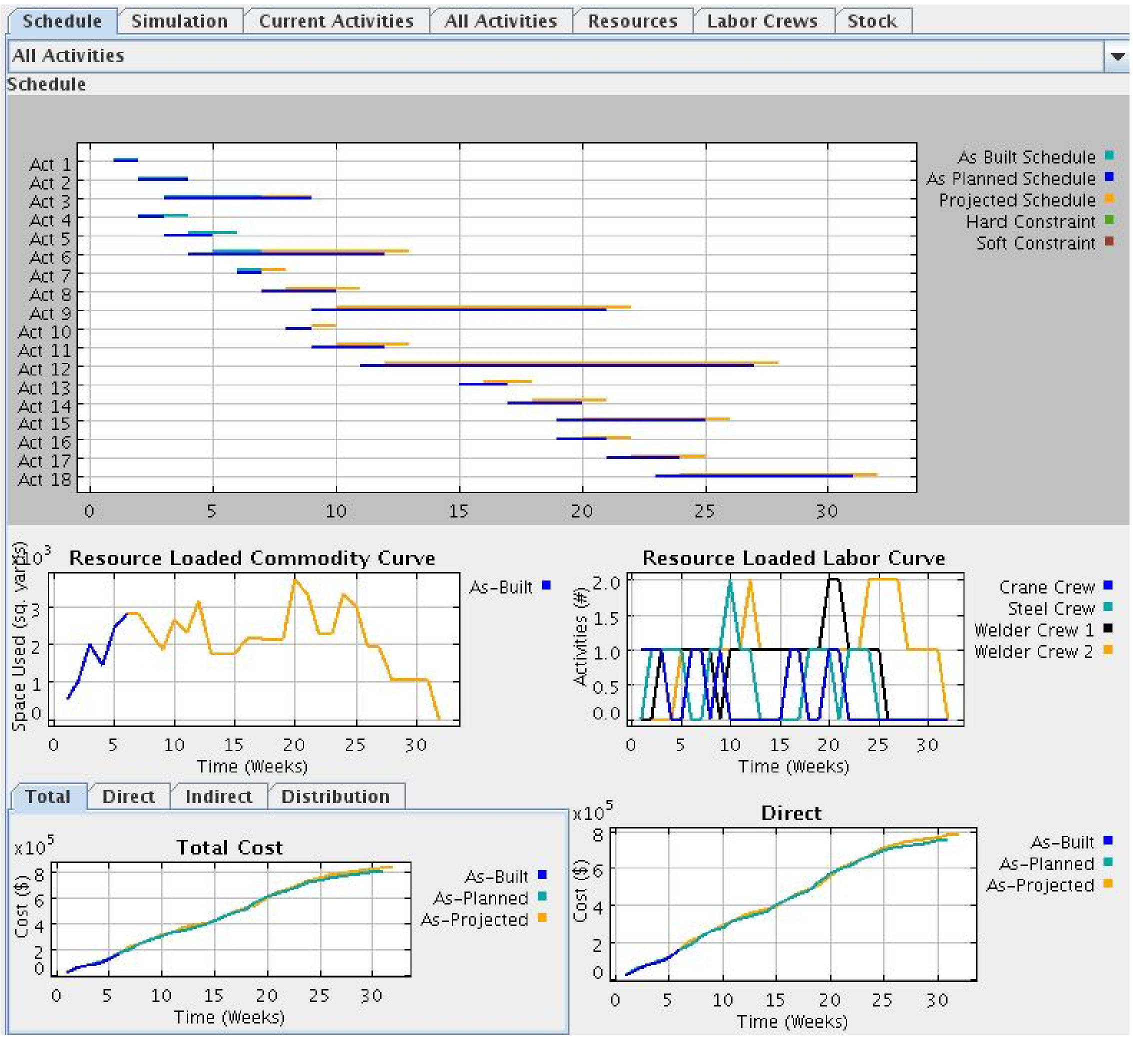

Figure 2: The ICDMA interface

activities (Activities 1,4,7 etc. in Figure 2) Bolting activities (Activities 2,5,8 etc. Figure 2) and Decking activities (Activities 3,6,9 etc. Figure 2). (A detailed discussion of the constraints relating these groups of activities and their description can be found in Anderson et al. (2007)). Each of these groups of activities are assigned main driving materials and labor crews that are unique to them. Then we follow the activities of each labor crew with respect to the three performance parameters: crew size, worker hours and material installed. Specifically we keep track of positive or negative deviances from the as-planned performance. This organization is depicted in Figure 3. While this data organization approach is limited in its simplicity, it is well founded and in future work has the ability to be extended to include more performance parameters (for example, space) as well as to be scaled to include more activity-material-labor crew groups. At this early stage of our investigation, we consider this a very good place to start.

Data collected from the simulation consists of a complete project history and a list of decisions made at each time point within the simulation. Decision data captured is organized by its effect on each of these resources. By tracking crew histories, it is expected that decisions which affected crew productivity can be identified.

Next, we discuss a discipline that supports our data collection. The study of decision making in a simulated construction environment can be divided into four different categories as detailed in Figure 4. Each of these four categories can be used to study a different aspect of decision making. There are two main categories of variables to be controlled in an experiment: the variables involving the project, and the variables involving the decisions. In the

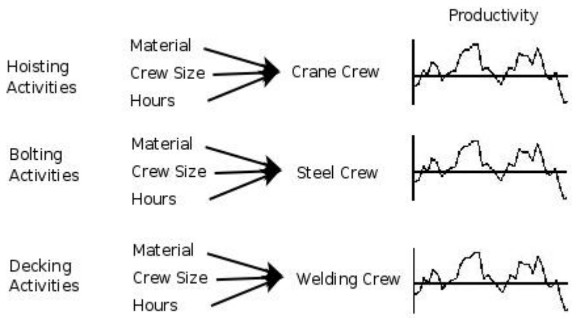

Figure 3: Organization of data collected from ICDMA

experiments where data is collected from a single project, the project variables are controlled so that aspects of decision making can be studied without interference from the changes in the project environment.

Number of projects \ Number of users	1	>1
1	**SUSP** Project variables controlled User variables controlled	**MUSP** Project variables controlled User variables studied
>1	**SUMP** Project variables studied User variables controlled	**MUMP** Project variables studied User variables studied

Figure 4: Four categories of decision making experiments

- **Single User Single Project (SUSP)** - In this type of experiment, data collected from a single user making multiple simulation runs on the same project is analyzed. In this type of experiment, because both the project variables and the user variables are controlled, the difference between each run will be the random events triggered throughout the simulation. Thus, the interactions between random events and decision making can be studied.
- **Multiple User Single Project (MUSP)** - This type of experiment analyzes the data collected from multiple users each running the simulation on the same project. Because the project variables are controlled, the differences between the decision makers can be studied with fewer project specific variables to analyze. This might be used, for example, in research studying the difference between expert and novice decision makers.
- **Single User Multiple Project (SUMP)** - This type of experiment analyzes data collected from a single user across various different projects. In this case, user variables are controlled, so the differences between decisions made in different scenarios can be studied. Research which attempts to find patterns in the planning of decisions might benefit from this, since many scenarios requiring different plans can be analyzed.
- **Multiple User Multiple Project (MUMP)** - This type of experiment studies data from multiple users across multiple projects. While few variables are controlled, data collected in this manner can be useful for validation, since it provides a broad range of data to test any hypothesized patterns.

Studying decisions made in dynamic task environments within a simulation is very advantageous because often it is difficult to collect large amounts of data from SUSP or MUSP categories. This is because it is rare for an exact project to be repeated multiple times. By studying decisions in a simulated environment, new types of experiments can be performed. In this paper, we limit our scope to the discussion of the SUSP data collection discipline.

4 REPRESENTATION OF A DECISION

In order to analyze the collected data and draw quantitative or qualitative conclusions regarding dynamic decision-making, it is critical to represent the collected data mathematically. In this section we define the syntax to represent the decision-making data that are collected according to any of the above disciplines and organized according to the semantics defined.

For each time point t in the simulation, E_t is used to denote the state of the simulation at that time point. The decision provided by the user at time t is denoted by D_t. Given E_t and D_t, the simulation must be able to compute E_{t+1}. This process can be thought of as a function, which takes in the current state of the simulation and the decision produced by the user, and outputs the next state of the simulation. This updating function is denoted as follows:

$$E_{t+1} = update(E_t, D_t) \tag{1}$$

and is depicted in figure 1. Previous work (Rojas and Mukherjee 2005) describes E_t and the reasoning driving the *update* function in Eq. 1. Similarly, the process by which the user produces a decision can be thought of as a function which takes the current state of the simulation in as input and outputs a decision, denoted as follows:

$$D_t = MM(E_t) \tag{2}$$

where MM refers to the cognitive mental model the subject uses to produce a decision. From these equations, it can be seen that in order to capture the decision data, D_t must be captured at each time point. It is also important to capture E_t at each time point in order to study the relationship between the environment and the decision that was made. This allows us to study the interactions between decisions taken and their impact on the simulated environment.

Within the simulation, the user is presented several variables that they can use to control material and labor allocation to activities and labor crews. For example, there would be three variables, denoting the number of $W10 \times 12$ beams available for a hoisting activity, the number of workers in the hoisting crew available, and the number of worker-hours assigned to the hoisting of the $W10 \times 12$ beams in the as-planned schedule. If the user realizes that the number of beams available in stock is less than what is required to complete the activity, or the crew size needs to be altered, or the number of work hours adjusted (s)he will assign a different value to each of the three variables respectively. Multiple such variables make up the total material allocation for each of the primary labor crews. D_t is then defined as a vector of values specified for each of these variables. These values are passed into the update function for the simulation, and the state of the simulation is modified accordingly. The user input assigns values to two different types of variables in D_t. The first type of variables take in continuous numeric inputs, while the second type of variable takes in discrete inputs from well defined sets of values.

In the simulated environment, the user will make a decision every turn, yielding a vector of decision vectors $\mathbf{D} =< D_1, D_2, D_3, \ldots, D_{n-1} >$, where n is the number of turns the simulation takes to complete. At each step of the simulation, there is also an as-planned decision P, which is the decision that would be made based on the as-planned schedule for the construction project. A vector of as-planned decision vectors $\mathbf{P} =< P_1, P_2, P_3, \ldots, P_{n-1} >$ is also defined. Given $\mathbf{P}$ and $\mathbf{D}$, a *decision shape vector* $\mathbf{DS}$ can be defined as $\mathbf{DS} = \phi(\mathbf{D} - \mathbf{P}) =< \phi(D_1 - P_1), \phi(D_2 - P_2), \phi(D_3 - P_3), \ldots, \phi(D_{n-1} - P_{n-1}) >$, where

$$\phi(x) = \begin{cases} + & x > 0 \\ = & x = 0 \\ - & x < 0 \end{cases} \tag{3}$$

for continuous variables and

$$\phi(x) = \begin{cases} = & x = 0 \\ \neq & x \neq 0 \end{cases} \tag{4}$$

for discrete variables. This decision shape vector, gives a simple trace of the positive or negative deviation of as-planned performance from the decision driving as-built performance. This can be a starting point for the quantitative analysis of the decision-making data collected from the simulation. However, $\phi(x)$ can quite easily be extended to provide more detailed information regarding the shape and nature of the decision vector.

5 EMPIRICAL WORK

An as-planned schedule was generated from the project detailed in section 2.3 to be used in ICDMA. Several errors were added to the as-planned schedule, such that delays were introduced to the project unless the user deviated from the as planned schedule. These errors include two space conflicts, where the material needed for the day's activities would not fit into the allowed area. They also include scheduling conflicts, where several labor crews were over allocated, such that they were scheduled to work on two activities at once. The simulation also used the following random events, so that the course of the simulation was not predictable:

- A 5% probability of snow, which caused productivity to halt on all activities
- A 5% probability of rain, which caused productivity to be cut in half for all activities
- A 5% probability that a labor strike would occur, during which time there is no productivity, but the laborers are not paid
- A 5% probability that the material purchased for that week would not arrive, resulting in a material shortage
- A 5% probability for each activity that a member of the labor crew working on that activity would call in sick

When the schedule fell behind due to a random event, the user had the opportunity to decide whether the work rate should be modified to restore the planned schedule. The user also had the options to purchase materials for each activity and to manage the labor crews to control the rate of work. In addition, constraints were placed on the start times of certain activities. For example, a bolting activity for the second floor could not start until the decking for the first floor was half way done, to reduce the fall distance for workers. Such constraints caused the delays in the schedule cascade and affected other activities. The objective of the simulation was to allow the user to complete the project within the shortest time and lowest cost possible.

The data captured from the simulation during a run included the labor allocation to each crew, any extra labor hired to change the crew size, and the materials purchased for each activity. This data was captured at each step of the simulation. Data regarding the state of the environment, and random events triggered through the simulation was also captured.

Data was collected from a human subject based on two simulation runs on the same project, i.e., the SUSP discipline was used. For this analysis, we define the schedule performance variance (SPV) as the ratio of the difference between as-built and as-planned schedule performance to as-planned schedule performance. Hence, when the project is running on schedule, the SPV is equal to zero. Negative deviations denote that the project is falling behind schedule as the project falls behind schedule.

In figure 5 the primary Y-axis plots the shape function (ϕ) of the user's decisions with respect to the *worker hours* component of a welding crew. On the secondary Y-axis it plots the SPV for the project. The X-axis plots the time line and the markers on it indicate the external events. We can see that the schedule reacts to both the decisions made by the user and external events. During periods in which the schedule is crashed ($\phi(x) = +$), the schedule hastens, since more work is being completed at each time step. The schedule falls behind when external events that delay the schedule occur. For example, we see that the user crashes the schedule on day 7 in apprehension of a potential conflict. This is reflected in the positive spike in the SPV during days 7 and 8. Similarly, we can trace the response of the user on day 14 to declining SPV during days 12 and 13 which happened very likely due to the external event in day 10. As the project undergoes more external events till day 17, we see the user struggling to keep the project on schedule till day 20 when the CPV is back to zero. This presents us the ability to trace the impacts of decisions, and to correlate them to external and internal events. Most importantly it allows us to study the impact of time lags between decisions and their impacts and also, the time lags between an events, their impacts on the schedule and cost, and to formulate reaction/apprehension times. Figure 6 shows similar trends for another run of the same simulation by the same user. It relates the decision shape vector with respect to the *crew size* component of the welding crew's fate to external events and SPV. In this case we find that in spite of corrective measures on day 2 and day 6 in apprehension of crisis, the SPV remains unaffected.

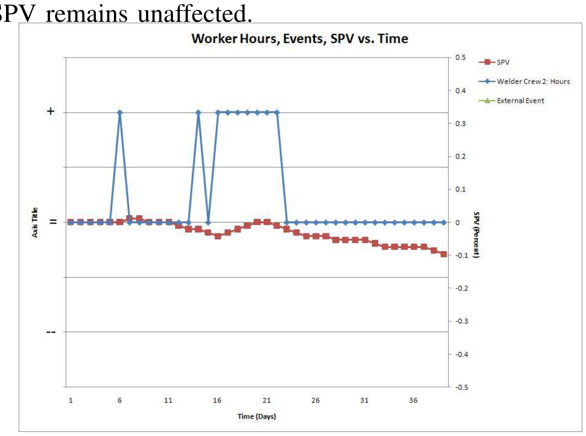

Figure 5: Worker hours, schedule, and external events vs. time

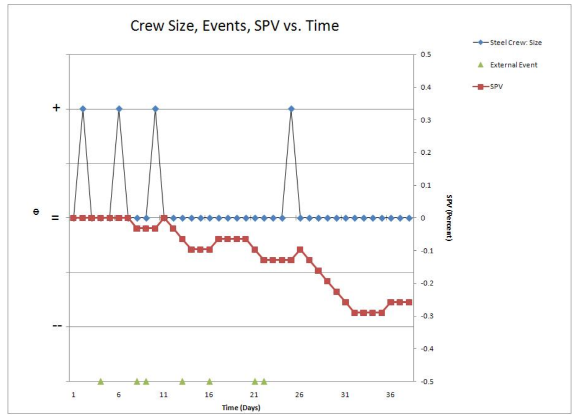

Figure 6: Crew size, schedule, and external events vs. time

6 DISCUSSION

In this paper we lay the foundations for studying decision-making in complex dynamic construction management scenarios using situational simulations as experimental testbeds. We address the challenges in the collection, organization and analysis of human subject data in the ICDMA - a situational simulation of a four story steel frame office building construction project. We define a discipline driving the collection of human decision-making data, establish a semantics to organize the data and a simple mathematical syntax to represent it. We also present an analysis of preliminary experimental work and show that the our method can be used to analyze complex decision-making behavior. The limitations of this framework in its current state lies in its simplicity; however, we believe that the presented framework can be extended and scaled in future work to reflect the decisions more accurately.

The framework in this paper also sets an agenda that can drive future research in studying construction decision-making. Each of the data collection methods in the defined discipline can lead to a different direction of study. The SUSP protocol, focuses on correlating the state of the simulation environment and events that occur in it (both external and internal) to decisions taken by an individual. For a particular individual this can help us analyze correlations between decisions pertaining to:

- Different labor crews: does the decision-maker prioritize a specific project thread over another in a crisis?
- Shape functions for worker-hour decisions, crew size and material installed for a particular labor crew: can the same impact be achieved on the schedule by different combinations of any two given the third, i.e., if there is no delay in material

delivery can we have equivalent impacts on the schedule by manipulating worker hours (overtime) and/or crew size (hiring labor)?

As we move from SUSP to MUSP, the above questions continue to be relevant but now can be studied across users of different kinds of expertise. This will allow us to study expert and novice cognition in construction management. The SUMP and MUMP methods will provide a way of validating results that we can get across the SUSP and SUMP tests. The eventual goal of this research agenda will be to develop a theory of construction management decision-making.

Some of the primary challenges that will need to be addressed in this research agenda will be both methodological and analytical. Methodologically, the data representation presented in this paper and the complexity of the situational simulations will have to be further developed so that the experimental testbeds can appropriately model the construction domain. The analysis presented in this paper is a simple first step. It lays the ground for building on future statistical finesse in analyzing large bodies of human subject data. We believe that by applying graphical models to analyze multi-variate decision data, we can discover underlying hierarchical graphical structures to decisions. Future work will establish and address the challenges in achieving these goals.

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REFERENCES

Anderson, G. R., N. Onder, and A. Mukherjee. 2007. Expecting the unexpected: Representing and reasoning about construction crisis scenarios. In *Winter Simulation Conference, ACM/SIGSIM*.

Bransford, J. D., A. L. Brown, and R. R. Cocking. 1999. How people learn. *National Academy Press*.

Chi, M. T. 1988. *The nature of expertise*. Lawrence Earlbaum, First Edition.

Daccarett, V., and T. Mrozowski. 2005. Aisc digital library: Construction management of steel construction. Available via <http://www.aisc.org/>[accessed 01/10/2007].

De Keyser, V. 1990. Temporal decision making in complex environments.

Diehl, E., and J. Sterman. 1995. Effects of feedback complexity on dynamic decision making. *Organizational Behavior and Human Decision Processes* 62:198–215.

Dissanayake, M., and S. AbouRizk. 2007. Qualitative simulation of construction performance using fuzzy cognitive maps. In *Winter Simulation Conference, ACM/SIGSIM*.

Edwards, W. 1962. Dynamic decision theory and probabilistic information processing. *Human Factors* 4:59–73.

Ford, J. K., N. Schmitt, S. L. Schechtman, B. M. Hults, and M. Doherty. 1989. Process tracing methods: contributions, problems and neglected research questions. *Organizational Behavior and Human Decision Processes* 43:75–117.

Gonzalez, C., R. P. Thomas, and P. Vanyukov. 2005. The relationships between cognitive ability and dynamic decision making. *Intelligence* 33:169–186.

Gonzalez, C., P. Vanyukov, and M. K. Martin. 2005. The use of microworlds to study dynamic decision making. *Human Factors* 21:273–286.

Kerstholt, J. H. 1994. The effect of time pressure on decision making behavior in a dynamic task environment. *Acta Psychologia* 86:89–104.

Kerstholt, J. H. 1995. Decision making in dynamic situations: the effect of false alarms and time pressure. *Journal of Behavioral Decision Making* 8:181–200.

Kerstholt, J. H., and J. G. Raaijmakers. 1997. *Decision making: Cognitive models and explanations*, Chapter 12, Decision making in dynamic task environments, 205–217. Routledge.

Lusk, C. M., and K. R. Hammond. 1991. Judgment in a dynamic task: microburst forecasting. *Journal of Decision Making* 4:55–73.

Payne, J. W., J. R. Bettman, and E. J. Johnson. 1993. *The adaptive decision maker*. New York, Cambridge University Press.

Pennell, R., M. Durham, C. Ozog, and A. Spark. 1997. Writing in context: situated learning on the web. In *ASCILITE 97*.

Rojas, E., and A. Mukherjee. 2003. Modeling the construction management process to support situational simulations. *Journal of Computing in Civil Engineering, ASCE* 17 (4): 273–280.

Rojas, E., and A. Mukherjee. 2005. Interval temporal logic in general purpose situational simulations. *Journal of Computing in Civil Engineering, ASCE* 19 (1): 83–93.

Rojas, E., and A. Mukherjee. 2006. A multi-agent framework for general purpose situational simulations in the construction management domain. *Journal of Computing in Civil Engineering, ASCE* 20 (6): 1–12.

Soibelman, L., M. ASCE, and H. Kim. 2002. Data preparation process for construction knowledge generation through knowledge discovery in databases. *Journal of Computing in Civil Engineering* 16 (1).

Sterman, J. D. 1992. Systems dynamics modeling for project management. *Systems Dynamics Group*.

Thomas, H. R. 2000. Schedule acceleration, work flow and labor productivity. *Journal of Construction Engineering and Management, ASCE* 126 (4): 261–267.

Thomas, H. R., M. J. Horman, R. E. M. Jr., and D. Chen. 2003. Improving labor flow reliability for better productivity as lean construction principle. *Journal of Construction Engineering and Management, ASCE* 129 (3): 251–261.

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