A Review of Modeling and Simulation Techniques

Abhinav Sharma[1] Aman Sharma[2]
[1,2]B.Tech Student(7TH sem)
[1,2]Department of Electronics and Computers Engineering
[1,2]Dronacharya College of Engineering, Gurgaon, India

***Abstract*—** this paper reviews about modeling and simulation techniques for complex systems such as life support systems. One uses a model instead of real situation or system to understand something about it. Simulation with model helps us in making decisions and raise hypothetical scenarios. If the model is valid experimenting with it by computer can save money, time and efforts. Computer simulation designs a model of a studied object, executes the model on a digital computer, and analyzes the execution output. The knowledge base of data contains coordinated determination of the model external variables and parameters and information regarding model expected behavior. The first and the hardest problem in simulation are determining the exact method to use for creating a model. The chapter presents a review on techniques used in model design (conceptual, declarative, functional, constraint, and multi), techniques used in simulation model execution (serial and parallel discrete-event simulation), and techniques used in simulation model analysis (calibration, validation, verification, goal- seeking).

Keywords— calibration, validation, verification, goal-seeking

I. INTRODUCTION

Modeling and simulation (M&S) is getting information about how something will behave without actually testing it in real life. For instance, if we wanted to design a race car, but weren't sure what type of spoiler would improve traction the most, we would be able to use a computer simulation of the car to estimate the effect of different spoiler shapes on the coefficient of friction in a turn. We're getting useful insights about different decisions we could make for the car without actually building the car. More generally, M&S is using models, including emulators, prototypes and stimulators, either statically or over time, to develop data as a basis for making managerial or technical decisions. The terms "modeling" and "simulation" are often used interchangeably. The use of M&S within engineering is well recognized. Simulation technology belongs to the tool set of engineers of all application domains and has been included in the body of knowledge of engineering management. M&S has already helped to reduce costs, increase the quality of products and systems, and document and archive lessons learned. M&S is a discipline on its own. Its many application domains often lead to the assumption that M&S is pure application. This is not the case and needs to be recognized by engineering management experts who want to use M&S. To ensure that the results of simulation are applicable to the real world, the engineering manager must understand the assumptions, conceptualizations, and implementation constraints of this emerging field.

II. MODELING AND SIMULATION AS AN EMERGING DISCIPLINE

The emerging discipline of M&S is based on developments in diverse computer science areas as well as influenced by developments in System Theories, Systems Engineering, Software Engineering, Artificial Intelligence, and more. This foundation is as diverse as that of engineering management and brings elements of art, engineering, and science together in a complex and unique way that requires domain experts to enable appropriate decisions when it comes application or development of M&S technology in the context of this paper. The diversity and application-oriented nature of this new discipline some-times results in the challenge, that the supported application domains themselves already have vocabularies in place that are not necessarily aligned between disjunctive domains. A comprehensive and concise representation of concepts, terms, and activities is needed that make up a professional Body of Knowledge for the M&S discipline. Due to the broad variety of contributors, this process is still ongoing. To come to a decision on practical needs by model and simulation it is necessary to interpret them in model terms. A problem of interpretation for matters reach in content of reality in model terms cannot be resolved one day forever or automatically. As a rule they divide the problem into two parts:

- description of a knowledge base which is used also for model validation and verification,
- choice of the model parameters by techniques of calibration and identification.

III. MODELING AND SIMULATION IN PHARMACY EDUCATION

The shortage of pharmacists in the United States has prompted increases in class sizes and the number of satellite and distance-learning programs at colleges and schools of pharmacy. This rapid expansion has created a burden on existing clinical experimental sites. The Accreditation Council on Pharmacy Education (ACPE) requires at least 1440 hours of advanced pharmacy practice experience (APPE); included among the 1440 hours of APPE, the ACPE requires colleges and schools of pharmacy to provide a minimum of 300 hour of introductory pharmacy practice experience (IPPE) interspersed throughout the first three years of the pharmacy curriculum. Simulation training may be one such model to provide students with the opportunity to apply didactic knowledge and reduce the burden on experiential sites.

Fig. 1: The modeler chooses a modeling method

The inclusion of simulation in IPPEs has gained acceptance and is encourages by ACPE as describe in the Policies and Procedures for ACPE Accreditation of Professional Degree Programs – January 2010. Addendum 1.3, Simulations for Introductory Pharmacy Practices Experiences – Approved June 2010, states: Simulation may not be utilized to supplant or replace the minimum expectation for time spent in actual pharmacy practice settings as set forth in the previously established policy. Beyond the majority of time in actual pharmacy practice settings, colleges and schools may utilize simulation to account for no greater than 20%(e.g., 60 hours of a 300 hour IPPE program) of total IPPE time. Several pharmacy colleges and schools have incorporated simulation as part of their core curricula. At the University of Pittsburgh School of Pharmacy, high-fidelity patient simulators are used to reinforce therapeutics. While the University of Rhode Island College of Pharmacy integrated their simulation program into their pharmacology and medicinal chemistry coursework; and was the first college of pharmacy to purchase a high-fidelity patient simulator. Some pharmacy colleges and schools host virtual reality and full environment simulation programs. For example, Purdue University School of Pharmacy and the university's Envision Center for Data Perceptualization collaborated with the United States Pharmacopeia (USP) to create a virtual clean room that is USP 797 standards compliant.

IV. Methods In Simulation Modeling

By method in simulation modeling, we mean a general framework for mapping a real world system to its model. A method suggests a type of language, or "terms and conditions" for model building. To date, there exist three methods:

(1) System Dynamics
(2) Discrete Event Modeling
(3) Agent Based Modeling

The choice of method should be based on the system being modeled and the purpose of the modeling – though often it is most heavily influenced by the background or available tool set of the modeler. Consider the Figure where the modeler is deciding how best to build a model of a supermarket. Depending on the problem, he may: put together a process flowchart where customers are entities and employees are resources; an agent based model, where consumers are agents affected by ads, communication, and interaction with agents-employees; or a feedback structure, where sales are in the loop with ads, quality of service, pricing, customer loyalty, and other factors.

A. System Dynamics

System dynamics is an approach to understanding the behaviour of complex systems over time. It deals with internal feedback loops and time delays that affect the behaviour of the entire system. What makes using system dynamics different from other approaches to studying complex systems is the use of feedback loops and stocks and flows. These elements help describe how even seemingly simple systems display baffling nonlinearity. In the system dynamics methodology, a problem or a system (e.g., ecosystem, political system or mechanical system) is first represented as a causal loop diagram. A causal loop diagram is a simple map of a system with all its constituent components and their interactions. By capturing interactions and consequently the feedback loops (see figure below), a causal loop diagram reveals the structure of a system. By understanding the structure of a system, it becomes possible to ascertain a system's behavior over a certain time period.

The causal loop diagram of the new product introduction may look as follows:

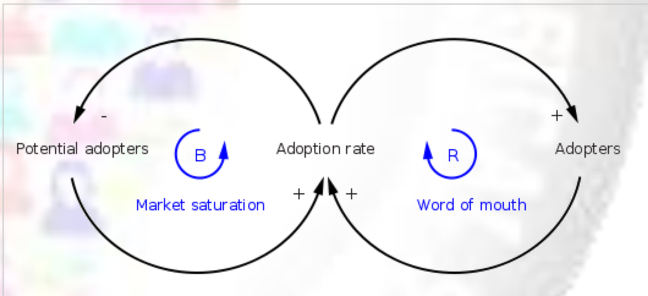

Fig. 2: Causal loop diagram of New product adoption model

There are two feedback loops in this diagram. The positive reinforcement (labeled R) loop on the right indicates that the more people have already adopted the new product, the stronger the word-of-mouth impact. There will be more references to the product, more demonstrations, and more reviews. This positive feedback should generate sales that continue to grow. The second feedback loop on the left is negative reinforcement (or "balancing" and hence labeled B). Clearly, growth cannot continue forever, because as more and more people adopt, there remain fewer and fewer potential adopters. Both feedback loops act simultaneously, but at different times they may have different strengths. Thus one would expect growing sales in the initial years, and then declining sales in the later years.

B. Discrete Event Modeling

A discrete-event simulation (DES), models the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation can directly jump in time from one event to the next. Another alternative to event-based simulation is process-based simulation. In this approach, each activity in a system corresponds to a separate process, where a process is typically simulated by a thread in the simulation program. In this case, the discrete events, which are generated by threads, would cause other threads to sleep, wake, and update the system state.

A more recent method is the three-phased approach to discrete event simulation (Pidd, 1998). In this approach, the first phase is to jump to the next chronological event. The second phase is to execute all events that unconditionally occur at that time (these are called B-events). The third phase is to execute all events that conditionally occur at that time (these are called C-events). The three phase approach is a refinement of the event-based approach in which simultaneous events are ordered so as to make the most efficient use of computer resources. The three-phase approach is used by a number of commercial simulation software packages, but from the user's point of view, the specifics of the underlying simulation method are generally hidden.

C. *Agent Based Modeling*

An agent-based model is a class of computational models for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole. It combines elements of game theory, complex systems, emergence, computational sociology, multi-agent systems, and evolutionary programming. Monte Carlo Methods are used to introduce randomness. Particularly within ecology, ABMs are also called individual-based models (IBMs) and individuals within IBMs may be simpler than fully autonomous agents within ABMs. A review of recent literature on individual-based models, agent-based models, and multiagent systems shows that ABMs are used on non-computing related scientific domains including biology, ecology and social science. Agent-based modeling is related to, but distinct from, the concept of multi-agent systems or multi-agent simulation in that the goal of ABM is to search for explanatory insight into the collective behavior of agents obeying simple rules, typically in natural systems, rather than in designing agents or solving specific practical or engineering problems.

The agent-directed simulation (ADS) metaphor distinguishes between two categories, namely "Systems for Agents" and "Agents for Systems." Systems for Agents (sometimes referred to as agents systems) are systems implementing agents for the use in engineering, human and social dynamics, military applications, and others. Agents for Systems are divided in two subcategories. Agent-supported systems deal with the use of agents as a support facility to enable computer assistance in problem solving or enhancing cognitive capabilities. Agent-based systems focus on the use of agents for the generation of model behavior in a system evaluation (system studies and analyses).

Verification and validation (V&V) of simulation models is extremely important. Verification involves the model being debugged to ensure it works correctly, whereas validation ensures that the right model has been built. Verification and validation can be seen in the social sciences domain,[52] and validation seen in Computational Economics. Face validation, sensitivity analysis, calibration and statistical validation have also been demonstrated. Discrete-Event Simulation Framework approach for the validation of Agent-Based systems has been proposed in. A comprehensive resource on empirical validation of agent-based models is. VOMAS provides a formal way of Validation and Verification. If you want to develop a VOMAS, you need to start by designing VOMAS agents along with the agents in the actual simulation preferably from the start. So, in essence, by the time your simulation model is complete, you essentially can consider to have one model which contains two models:

(1) An Agent Based Model of the intended system
(2) An Agent Based Model of the VOMAS

V. Conclusion

In conclusion, three activities have to be conducted and orchestrated to ensure success: a model must be produced that captures formally the conceptualization, a simulation must implement this model, and management processes must ensure that model and simulation are interconnected and on the current state (which means that normally the model needs to be updated in case the simulation is changed as well).

The military and defense domain, in particular within the United States, has been the main M&S champion, in form of funding as well as application of M&S. E.g., M&S in modern military organizations is part of the acquisition/procurement strategy. Specifically, M&S is used to conduct Events and Experiments that influence Requirements and Training for military Systems. As such, M&S is considered an integral part of systems engineering of military Systems. Other application domains, however, are currently catching up. M&S in the fields of medicine, transportation, and other industries is poised to rapidly outstrip DoD's use of M&S in the years ahead, if it hasn't already happened.

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