Grand Challenges in Simulation for the Architecture, Engineering, Construction and Facility Management Industry

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ABSTRACT

Today's Architecture, Engineering, Construction and Facility Management (AEC/FM) industry has to deal with complex obstacles (e.g., aging infrastructure, the protection of the natural environment, the need for resilient infrastructure). Among several technical fields that have been adopted and advanced, computer simulation has been widely researched and practiced for the effective delivery and maintenance of capital projects. Considering the unprecedented problems of today's infrastructure and the rapid advancements in simulation research, it is very timely to investigate what grand challenges exist in simulation that if properly addressed, can help create a more sustainable and resilient engineering of infrastructure lifecycle. To this end, this paper aims to identify grand challenges in simulation by presenting major areas of interest that can benefit the AEC/FM domain and discussing three specific areas identified as challenges in simulation: 1) realistic simulation modeling; 2) applicability of simulation models to the industry; and 3) academic and educational obstacles. Specific foci are the knowledge gaps in these major areas, and the current efforts to mitigate these gaps based on extensive literature reviews. This paper also proposes the next steps for addressing these challenges based on the findings herein.

INTRODUCTION

Following a major infrastructure expansion during the second half of the 20th century, today's AEC/FM industry has to deal with the technical issue arising from the aging U.S. infrastructure while thinking about protecting the natural environment (i.e., sustainability). Among several technical fields that have been adopted and advanced to address these challenges, computer simulation has been widely researched and practiced for the effective delivery and maintenance of capital projects. Computer simulation has thus demonstrated its usefulness in aiding AEC/FM engineers in designing, constructing, and operating infrastructure systems. However, taking into account the unprecedented challenges faced by today's infrastructure (e.g., aging, the need for resilience and sustainability), as well as the rapid advancement of new simulation techniques, it is very timely to investigate what grand challenges exist in simulation. This effort can transform the current practice of infrastructure lifecycle engineering into a more sustainable and resilient process. In this context, the Visualization, Information Modeling, and Simulation (VIMS) committee—one of the technical committees under the ASCE's Technical Council on Computing and Information Technology—recently initiated an expert taskforce to study and define grand challenges in VIMS. As its first effort, VIMS committee members had a focus-group-like discussion at their 2012 meeting, held in Clearwater Beach, FL. At this meeting, the committee identified several areas where challenges exist in VIMS, such as: 1) generating realistic simulation models (e.g., incorporating human behavior and addressing discrepancies between simulation models and reality); 2) improving the applicability of simulation models to the industry (e.g., accreditation and adoption of simulation models and real-world validation); and 3) addressing academic and educational obstacles (e.g., integration of simulation into engineering curricula and simulation for interdisciplinary research). This paper reports the knowledge gaps in the above areas and the current efforts to mitigate these gaps based on extensive literature reviews in order to continue to discuss grand challenges in simulation with potential benefits to the AEC/FM domain.

GENERATING REALISTIC SIMULATION MODELS

As computer simulation has been widely adopted, the need to incorporate more details for realistic model generation has become more imperative. Two identified topics that pose a great challenge in this area are incorporation of human and social behavior and realistic representation of simulation models that are responsive to real-world data.

Incorporation of Human Behavior

Throughout its lifecycle, a built environment has interactions with a large number of people. From the production perspective, the built environment is a physical product of integrating human labors of various forms, and from the use perspective (i.e., operation) it provides the setting for various human activities. Due to such a rich interaction, human factors greatly affect both the production and the use of built environments (Wickens and Hollands 2000). Therefore, the understanding of human factors is invaluable for sound decision making in the design, engineering, construction, and operation of the built environment. However, studying human factors is not easy and straightforward, mainly because of the difficulty in conducting human-centered experiments. One way to study human factors is to use computer simulation, which enables an end user to conduct experiments with a model as many times as they wish, and provides observations on the model's behavior (i.e., response) to different inputs (i.e., scenarios). Classes of research topics in this direction include building emergency evacuation simulation (Shi et al. 2009; Gwynne et al. 2005; Galea 2003; Proulx and Richardson 2002; Chu et al. 2011; An et al 2009), design performance simulation (Dijkstra 2008; Willis et al. 2004; Dijkstra and Timmermans 2002; Yan and Kalay 2006), occupant behavior for energy simulation (Clevenger and Haymaker 2006; Rijal et al. 2008; Azar and Menassa 2011; Hoes et al. 2009; Chen et al 2012; Anderson et al. 2012; Peschiera et al. 2010), construction worker behavior (e.g., productivity and absence) (Levitt et al 1999; Jin and Levitt 1996; Watkins et al. 2009; Ahn et al. 2012; Ahn and Lee 2011), and project organizations simulation (Comu et al. 2011; Chinowsky et al 2011; Chinowsky and Songer 2011). These topics are researched to increase the understanding of human behavior interacting with built environments and improve the realism of simulation models. For example, in the study of project organizations' performance, the focus has been placed upon the involvement of numerous people from diverse organizations (e.g., owners, designers, engineers, construction managers, contractors, and trade unions); this involvement can greatly affect project organizations' performance. At the organizational level, social interaction between parties affects a project's performance (Comu et al. 2011; Chinowsky 2011). At the personal level, interactions between project participants affect a project's performance. In turn, the performance of the entire project is affected (Chinowsky and Songer 2011). From this review, a number of new challenges can be identified. For instance, a comprehensive simulation framework is needed to integrate segmented human behavior simulation models and their other interactive models. For example, energy simulation can use DOE-2 to estimate energy consumption, but if the simulation needs to incorporate varying occupant energy consumption behavior, an occupant behavior model has to be integrated for a comprehensive analysis. In addition, modeling human behavior needs domain-specific knowledge; otherwise a model could remain distant from reality. For example, applying absence culture to construction workers' behavior can be valid only when the characteristics of construction projects are fully considered (e.g., workers move to different sites while existing theory about absence culture has been made for those who stay in their company indefinitely, such as nurses or bus drivers).

Realistic Simulation Model Responsive to Real-World Changes

Effective simulation-based decision making requires that all model parameters and variables are defined as real-time functions of ongoing project performance, and are modified with time if and when necessary, so that ultimately the simulation model is completely adaptable to the latest conditions on the ground (Xie and Abourizk 2011; Akhavian and Behzadan 2012). However, many existing simulation tools that have been developed for use by the AEC/FM industry are structured to create only intuitive means to study a facility or a project during early planning and design stages. As such, the resulting simulation models are built upon (often subjective) assumptions about major model parameters and performance indicators, which were made during the infancy stages of a project. Thus, a major research challenge is to generate realistic simulation models that are responsive to changes in the real engineering system during the execution phase. Such a comprehensive methodology for incorporating real time field data would release modellers from relying on data from previous projects, expert judgments, and rigid assumptions. Collecting reliable and accurate data from a highly dynamic environment such as a construction jobsite is almost impossible using traditional (manual) methods. Thanks to the latest technology advancements, several automated data collection and processing techniques have recently been introduced and used by researchers within the AEC/FM domain, including global positioning systems (GPS), radio frequency identification (RFID), ultra wide-band (UWB), and 3D laser scanners that assist in tracking objects (e.g., equipment, material, personnel), detecting unsafe work zones, or measuring productivity (Oloufa et al. 2003; Caldas et al. 2006; Song et al. 2006; Ergen et al. 2007; Jang and Skibniewski 2007; Teizer et al. 2008; Behzadan et al. 2008; Grau and Caldas 2009; Khoury and Kamat 2009; Brilakis et al. 2011; Andoh et al. 2012; Han et al. 2012). While an autonomous data collection system provides higher reliability and accuracy, it should also be able to process and use the collected data in (near) real time, thereby facilitating short-term decision making, planning, and control. For this purpose, the efficiency and robustness of the data collection process turns out to be as important as data reliability and accuracy. Once data about project entities is collected, it needs to be transformed into meaningful process information, and ultimately into operational knowledge. Without putting field data into proper context, it is impossible to generate simulation models that describe the real operations as they occur. Existing single-modal remote sensing and information extraction methods can be easily misled by incomplete detection. For example, most vision-based methods suffer from occlusions, and methods that rely on preinstalled infrastructure cannot detect events that constantly evolve (e.g., road construction). These issues can create problems when detecting all operational details as they occur, and thus highlight the need for a systematic approach to capturing and fusing data from multiple sources (Pradhan and Akinci 2012). The challenge is to find the “just right” volume of reliable data that represents a proper level of detail. Very often, captured data is of tremendously large volume and contains high noise ratio (Razavi and Haas 2012), such that data cleaning and analysis takes a considerable amount of time. For instance, to study the performance of a few workers, data collected using a video camera may take a large amount of time to process yet not yield the desired accuracy or robustness (Yang et al. 2010). Even if data can be collected in a timely manner, the desirable setting and the expected spatio-temporal relations between project entities may be adversely affected by unforeseen conditions. Thus, one has to also make sure that raw field data is rich enough to reflect such special cases. To this end, the main research challenge is to determine how much data, and with what resolution, is enough to represent the real world system with an acceptable level of detail in the least possible time.

IMPROVING THE APPLICABILITY OF SIMULATION MODELS TO THE INDUSTRY

Despite advancements in computer simulation, its usage in the AEC/FM industry has been limited. Two important topics for a wider adoption by the industry have been identified: how to increase the credibility of simulation models, and how to increase user confidence with validation and verification.

Credibility and Adoption of Simulation Models

The adoption of innovative and new technologies by the construction industry is not a trivial decision. A workshop sponsored by NSF and CII identified key factors that need to be fulfilled in order for a new technology to be accepted. These factors are 1) new technology compatibility with the "company culture"; 2) availability of a champion who can demonstrate the advantages of the new technology and push its adoption; and 3) realization that the new technology yields significant benefits relative to its overall cost (Oberlender 1997). It should be noted that the term "new" is relative to the industry as a whole, to a sector or specialization of it, to a particular company, or even to a department or work team within a company. Simulation is a technology that has been around and in use by different industries for decades. However, it may still be new for a particular construction firm relative to its common practice. Hence, the adoption of simulation models by the construction industry is a strategic decision. A few researchers have reported on this topic, and their successful adoption stories all seem to align with the above factors. For example, Halpin and Martinez (1999) identified the exact same factors as keys to the successful adoption of simulation technology by Dragados y Construcciones. AbouRizk et al. (2011) and AbouRizk (2010) also listed a number of successful cases of simulation adoption where the same factors were present. They added another key factor—"trust" that develops over time between a company and research team/simulation developer. The strategic level factors identified above are irrelevant to the type of simulation modeling approach or tools used. At a more detailed and operational level, many factors have been identified as important aspects of a simulation study to facilitate better credibility, acceptance and adoption of simulation results. Some of the factors sought by construction researchers are: better communication of model behaviors and output through advanced visualization (Kamat and Martinez 2003), faster model development cycle through easier-to-use tools (AbouRizk and Hajjar 2002), and more efficient construction operation knowledge acquisition (AbouRizk et al. 2011). Simulation researchers on the other hand have identified a much wider spectrum of factors that simulation studies have to fulfill to achieve success. For example, Robinson and Pidd (1998) identified 338 factors classified along 19 dimensions based on interviews with modellers and clients of simulation studies. It should be noted that software tools represent only one of these dimensions, while most of the dimensions relate to the development process and modeller capabilities. A key observation on discussions related to the acceptance and adoption of simulation within the construction domain and the simulation community at large (Robinson 2004), is that they are mostly based on experience rather than empirical evidence. There is a need in the construction domain to report cases of simulation studies, with various levels of success, to facilitate analysis and the development of a framework for the successful integration of simulation studies within construction decision-making processes. Such cases must include a description of the management process from start to end, and not only model algorithms and output analysis.

Verification, Validation, and Confidence

Verification, validation, and testing of simulation models are ways to build model credibility, which in turn raises confidence in model output and leads to adoption and implementation. However, simulation models, by design, are built to test situations and scenarios that are not present in the real world. Therefore, validating them against real-world data of the exact same situation they will be used for is, to an extent, an oxymoron. Alternatively, we try to test the model against historical data from a situation "close enough" to our intended use. This concept is discussed by several authors and they all seem to agree that validation is both an art and a science (Balci 1998). Robinson (2004) states that: "It is not possible to prove that a model is absolutely correct." In fact most verification and validation efforts and tests, including statistical ones, try to check if a model is incorrect. The more they fail at proving that a model is incorrect, the more our confidence in that model is increased (Sergant 2000). Another key aspect of the validation and credibility of a simulation model is their unification with the purpose and intended use of the model where a model is considered an accurate enough representation of a system for a particular study objective but cannot be generalized beyond that objective (Law 2009). Projecting these principles on construction simulation studies complicates things even further and calls for a special framework for assessing the validity and credibility of construction simulation models. The uniqueness of construction projects makes it difficult to validate a model against real world data. This challenge strengthens the need for full documentation and reporting of such simulation case studies. The documentation should provide access to datasets to enable the validation of new models. In addition, efforts made in other domains with similarities to construction are worth considering. For example, building stochastic simulation models of combat scenarios in defense modeling and simulation is similar to a construction project in that a combat scenario is unique too and thus, validating a computer simulation model with limited actual data becomes a challenge. To this end, Champagne and Hill (2009) proposed a statistical approach (i.e., a bootstrapping technique) to overcome this issue; their approach could be considered for construction projects as well.

ADDRESSING ACADEMIC AND EDUCATIONAL OBSTACLES

Another area that has been called for is how to maximize the benefits of simulation in academia. Two representative topics are the integration of simulation into engineering curricula and effectively conducting interdisciplinary research.

Integration of Simulation into Engineering Curricula

Integrating simulation technologies into engineering curricula can greatly contribute to students' learning, enabling them to model real-world problems and experiment with what-if scenarios. However, this integration also poses significant challenges such as the need for computational resources to be constantly updated. The computational resources that most schools focus on are the ones that get frequently used and are needed to train students to meet workplace demands. Therefore, the adoption of certain computational technologies has been gradual due to the fact that they have been slowly adapted by the industry (Sampio et al. 2009). The availability of computational resources is directly linked to the need for manual interaction with models in a shared workspace that characterizes collaborative learning (Dong et. al. 2012). This creates a challenge that is exasperated by the misconceptions that model developers often have about how actual systems operate. In order to avoid this major pitfall, models need to be validated in a process that recognizes and corrects modeling errors and determines how accurately a simulation model represents the real world. This process requires the involvement of practitioners and decision makers who have intimate knowledge of the actual system to insure its practical relevance (Dong et al. 2012; Sampio et al. 2009). Computational resources are extrinsic to the simulation model itself. An intrinsic challenge, then, is the extent to which students understand the structure of the simulation. This understanding greatly impacts how they learn. The students' understanding of simulation structure is directly impacted by the transparency of the underlying simulation structure made available to them. This transparency falls into one of three categories: (1) "black box" models that keep the structure of the model hidden from users, generating only model behaviors; (2) "cloudy box" models where the model structure is partially visible by [for example] providing conceptual model structures but not providing their formalizations; and (3) "glass box" models that are completely transparent such that the model structures that drive their behavior are visible to and understandable by the user. The factor that should be initially determined while ascertaining the degree of transparency is how much time and effort is needed to develop students' background and understanding of the model structure. Naturally, more transparent models would require additional time and effort (Ford 2010). To address this challenge, several issues should be considered in model selection, including: (1) the suitability of different simulations to specific learning contexts; (2) the pedagogical approaches that could be used to support learning outcomes; and (3) the validity of using a chosen game or simulation (Sampio et al. 2009; Wall and Ahmed 2008). This creates a need for research into how simulation can be integrated into the learning process (Wall and Ahmed 2008).

Finding Effective Ways to Conduct Interdisciplinary Research

In order to facilitate interdisciplinary research, simulation methodologies must allow researchers to: (1) integrate multiple modeling approaches that are suitable for different components or research disciplines; and (2) represent model outputs in a unified and readily accessible visualization method. Many real-world systems are composed of both feedback and sequential processes. These systems also include combinations of context and operation-level parameters, as well as discrete and continuous variables (Lee et al. 2009). Despite this reality, most simulation platforms do not permit the integration of methods that allow for the accurate representation of real-world processes. Therefore, system modelers are in many cases forced to make simplifying assumptions that reduce the fidelity of the simulation (Alvanchi et. al. 2010). One of the approaches to solving this problem is to develop custom software that allows for the integration of two or more simulation methods. These custom efforts, however, do not provide sufficient flexibility for modeling problems from different disciplines (Alvanchi et al. 2010). The integration of different simulation methods presents challenges such as the communication of data between different model components. Additionally, the main purpose of this integration is to reflect the effects of the latest changes in different parts of the system on the operation of other parts. This could potentially lead to a large simulation processing time overhead required for updating different system components (Alvanchi et. al. 2009). Another problem that hinders the widespread application of simulation methods is the difficulty faced by stakeholders in interpreting model outputs. Therefore, computer visualization methods have been proposed to generate more intuitive and easier to interpret output (Zhang et al. 2012). In the case of interdisciplinary research, the amount of programming needed to develop visualization tools (e.g., graphic engines) supporting those simulation methods is significant. Unfortunately, there is a very limited availability of ready-to-use generic graphics engines that could be used with simulation methodologies across disciplines (Zhang et al. 2012). There have been some attempts to address these limitations through distributed and interactive simulation design methodologies. The two notable efforts include the development of Distributed Interactive Simulation (DIS) (IEEE standard 1278) and the creation of High Level Architecture (HLA) (IEEE Standard 1516), which was a successor to DIS. Both DIS and HLA create architectures for interconnecting separate simulations (Zhang et al. 2012). HLA is popular in both the military and civilian domains that need high reusability and interoperability and its goal is to promote interoperability between simulation system, which would facilitate the reuse of models in different contexts and domains. This reuse ultimately reduces the time and cost needed to create new simulation environments (AbouRizk 2010). Despite such efforts and contributions made to enhance the use of simulation techniques in interdisciplinary research (AbouRizk 2010; Alvanchi et al; 2009), there is still a strong need for research in the area, specifically in developing simulation methodologies based on HLA. These simulation systems can then be integrated across disciplines and problem domains to create simulation models that accurately represent the real-world situation.

CONCLUSIONS

We discussed the details about three major challenging areas that were identified in the 2012 ASCE TCCIT VIMS committee meeting: realistic simulation model generation, wider applicability of simulation models to the industry, and academic and educational challenges. Based on these discussions, major research challenges were identified that included but were not limited to fusion of new multi-modal data-capture technologies, incorporation of newly introduced social science perspectives, and the need for interdisciplinary research. However, there are also challenges that have been lingering since the introduction of simulation to AEC/FM, such as model credibility, real-world validation, and integration of simulation topics into engineering curricula. Based on these observations, we concluded that the next logical steps would be to extend these areas and provide more inclusive solutions, and then to divide them into two major categories—new and existing challenges—identified by unique set of characteristics (e.g., why and how new challenges are different from existing ones, and what situations have been changed in the case of existing challenges). Consequently, a thorough discussion is needed on how our evolving knowledge on simulation, as well as the advancements in simulation technologies can address these challenges.

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