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Understanding Emergency Care Delivery through Computer Simulation Modeling

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Abstract

In 2017, *Academic Emergency Medicine* convened a consensus conference entitled, “Catalyzing System Change through Health Care Simulation: Systems, Competency, and Outcomes.” This manuscript, a product of the breakout session on “understanding complex interactions through systems modeling,” explores the role that computer simulation modeling can and should play in research and development of emergency care delivery systems. This manuscript discusses areas central to the use of computer simulation modeling in emergency care research. The four central approaches to computer simulation modeling are described (Monte Carlo Simulation, System Dynamics modeling, Discrete-Event Simulation, and Agent Based Simulation), along with problems amenable to their use and relevant examples to emergency care. Also discussed is an introduction to available software modeling platforms and how to explore their use for research, along with a research agenda for computer simulation modeling. Through this manuscript, our goal is to enhance adoption of computer simulation, a set of methods which hold great promise in addressing emergency care organization and design challenges.

Introduction

With over 130 million annual ED visits,[1] a declining number of EDs to provide emergency care,[2] and lengthening wait times to see providers,[3] EDs are operating under increasingly arduous conditions. One underutilized approach to addressing problems in healthcare quality and value, particularly in emergency care, is through the use of computer simulation modeling. Computer simulation is a method to build dynamic models that quantitatively abstract a system, such as a facility (e.g., ED) or a process (e.g., physician-in-triage). Not unlike “high-fidelity patient simulation” (HPS) for training clinicians in clinical care through the use of mannequins, computer simulation provides a platform to inform decision-making prior to implementation in the real-world.

First used as part of the Manhattan Project during World War II to design the nuclear hydrogen bomb, 75 years later, computer simulation models are now widely used with successful application in many industries (e.g., manufacturing, logistics, air transportation) to improve quality and efficiency. Over time, computer simulation has demonstrated benefits for:

1. visualizing complex interactions in dynamic systems;
2. providing results much faster than would be possible in real time; and
3. allowing “what if” analysis when changes to an actual system are difficult to implement, costly, or impractical.

All of these provide researchers the ability to design, create, and evaluate complex systems in a way that is faster, cheaper, and safer than conducting experiments in a real system. Healthcare as an industry has been slow to embrace computer simulation. More recently, the number of computer simulation publications in healthcare and emergency medicine has increased (see Table 1), but its use remains uncommon relative to the potential for application and the urgent need to do so.

As with any tool, computer simulation has limitations and drawbacks similar to other forms of modeling, namely expertise of the modeler and generalizability to other systems. In this manuscript, our objective is to describe the extensive potential for computer simulation to address challenges in emergency care delivery. Furthermore, we summarize available methods and tools with illustrative examples. Finally, we seek to encourage clinical researchers, administrators, and policy-makers to routinely partner with experts in system engineering and computer simulation to accelerate innovation in emergency care.

Conducting research with computer simulation modeling

Four primary approaches to computer simulation modeling are valuable for coping with complex issues in healthcare systems, policy, operations, and clinical care: Monte Carlo Simulation, System Dynamics modeling, Discrete-Event Simulation, and Agent Based Simulation. To ensure maximum benefits from the simulation, it is important to match the method with the problem and system under consideration. Factors guiding this decision include: (1) whether time is static (i.e., time-invariant) or dynamic (i.e., accounting for time-dependent changes in the state of the system); (2) if dynamic, whether time changes continuously or by discrete intervals (i.e., marked by relevant events rather than passage of time); and (3) the ways in which uncertainty is deterministic (i.e., without random input components, in which performance is evaluated by average estimates) or stochastic (i.e., incorporating statistical distributions for events with some randomness, such as arrival times or turnaround times for particular processes). The following sections discuss these four approaches, including their basic technical aspects and the attributes of problems and/or systems that are best suited for each.

Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a modeling technique that relies on repeated statistical sampling to approximate solutions to quantitative problems.[4] For the purposes of operations research, it is a static (time-invariant) method that allows decision makers to translate from risks and uncertainties in model inputs to uncertainties in model outputs. Inputs are typically represented by point estimates (deterministic simulation) such as best/worst guess by specifying probability distributions (stochastic simulation).

In stochastic MCS (optimal for medical simulations), the entire system is simulated for a large number of replications in which input parameters are sampled from a distribution of possible values. In other words, each replication is one sample path or a single realization of the range of possible inputs to the system. The outputs are not point estimates, but probability distributions of possible outcomes. The result of a single replication is a qualified statement, e.g., “if intervention X is used, patient outcome could be Y.” Whereas the result of multiple replications is a quantified probability, e.g., “if intervention X is used, there is a 60% chance that patient outcome would be Y.” The simulation will be repeated for each scenario and the performance of the system can be computed and compared.

For best results, researchers using MCS must construct a valid process map or a decision tree in collaboration with system experts. Validity of probabilistic MCS models also depends on access to sufficient data for estimating probability distributions for input parameters.

Monte Carlo Simulations are especially useful for simulating phenomena with significant variability in input probabilities, systems with a large number of uncertain parameters, and when it is infeasible to compute an exact result with a deterministic algorithm. As such, MCS is well-suited for modeling policy or medical decisions and quantifying the benefits or risks associated with them. MCS is a static technique appropriate for those decision-making problems in which the passage of time plays no substantive role.[5] Thus, MCS is not recommended for modeling patient flow and processes that involve delays such as waiting lines.

As an example, one study used MCS to decide how to deploy telemedicine in order to enhance the responsiveness and treatment timeliness of a regional stroke team.[6] Six scenarios were investigated, with results showing that centrally locating the on-call physician coupled with partial telemedicine deployment in the outer ring is not only most cost-effective but also results in eligibility and treatment times comparable to total deployment. Such analysis took much less time and money than traditional methods.

System Dynamics Modeling

System dynamics (SD) modeling and simulation are aimed at understanding the aggregate behavior of a system over time.[7] It is particularly useful in developing insight into the dynamic complexity of system behaviors. A key difference between the SD approach and other time-oriented approaches such as discrete event or agent based simulation is that SD takes an *endogenous stance,* meaning that it focuses on patterns of behavior generated by the structure of feedbacks within the system, more than the effects of largely stochastic external events. The goal is often to predict the qualitative nature of system performance (e.g., overshoot and collapse, damped oscillations, unstable oscillations, chaotic response) rather than specific numeric results.

System dynamic modeling begins by creating a causal loop diagram of the system showing how changes in key variables influence one another via positive and negative feedback loops. An important principle in such modeling is to circumscribe system boundaries as broadly as is feasible, in order to minimize exogenous causes. For example, an exogenous view of inter-departmental conflict might begin with the surgery department’s aggressive behavior which causes problems in the ED; an endogenous view might include a feedback loop whereby ED actions also influence the surgery department’s behavior. That diagram is then enhanced by identifying level variables called ‘stocks’ representing accumulations (e.g., the number of patients awaiting triage) and rate variables called ‘flows’ representing activities per unit time (e.g., the number of walk-in patient arrivals per hour). Other variables represent influences on stocks and flows (and vice versa); for example, news stories about Zika virus may increase the rate (flow) of patients seeking care. Such influences can be simulated either with either stochastic or static inputs to explain how the causal structure can yield desired or undesired behaviors, and to identify points of leverage where variables might be influenced towards desired goals.

System dynamics modeling and simulation have been used in a variety of ways relevant to emergency medicine. The crowding problem has been a frequent target.[8–15] Morrison and Wears used SD modeling to uncover inherent contradictions in an ED teamwork scheme.[16] The broad utility of the SD approach is illustrated by Rudolph's study of decision-making in crises in the operating theatre,[17] although it seems highly applicable to emergency medicine.

Discrete-Event Simulation

Discrete-Event simulation (DES) is a modeling technique used to model the evolution of a real system's state or behavior over specific points in time. Changes in the state of the system are driven by events that occur instantaneously in time at processing nodes or locations. DES is stochastic (i.e., probabilistic), dynamic (i.e., changing over time), and discrete (i.e., state changes are instantaneous events separated by time).[5, 18–20]

The state of the system at a point in time is described by the values of model variables. Dynamic behavior of the system may be observed by tracking model variables over time as "entities" (e.g., patients or staff) pass through the system to and from "resources," which perform relevant processes (i.e., events). Each event is modelled as a time delay, after which the state of the entity or entities may change. DES assumes no changes occur in the system between events, in contrast to Agent-Based Simulation (see below). The model is constituted by the rules governing the motion of entities, the processing activity of the resources, and the state variables collected by the user. Since these rules must capture the uncertainty associated with arrivals to the system and interactions between humans and machines or other humans, the processing logic of DES should be based on probabilistic or stochastic processes. The applicability of a DES to the real-world system it simulates is enhanced by iterative verification and both conceptual and mathematical validation, with the primary goal of understanding how the simulated system changes in response to differing conditions.

DES methodology is well-suited for simulating 1) the performance of existing or planned healthcare systems, and 2) processes that provide diagnostic and/or therapeutic services (e.g., information, labs, medications, radiographs, etc.), and other processes associated with that care, at uncertain time intervals. Patients and the items or elements that are generated or required during their episodes of care are classified as entities. DES uses probabilistic logic to guide the flow and processing of independent entities through specialized care systems (e.g., an ED) or subsystems (e.g., a chest pain pathway or phlebotomy process). Entities are prioritized based on arrival order or other attributes (e.g., acuity, age, or gender) so that the model can determine who is served first when resources (e.g., beds, nurses, or diagnostic equipment) are not immediately available.[21–22]

In one of many examples, DES was used at a large academic medical center to assess how bed demand from competing cardiology admission sources affected ED patient access to inpatient cardiac care.[23] Measurements of bed demand from competing admission sources accurately predicted boarding time, with cardiac catheterization laboratory demand being most influential. The simulation showed that moving one scheduled catheterization case from afternoon to morning could reduce ED boarding time by 20 minutes, whereas adding another telemetry bed reduced boarding by only 9 minutes.

Agent-Based Simulation

Agent-Based Simulation (ABS) is used to model the actions and interactions of “agents” with a view of assessing their effects on a system as a whole. Although there is no universally accepted definition of “agent”, this term is typically defined as an autonomous entity which makes decisions based on a set of rules.[24–25] In comparison to DES entities, which can only follow a predefined path through the system’s flowchart, individual agents are capable of assessing their status and making decisions on the basis of a set of behavioral rules unique to each agent.

ABS models are comprised of three main components: 1) “agents” characterized in terms of their attributes (e.g., static or dynamic variables) and behaviors (e.g., conditional or unconditional actions), 2) “environment” surrounding agents, and 3) “interactions” defined as relationships between agents and their environment. As agents continue to depict various behaviors in response to other agents (interactions) and their environment (feedback) over numerous simulation events, complex global (and often unanticipated) behaviors will “emerge” at a population-level providing valuable information about the dynamics of the real-world system. The generative nature of ABS models allow for the study of systems at various levels (e.g., study of micro-behaviors at the individual-level as well as system outcomes at the macro-level), and provides the following advantages: (i) ability to capture complex emergent phenomena from simple rules; (ii) provide a natural representation of a system with minimum restrictions; and (iii) flexibility in incorporating detailed assumptions related to agent and their environment.[26–28]

While there is a large and growing body of literature involving DES and SD models in emergency medicine, few studies have applied ABS models to study EDs. Kanagarajah et al. (2006) describe an ED ABS model intended to demonstrate the effects of fluctuations in workload and economic forces on patient safety.[29] This model incorporated various classes of agents representing patients, physicians, and staff. Using a controlled set of experiments, the authors explored various scenarios of patient arrival and resource availability and study the subsequent changes in simulated outcomes within the scope of each boundary. The generative nature of ABS model allows for modeling realistic scenarios in which agents are allowed to change their behavior as a result of system demand and therefore provides a reliable representation of system’s operation under extreme workload scenarios.

Computer Simulation Projects

When pursuing a project involving computer simulation modeling, a simulation modeler and software platform must be thoughtfully chosen. Proper design of complex models requires understanding of, and adherence to, best practices. Improper technique may result in invalid models, and thus misleading results. Sound design involves rigorous methods, such as internal validation with single-patient runs and massive-patient stress tests.[30] A discussion of the considerations to consider when selecting a simulation modeler and the types of software modeling platforms to consider are discussed in the Supplemental File.

Consensus Recommendations: Future Agenda/Research Gaps

Our discussion thus far illustrates that computer simulation is an established, yet underutilized, technique to address healthcare performance, particularly in emergency care. We recommend that emergency care researchers and decision-makers expand the use of computer simulation, expedite the adoption of seminal study results, and seek innovations in modeling methods. The next section offers suggestions to achieve these goals, as well as comments regarding funding for relevant work that were developed through this conference.

A Call for Expanded Use of Computer Simulation

We recommend the consideration of computer simulation broadly for any healthcare activities that may affect health outcomes, healthcare systems, or costs. There are several questions researchers may have about getting started with computer simulation modeling that we address below.

1. How can computer simulation be used to guide operational decisions in emergency medicine?

   Computer simulation should be viewed as a necessary first step prior to implementation of a change in procedure or practice. This "in vitro" approach is common in other aspects of medical research (e.g., use of animals models prior to human testing). A similar approach in emergency care practice would create evidence to guide operational decisions, what we term "evidence-based operations."

2. How should practice change to further enhance acceptance of computer simulation modeling in emergency medicine?

   Potential changes in clinical practice should be viewed as an opportunity to measure outcomes of that change. This would facilitate validation of the simulation models and to further enhance acceptance of their use. Moreover, use of simulation may enhance early identification of such errors and reduce downstream project costs by fostering identification of errors early in a project's life cycle, as costs (financial and otherwise) may be greater when identified after implementation.[31]

3. How can future studies using computer simulation improve upon prior publications?

   Whenever possible, simulation studies should include health outcomes as well. For example, a given intervention (e.g., physician-in-triage) might improve patient flow through an ED, but miss opportunities for health intervention. This approach acknowledges that there is no objectively optimized setting, but instead allows outcomes to be weighed against each other and against their costs, including operational disruption and opportunity costs.

Adoption of Simulation Study Results

An important barrier to expanding the use of computer simulation is that targeted healthcare audiences may not be receptive to simulation results. Achieving generalizability through simulation is challenging because operating conditions and model assumptions vary tremendously among settings.

- How can future studies using computer simulation be designed to enhance the adoption of simulation study results?

  Evaluating operational policies – for example, the use of flexible treatment spaces in the ED[32] – rather than site-specific interventions (e.g., implementing physician-in-triage), may enhance the generalizability of simulation results. In addition, engaging a simulation project's local end-users throughout the project life cycle may further enhance adoption and subsequent implementation of simulation results. Similarly, researchers seeking to publish simulation studies need to better understand the priorities of the intended audience (e.g., policymakers, administrators, practitioners, or patients).

Advancing Computer Simulation within Emergency Care

While we have presented four primary methods for computer simulation, simulation as a discipline continues to develop. Technical innovations in computer simulation are left to methodological experts, but there should be general recognition that computer simulation methodology is an evolving academic discipline. New questions may present considerable opportunities for innovation in the technical aspects of the three established techniques we have discussed. For instance, hybrid types of simulation [33] may hold promise in expanding the repertoire of operational concerns amenable to such research.

- What types of changes could help bridge the interdisciplinary divide between in the academic and practice community of computer simulation methodologists?

  We recommend the publication of a registry of questions, methods, study results, validations, and researchers conducting computer simulation models. This effort could enhance communication between modelers and clinician researchers while promoting efficiencies in design and innovation. For example, important questions about patient flow in the ED may be published in the operations management literature leaving many emergency physicians and administrators unaware of such work. This type of registry could decrease duplicative efforts on related research questions and improve the potential implementation of such projects. Additionally, initiatives to cross-train healthcare practitioners in computer simulation would be highly advantageous to projects while bridging the interdisciplinary communications divide. Finally, making research published in the operations literature that is healthcare-oriented available through PubMed will increase the visibility of relevant work.

Enhanced Funding for Computer Simulation Research

In healthcare, research questions amenable to computer simulation are typically in the health services research domain, focused on organization and optimization of care delivery as a system. We offer four strategies to increase the amount of funding directed to such research.

1. *Funding*. While the Veterans Health Administration prioritizes health services research, other funding agencies such as the National Institutes of Health (NIH) and the Patient-Centered Outcomes Research Institute (PCORI), emphasize organ- or disease-specific problems. Increased federal funding for health services research is needed.

2. *Protected time*. Recognizing that increased funding may not occur, in the process of forming multidisciplinary research teams, investigators must realize that there are competing motivations for researchers' time. Many simulation experts do not work in healthcare and come from business (operations management and operations research), engineering (industrial or systems), or social science disciplines where the teaching load, and not grant funding, determines a researcher's protected time. Alternative mechanisms that allow simulation experts to protect their time (e.g., reduce teaching load) may promote collaboration and innovation among disciplines.

3. *Reframing research questions.* Asking research questions in a way that aligns with clinical research funding agency priorities, may increase opportunities for funding. For example, can the question be considered patient-centered and thus of interest to PCORI? Similarly, addressing practical challenges in the dissemination and implementation of a particular therapy for a specific disease process, the predominant focus for most research funding, might answer translational research questions.

4. *Local Investment.* Perhaps most immediately impactful, investigators should seek out opportunities for individual healthcare organizations (i.e., hospitals and clinics) to invest in local simulation efforts. This approach not only addresses key local problems generating their own return on investment, but also produces preliminary data for grants. While funding would likely come from discretionary centers, return on investment would be expected in the form of improved operations. Similarly, this approach supports a natural validation of simulation results.

Conclusion

Computer simulation modeling is an established, yet underused methodology to integrate evidence-based operations within emergency care. Through this consensus conference, interdisciplinary experts have identified key challenges to the use and further adoption of computer simulation modeling, particularly within emergency care. Though challenges exist, such as the low penetrance of simulation research findings, computer simulation provides a unique opportunity to identify, evaluate, implement, and disseminate strategies that will substantially advance the science of emergency care delivery.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

References for Simulation-Based Studies in Emergency Care.

	Monte Carlo Simulation	System Dynamics Modeling	Discrete Event Simulation	Agent-Based Simulation
Patient Flow	21,34–38	8,13,39–52	8,21–23,32,34,39,41,49,50,53–100	45,49,53,85,90,98,101–123
Cost	124–138	40,50	50	
Ambulance flow			90,139,149	90,141
Decision making	142	143	144	145
Resource planning		45	146	45,109
Disease spread				24,147
ED Information Technology			148,149	
Other	38,150	50,151	50,85,152–156	85,152

Table 2

Examples of commercial software packages for computer simulation modeling.

Product	Platform	Supported model types				Graphical interface	Strengths	Weaknesses
		Monte Carlo	SD	DES	ABS			
GoldSim	Excel add-on	Yes	Yes	Yes	No	2D		Monte-Carlo focus
SIMUL8	Web-based	No	No	Yes	No	3D	Multiple comparators	Limited repertoire, cost
MedModel	Stand-alone	No	No	Yes	No	2D	Healthcare specific	
Simio	Stand-alone	No	No	Yes	No	3D		
AnyLogic	Stand-alone	No	Yes	Yes	Yes	2D	Multi-paradigm, extensible with Java	Learning curve

(Information is up to date as of the time of article review. Perceived strengths and weaknesses are meant to be a general guideline from authors' experience and should not supplant a more comprehensive evaluation, nor is this table intended as an endorsement of any particular software.)