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INTEGRATED SIMULATION APPROACH FOR ASSESSMENT OF PERFORMANCE IN CONSTRUCTION PROJECTS: A SYSTEM-OF-SYSTEMS FRAMEWORK

Jin Zhu

Civil and Environmental Engineering Department
College of Engineering and Computing
Florida International University
10555 W Flagler St
Miami, FL 33174, USA

Ali Mostafavi

OHL School of Construction
College of Engineering and Computing
Florida International University
10555 W Flagler St
Miami, FL 33174, USA

ABSTRACT

This research proposes and tests an integrated framework for bottom-up simulation of performance in construction projects. The proposed framework conceptualizes construction projects as systems-of-systems in which the abstraction and micro-simulation of dynamic behaviors are investigated at the base-level consisting of the following elements: human agents, information, and resources. The application of the proposed framework is demonstrated in a numerical example related to a tunneling project. The findings highlight the capability of the proposed framework in providing an integrated approach for bottom-up simulation of performance in construction projects.

1 INTRODUCTION

One of the major challenges facing the construction industry is the low efficiency of projects in terms of time, cost and quality. Based on a recent study by the Construction Industry Institute, only 5.4% of the construction projects investigated met both authorized goals in time and cost within an acceptable margin (CII 2012). Better understanding of the determinants of performance is critical in enhancing the performance of construction projects. Construction simulation models (e.g., Cyclone by Halpin (1976), STROBPSCOPE by Martinez (1996), Simphony by Hajjar and AbouRizk (1999)) have been used over the past three decades to facilitate a better understanding of the underlying dynamics affecting the performance of construction projects. However, context-related factors (e.g. human behaviors and organizational culture), which have been proved to have significant impact on the performance of construction projects, cannot be captured by traditional construction simulation models (Lee et al. 2007; CII 2013). Recent studies in construction simulation filed have developed methodologies to incorporate some of these context-related factors into consideration (Lee et al. 2006). Despite the efforts have been made, an integrated framework facilitating a bottom-up understanding of the dynamic behaviors, uncertainties, and interdependencies between the constituents in construction projects is still missing. The major limitation of the existing construction simulation models is the lack of appropriate conceptualization of construction projects. In the existing models, construction projects are conceptualized as monolithic systems. However, construction projects are actually systems-of-systems (SoS) consisting of networks of interconnected human agents, information, and resources. Conceptualization of construction projects as SoS facilitates identification of the dimensions of analysis required for an integrated assessment of performance. The objective of this research is to propose and test an integrated framework for bottom-up simulation of construction projects using a SoS approach. In the following sections, first, the dimensions of analysis related to the proposed framework are introduced. Then, the application of proposed SoS framework is demonstrated in a numerical example.

2 SYSTEM-OF-SYSTEMS FRAMEWORK

The existing construction simulation models conceptualize construction projects as monolithic systems. Improper conceptualization of the nature of construction projects has led to inappropriate level of abstraction in the existing simulation models. The level of abstraction is the level at which the dynamics of construction projects are captured for simulation. In the existing construction simulation models, the level of abstraction is at the activity level. Abstraction of the dynamics of construction projects at the activity level leads to the following limitations: (i) lack of consideration of the autonomy of constituents in projects (e.g., creativity and flexibility of first-line workers), (ii) lack of consideration of the micro-behaviors (e.g., different human agents have different behavior attitudes in conducting same activity), (iii) lack of consideration of the interdependencies between constituents (e.g., the impact of information uncertainty on the decision-making behaviors of agents).

In reality, construction projects are systems-of-systems (SoS) consisting of networks of interconnected human agents, information, and resources (Zhu and Mostafavi 2014). A system-of-systems is an assemblage of components which individually can be regarded as systems (Maier 1998). SoS has five distinguishing traits: *operational independence of the components*, *managerial independence of the components*, *geographic distribution*, *emergent properties and evolutionary development* (Maier 1998). A close examination of construction projects shows that all these traits can be identified in construction projects, and thus, they can be investigated as SoS (Zhu and Mostafavi 2014).

The main principles in analysis of SoS include (DeLaurentis and Crossley 2005): (i) analysis of multiple levels in which the outcomes of each level is obtained by aggregating the dynamics at the levels below; and (ii) abstraction of the dynamics of SoS at the base level in which further decomposition is not possible. Hence, analysis of construction projects should be based on these principles. Zhu and Mostafavi (2014) proposed a framework (so-called construction projects system-of-systems (CPSoS)) for conceptualizing construction projects as SoS. In the proposed framework, construction projects are analyzed across four levels: base level (α), activity level (β), process level (γ), and project level (δ). The outcomes of each level of analysis are obtained by aggregating the components and interdependencies at the levels below. The abstraction of the dynamics of construction projects is made at the base level, which consists of three main elements: human agents, resources, and information (Zhu et al. 2014). Human agents are entities who conduct three major tasks: production work, information processing, and decision making. Resources and information are important elements facilitating these tasks of human agents. The proposed CPSoS framework identifies different classifications and attributes pertaining to the three base-level elements (Table 1). The detailed information pertaining to the classifications and attributes of base-level elements can be found in Zhu and Mostafavi (2014).

Table 1: Attributes of base-level elements in the CPSoS framework.

Category	Classification	Attributes
Human Agent	Production work-Agent	Productivity, cost
	Information processing-Agent	Response time
	Decision making-Agent	Behavior attitude, risk attitude
Resource	Material	Quantity, quality, cost, availability
	Equipment	Productivity, cost, availability
	Capital	Quantity, availability
Information	Static information	Availability, accessibility, completeness, accuracy
	Dynamic information	Availability, accessibility, completeness, accuracy, recency

3 NUMERICAL CASE

The application of the proposed CPSoS framework is demonstrated in bottom-up assessment of performance in a numerical example related to a tunneling project. In the numerical example, the base-level elements pertaining to design, construction, and risk management processes are abstracted and simulated using agent-based modeling.

3.1 Case Description

In this illustrative example, a case related to construction of a 1600-meter long tunnel is investigated. The ground conditions vary along the length of the tunnel and are represented by three categories as Good (1), Medium (2), and Poor (3). The ground condition persists for at least 100 meters. At the beginning of the project, only the ground condition of the first 100 meters is known. The project is conducted in sections. Each section has a step length of 100 meters, 200 meters or 400 meters. The design and construction of this project follow an adaptive approach based on the category of ground condition in different sections. For each section, the designer makes a decision about the excavation rate and type of support for that tunnel section based on the ground condition discovered at the end point of the previous section, the state transition probability matrix, and the designer's risk attitude. The state transition probability matrix (Table 2) is a piece of static information obtained from historical data. This information can be used to predict the ground condition of the next section. For example, if the ground condition at the end point of the previous section is found to be good (1), then according to historical data, there is 60% probability for the ground condition of the next section to be also good (1), 25% probability of being Medium (2), and 15% probability of being Poor (3). The designer then uses this prediction to adopt the appropriate excavation rate and type of support based on his own risk attitude. A risk-neutral designer uses exactly the predicted ground condition as the basis for making decision. A risk-seeking designer tends to be more optimistic. For example, as shown in Table 3, if the ground condition is predicted to be in the Medium category, a risk-seeking designer will choose both the excavation rate and type of support appropriate for Medium ground condition with 60% likelihood. The likelihood that the designer selects excavation rate and type of support appropriate for Good ground condition is 40%. A risk-averse designer has the opposite attitude in which more conservative decisions about excavation rate and type of support are made. After the designer make the decision based on the judgment, the workers start constructing that section. There are two activities in the construction process considered in this example: excavation and support placement. The productivity and corresponding cost rate related to these two activities are different based on different decisions made by the designer (Table 4). Table 4 shows the probability distributions pertaining to the productivity and cost rate under different designs.

Table 2: State transition probability matrix.

From Ground Category	**To Ground Category**		
	1 (Good)	**2(Medium)**	**3 (Poor)**
1 (Good)	0.60	0.25	0.15
2 (Medium)	0.10	0.80	0.10
3 (Poor)	0.05	0.20	0.75

Table 3: Decision probability matrix of a risk-seeking designer.

Predicted Ground Condition Category	**Design Basis**		
	1 (Good)	**2 (Medium)**	**3 (Poor)**
1 (Good)	1	0	0
2 (Medium)	0.40	0.60	0
3 (Poor)	0.10	0.30	0.60

Table 4: Productivity and cost rate in construction.

	Design Basis		
	1 (Good)	**2 (Medium)**	**3 (Poor)**
Excavation Rate (meter/hr)	Triangular (0.37,0.38,0.43)	Triangular (0.32,0.33,0.40)	Triangular (0.13,0.17,0.32)
Excavator Operating Cost ($/hr)	2019	1760	1750
Support Placement Rate (meter/hr)	Uniform (0.55,0.65)	Uniform (0.37,0.47)	Uniform (0.15,0.30)
Support Cost ($/meter)	940	1160	1350

After the construction of one section is finished, the workers test the actual ground condition at the end point of that section. This ground condition is reported to both the designer and the risk manager who utilize this information for making decisions. The workers report the ground condition to the designer at the end of each section, while the reporting to the risk manager is conducted randomly. Once the ground condition is reported, the risk manager compares this information with the excavation rate and type of support used for that section. If the design basis for excavation rate and type of support used in the section does not match with the reported ground condition, the risk manager identifies it as a "near miss" or "overdesign". In the case of a "near miss", designer's decision on the excavation rate and type of support does not meet the requirement based on reported ground condition. For example, if the ground condition at the end point of a section is reported as "Medium", while the excavation rate and type of support decided by the designer are appropriate for the "Good" ground condition, it is a "near miss". Overdesign is an opposite case in which the decision made by designer exceeds the requirement. In either case, the risk manager will make the decision of decreasing the step length for the next section to reduce the risks as the designer will have more chances to adjust the design according to reported ground conditions. In contrast, if the excavation rate and type of support used match with the reported ground condition, the risk manager considers this section as designed and built appropriately and increases the step length for the next section since the risk manager is more confident in the design capability of the designer and evaluates the situation as of low risk. The decision related to the step length made by the risk manager is reported to the designer and workers and the next round for design and construction continues. However, the ground condition in one section may vary. Using the ground condition discovered at the end point to represent the whole section does not provide the objective results of near misses and overdesigns. Therefore differences exist between the actual and reported near misses as well as overdesigns.

3.2 Abstraction at the Base Level

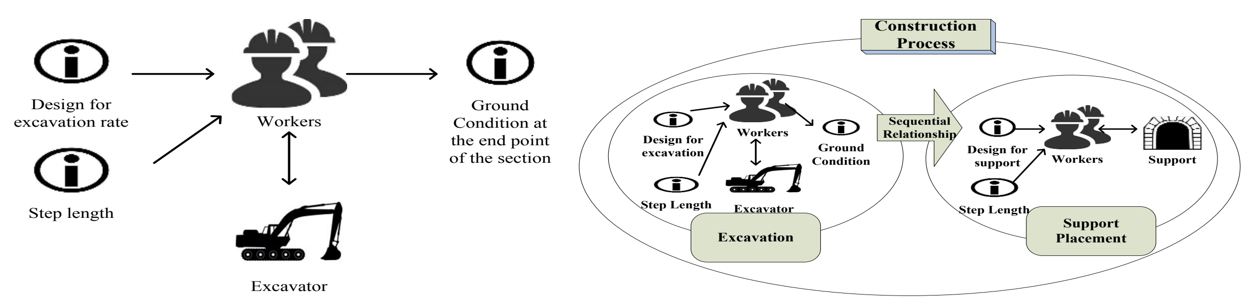
The CPSoS framework is used to evaluate the base level components and their attributes in the numerical example. Table 5 summarizes the human agents, resources, and information in the tunneling project described in the numerical example. The key attributes of each component are highlighted in Table 5 and used in creation of a simulation model for assessment of performance in the example.

3.3 Aggregation at Higher Levels

In the CPSoS framework, the level of aggregation can be made at activity, process and project levels based on the abstraction of base-level elements. In this numerical example, since not all the activities in all processes are considered, the level of aggregation is at activity and process levels. At the activity level, each activity can be represented as a network aggregating the interactions between different human agents, resources, and information. Figure 1(a) shows an example of the network related to the excavation activity in the construction process for the numerical example. This network consists of human agents (workers), resource (excavator), and information (design of excavation rate, step length, and ground condition at the end of the section). In this activity, workers receive information related to the excavation rate and the step length for the section from the designer and risk manager, respectively. Then, the workers excavate using the excavator (equipment) with certain productivity throughout the determined step length. Finally, they report the ground condition discovered at the end point of the constructed section. In the numerical example, other activities are involved in the design, construction and risk management processes. For example, support placement in the construction process, determining the excavation rate and the type of support in design process, and monitoring the step length in risk management process are examples of other activities in the process networks. At the process level, a process is shown as a network aggregating the interactions between different human agents, resources, and information across different activities. Figure 1(b) shows an example of network of construction process in the numerical example. In the construction process, human agents, resources and information pertaining to the two activities (i.e., excavation and support placement) are aggregated in a network, and the outcomes of this construction process network can be assessed by simulating the interactions of the base-level elements in the process network. In the numerical example, three processes are considered: design, construction and risk management. Information interdependencies such as design information, ground condition and step length create the linkages between different processes and affect the performance outcomes assessed at each single process in the example.

Table 5: Base-level components in the numerical example.

Base-level Components	**Type**	**Classification**	**Key Attributes**
Human Agent	Designer	Production work/ information processing/decision making	Risk Attitude
	Workers	Production work/information processing	Productivity
	Risk Manager	Information processing/decision making	-
Resource	Excavator	Equipment	Productivity and Cost
	Support	Material	Cost
Information	State transition matrix	Static information	Availability
	Ground condition prediction	Dynamic information	-
	Design Decision	Dynamic information	-
	Current ground condition	Dynamic information	Accessibility and Recency
	Step length	Dynamic information	-

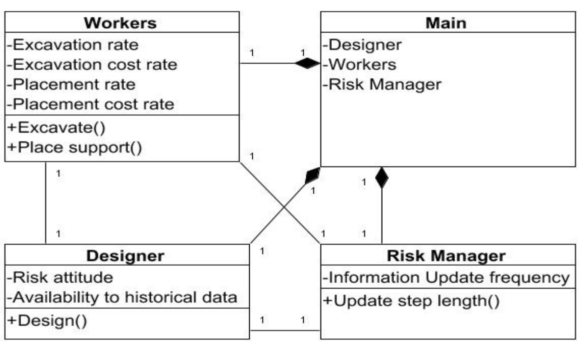


(a) (b)

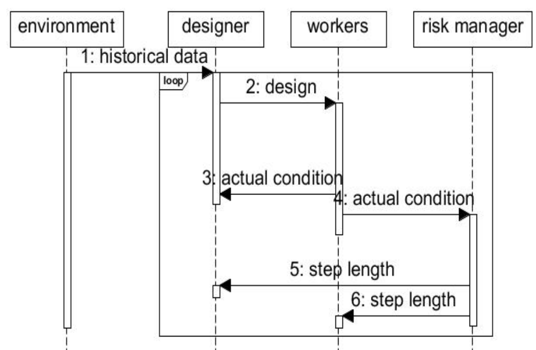
Figure 1: Activity network (a) and process network (b) examples in the numerical example.

3.4 Bottom-up Simulation

The dynamic behaviors and the interdependencies between the base level components in the example were captured and modeled using Agent-Based Modeling (ABM). ABM is a widely used modeling approach for micro-simulation in systems with adaptive and dynamic components (Mostafavi et al. 2013). Figure 2 demonstrates the Class and Sequence diagrams related to the simulation model using a Unified Modeling Language (UML) protocol. As shown in Figure 2(a), the class diagram defines the static relationships of the model. Four classes of objects are: *Designer*, *Workers*, *Risk manager* and *Main* class. The *Main* class has a composition relationship with the other agent classes. All the agents and their actions are embedded in the *Main*. In each agent class, attributes and operations are defined based on the dimensions of analysis identified in the CPSoS framework. For example, for the *Designer* agent, *risk attitude* is used to model the attributes of this human agent, and the *availability* to the static information "state transition probability" is also an attribute of the *Designer* agent. The *Designer* agent also conducts decision making and information processing task which is *design*. In the *design* task, the designer uses the available information to design and the outcome of the design task is information related to *excavation rate* and *type of support*. The information of *excavation rate* and *type of support* then can used by other agents. Figure 2(b) shows the sequence of events that characterize the simulation experiment in a dynamic view by focusing on the message interchanges between agent classes. For example, *Workers* start working after receiving the design information sent by *Designer*. After *Workers* finish the construction work for a section, a message about the actual ground condition discovered at the end point will be sent to *Designer* and *Risk Manager* to trigger their operations.



(a)



(b)

Figure 2: Class diagram (a) and Sequence diagram (b) of agent-based model for the numerical example.

3.5 Computational Model

AnyLogic 7.0.0 is used to create the computational model related to the numerical example. For each agent class, action charts are created to capture their dynamic behaviors. In the *Main* class, dynamic behaviors of different agents are aggregated based on the interdependencies between base-level elements.

3.5.1 Designer agent class

As described in the example, the designer agent makes the decisions pertaining to the excavation rate and type of support based on the prediction of the ground condition as well as risk attitude. Figure 3 shows an example related to the decision making process of a risk-averse designer when the prediction information indicate that the ground condition is Good. The first decision node in the action chart shows that, although the prediction of the ground condition is Good, there is 60% likelihood that the risk-averse designer designs this section according to a Good ground condition. The second decision node shows that the designer have

30% likelihood of designing according to a Medium ground condition. Otherwise, the designer will design according to a Poor ground condition. This action chart is called "Good" since it represents the designer's behavior when the predicted ground condition is Good. There are other action charts called "Medium" and "Poor" for scenarios in which the ground condition is predicted to be Medium and Poor, respectively. For different types of designer (i.e., risk-neutral, risk-averse and risk-seeking), the probabilities of decisions under the same situation are different.

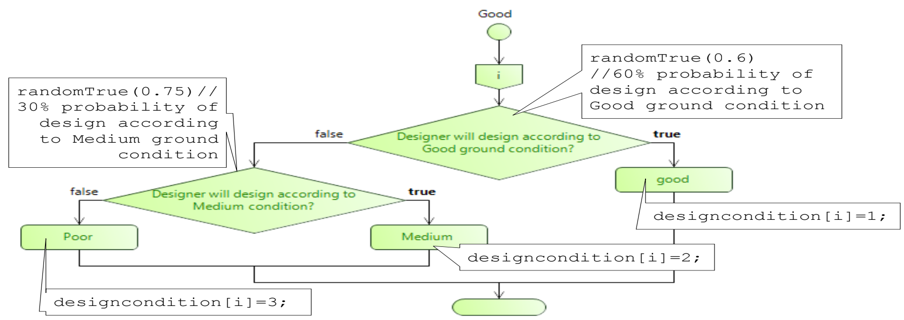


Figure 3: Action chart of a risk-averse designer agent for good ground condition.

3.5.2 Workers agent class

As shown before in Table 4, workers and equipment have different productivities and cost rates under different design decisions. Figure 4 shows the action chart of *Workers* in the computational model. The action chart defines the attributes of the workers using different values of "ExcavationRate", "ExcavationCostRate", "PlaceRate", and "PlaceCostRate".

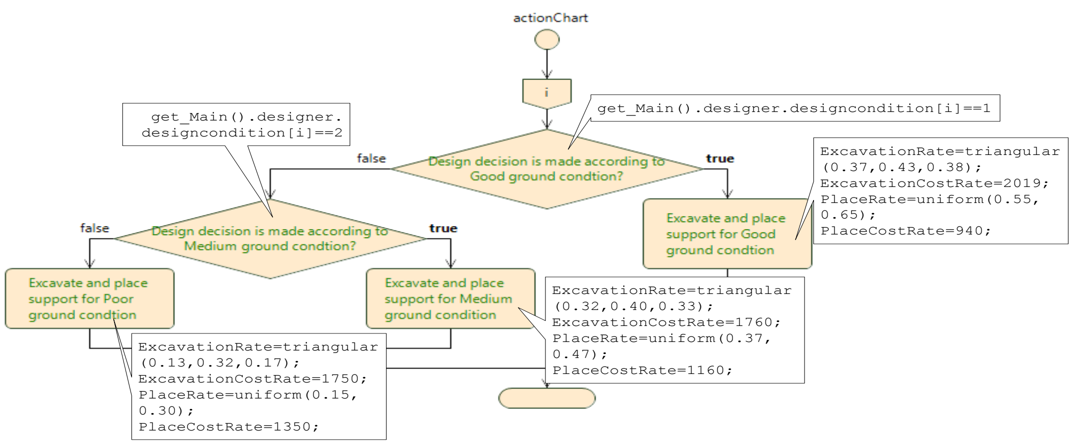


Figure 4: Action chart of workers agent.

3.5.3 Risk manager agent class

The action chart for the *Risk manager* agent is shown in Figure 5. Since the actual ground conditions discovered at the end point of the sections are reported to the risk manager in a random fashion, the recency of the base-level information "ground condition report" depends on the probability of reporting. The likelihood that the workers report the ground condition to the risk manager varies from 0 to 1 at the end of each section. The higher the probability, the more recent the information. In the action chart, the probability values can change to simulate different levels of recency in formation. If the ground condition is reported, the risk manager will have the chance to check if the work conducted matches with this reported ground condition. In the action chart, it is shown that if the work does not match with the reported condition (e.g. reported ground condition is Good while the design and construction are made appropriate for Medium condition), the section just constructed is documented as “Reported near miss”, and the risk manager will decrease the step length instantly (decreasing the step length leads to having more information related to the ground condition in the following sections). The step length will also be decreased if there is an instance of overdesign, in which case, the section is documented as “Reported overdesign”. If the design and construction criteria exactly matches with the reported ground condition, no instance of near miss or overdesign is documented and the risk manager increases the step length for the next section. As demonstrated previously, the “Reported near miss” and “Reported overdesign” obtained may not be accurate information since the ground condition in one section may not be consistent, thus the reported ground condition cannot be completely representative for the actual ground condition throughout the section. In the simulation model, actual near miss and overdesign instances are obtained by comparing the actual ground conditions with design and construction every 100 meters. Thus, the difference between the actual and reported instances of near miss and overdesign can be determined.

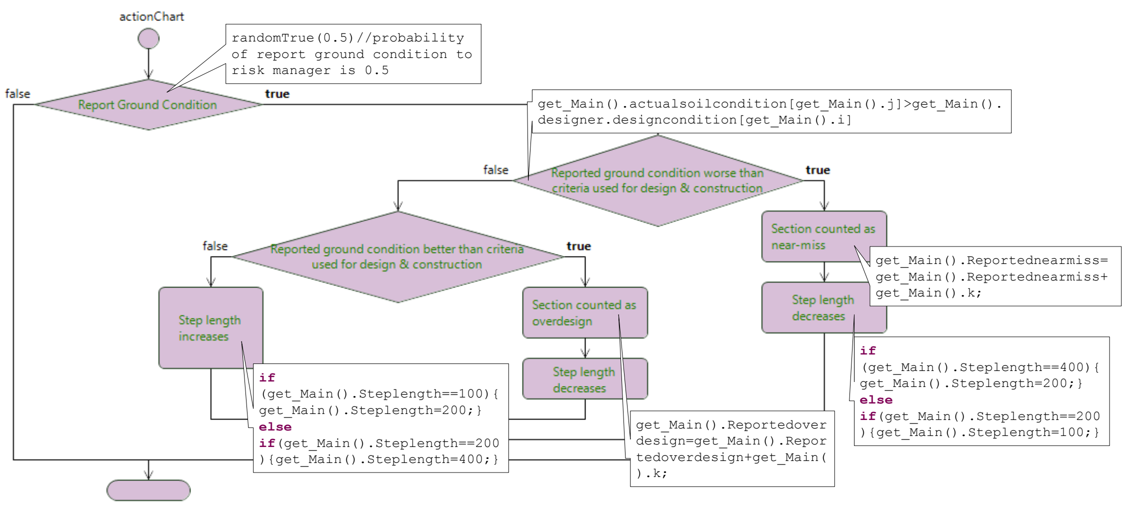


Figure 5: Action chart of risk manager agent.

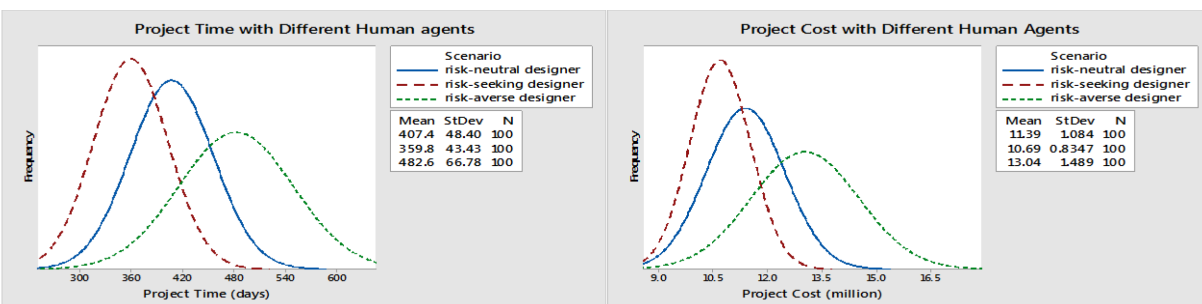
3.6 Results

The created simulation model is used in conducting Monte-Carlo experimentations to investigate the impacts of base-level components and their interdependencies on the performance of the project in the illustrative example. Specifically, impacts of information and agents’ attributes are investigated to highlight the significance of the proposed CPSoS framework for bottom-up modeling of performance in construction projects.

3.6.1 Impacts of human agents

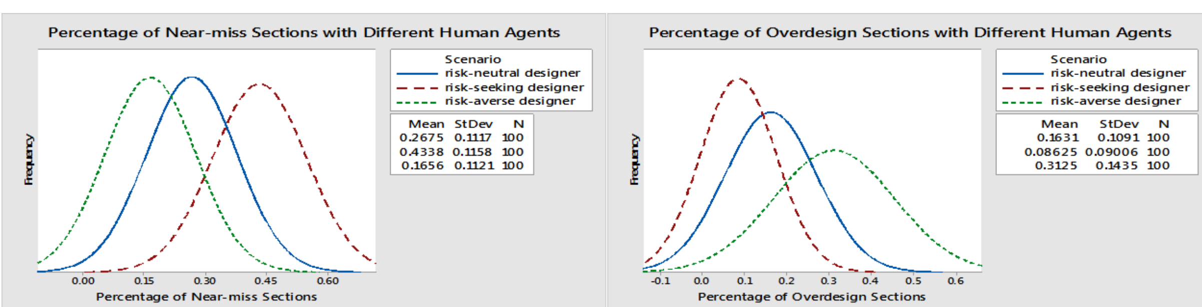
The results of the simulation model reveal that the risk attitude of human agents affect the performance of the project in the numerical example. For example, the risk attitude of the designer affects the decision making processes pertaining to determining the rate of excavation and implementing support based on the prediction of the ground condition. Figure 6(a) shows that if the risk attitude of the designer is “risk-averse”, the average duration of the project will be 482.6 days. The mean value pertaining to the duration of the project decreases by 15.58% if the risk attitude of the designer is “risk-neutral”, and by 25.45% if the risk attitude of the designer is “risk-seeking”. The results also show that the standard deviation pertaining to the duration of the project is the greatest if the risk attitude of the designer is “risk-averse” and the lowest if the risk attitude of the designer is “risk-seeking”. Similarly, Figure 6(b) shows the impacts of the risk attitude of the designer on the project cost. The mean value pertaining to the project cost is \$13.04 million if the risk-attitude of the designer is “risk-averse”. This mean value of cost decreases by 12.65% and 18.02% if the risk attitude of the designer is “risk-neutral” and “risk-seeking”, respectively. In addition, the standard deviation values pertaining to the project cost vary based on the risk attitude of the designer. Similar to the results related to the project duration, the standard deviation pertaining to the cost of the project is the greatest if the risk attitude of the designer is “risk-averse” and the lowest if the risk attitude of the designer is “risk-seeking”.

Besides construction time and cost, designers with different risk attitudes also affect the performance outcomes in terms of design quality. As shown in Figure 7(a), the mean value pertaining to the percentage of sections identified as near-miss sections is 16.56% if the risk attitude of the designer is “risk-averse”. However, with a risk-seeking designer, the mean value pertaining to the percentage of near-miss sections grows to 43.38%. The other quality measure considered in the analysis is percentage of sections that are overdesigned. Figure 7(b) shows that the mean value pertaining to the percentage of overdesigned sections is 8.63% if the risk attitude of the designer is “risk-seeking”, while the mean value pertaining to the percentage of overdesigned sections increases to 31.25% if the risk attitude of the designer is “risk-averse”. These findings have important implications for performance assessment. Based on the findings, selection of a risk-seeking designer can improve the performance of the project with respect to time, cost, and overdesign measures. In contrast, selection of a risk-seeking designer can exacerbate the performance of the project in terms of near-miss situations. In a counter intuitive finding, the results show that the selection of a risk-seeking designer reduces the uncertainties (measured by standard deviation values) pertaining different performance measures. These findings demonstrate the varying effect that the attributes of human agents could have on the performance measures.



(a) (b)

Figure 6: Time (a) and cost (b) with different designers

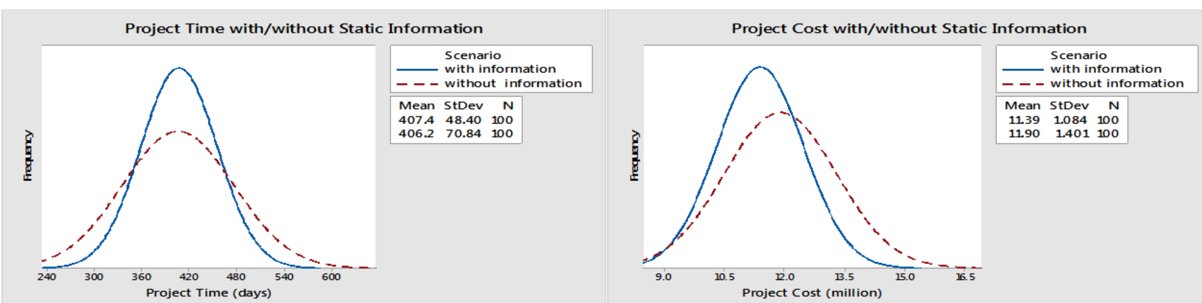


(a) (b)

Figure 7: Percentages of near-miss (a) and overdesign (b) sections with different designers.

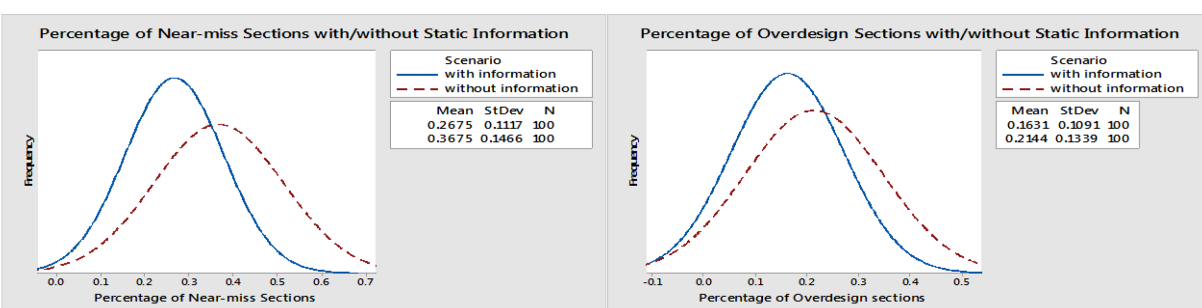
3.6.2 Impacts of static information

The results of the simulation model reveal that the attributes of static information affect the project performance. The results of the Monte-Carlo experimentations are used to evaluate the impact of the availability of one piece of static information (state transition probability matrix) in the numerical example on performance measures. Figure 8 demonstrates the probability distributions pertaining to the cost and schedule in two scenarios: (i) the static information is not available; and (ii) the static information is available. As shown in Figure 8(a), the availability of the static information significantly affects the standard deviation pertaining to the project duration. The level of uncertainty (measured by the coefficient of variation) in the performance measure of duration is greater when the static information is not available. The coefficient of variation related to the project duration is 11.8% if the static information is available and is 17.4% if the static information is unavailable. Also, Figure 8(b) shows that the availability of the static information significantly affects the level of uncertainty pertaining to project cost. The coefficient of variation related to the project cost is 9.5% if the static information is available and is 11.8% if the static information is unavailable. The availability of the static information also affects the quality performance measures. As shown in Figure 9(a), when the static information is available, the mean value pertaining to the distribution of the percentage of near-miss sections is 26.75% and is 36.75% when the information is not available. According to Figure 9(b), the mean value pertaining to the percentage of overdesigned sections is 16.3% when the static information is available, and is 21.44% if the static information is not available. The results also show that the level of uncertainty varies for both near-miss and overdesign measures based on the availability of the static information. The availability of the static information decreases the level of uncertainties in the performance measures. These findings could be used in quantification of the value of the static information in terms of reducing the level of uncertainties in project performance measures.



(a) (b)

Figure 8: Time (a) and cost (b) with/without static information.



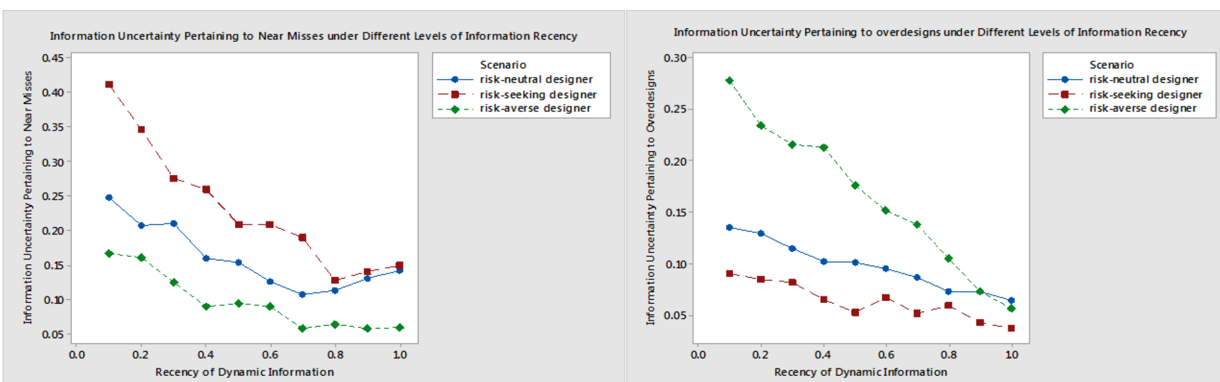
(a) (b)

Figure 9: Percentages of near-miss (a) and overdesign (b) sections with/without static information.

3.6.3 Impacts of dynamic information

The results of the simulation model also reveal the impact of the attributes of dynamic information on project performance. Recency is the distinguishing attribute of dynamic information compared to static information. Recency of dynamic information determines the frequency at which a piece of dynamic information gets updated with more recent information. An example for a piece of dynamic information in the numerical example is the actual ground condition. Every time a section is completed, the actual ground condition at the end point of the section may be reported to the risk manager. The risk manager then uses this updated information to evaluate whether there is a near-miss or overdesign instance in the completed section, and changes the step length for the next section if necessary. The recency of this dynamic information increases if the ground condition is updated to the risk manager more frequently. The results of the Monte-Carlo experimentations show no significant differences in time, cost, actual near-miss or overdesign instances due to changes in recency of the dynamic information.

However, the recency of the dynamic information affects the level of “information uncertainty”. Information uncertainty is defined as the difference between the actual state and the perceived state based on the available information. In this example, information uncertainty is the difference between the actual and reported values pertaining to the percentage of near-miss and overdesign instances. As shown in Figure 10, the level of information uncertainty reduces with increasing the recency of the dynamic information. The results also show that the extent to which the recency of the dynamic information affects the level of information uncertainty varies based on the risk attitudes of the human agents. For example, as shown in Figure 10(a), the recency of the dynamic information has a more significant impact in reducing the level of information uncertainty pertaining to the near-miss instances for a risk-seeking designer. Similarly, the recency of the dynamic information has a more significant impact in reducing the level of information uncertainty pertaining to the overdesign instances for a risk-averse designer. These results highlight the interdependencies between the attributes of base-level components and their impacts on the performance of construction projects.



(a) (b)

Figure 10: Differences between reported and actual near miss (a) and overdesign (b).

4 CONCLUSION

This paper proposed and tested a framework for integrated simulation of performance in construction projects using a system-of-systems approach. The proposed framework is based on the abstraction and simulation of human behaviors, information processing, and resource utilization in construction projects. The application of the framework was demonstrated in a numerical example related to a tunneling project using agent-based modeling. The simulation results of the tunneling project highlight the significance of the impacts of base-level components’ attributes on the performance of construction projects, as well as the capability of the proposed framework for providing a tool for integrated assessment of performance in construction projects. The proposed framework addresses the methodological challenges of existing simulation models of construction projects by appropriately conceptualizing construction projects as systems-of-systems. The proposed framework has the potential to be adopted and tested in future studies to develop and test solution concepts for improving the performance of construction projects.

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AUTHOR BIOGRAPHIES

JIN ZHU is a PhD candidate in Civil and Environmental Engineering Department at Florida International University. Her research aims at better assessment and management of performance in complex construction projects. Her email address is jzhu006@fiu.edu.

ALI MOSTAFAVI is an Assistant Professor at Florida International University. He obtained his Ph.D. in Civil Engineering from Purdue University. His research expertise is in the area of sustainable and resilient infrastructure systems, system-of-systems modeling, and construction engineering. His email address is almostaf@fiu.edu.