Simulation as a High Technology that Contributes to the Learning Process at the University*

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Abstract. The features of various methods of simulation modeling, their unity are considered. We discuss implementation features of the system time promotion in existing simulation paradigms: discrete event, dynamic, system dynamics, and multi-agent approach. In the models with continuous processes, the value of the promotion step in time is proposed to be chosen according to the Nyquist-Kotelnikov theorem. We have substantiated a formalized approach to the choice of the system time promotion step. The schemes of events and processes are compared, realizing different approaches to modeling algorithm creation. The unity of paradigms contributes to the implementation of the integrated simulation environment. Recommendations for choosing a step in the system time promotion, given in the paper, enable to speed up the process of modeling and save computing resources. The importance of simulation in the process of training specialists at a university is discussed. The advantages of simulation modeling as a means of promoting the formation of a systematic approach in students are discussed.

Keywords: simulation, simulation, simulation paradigm, system time, process diagram, event diagram problematic training, approaches of simulation, the role of simulation in the training of specialists.

1 Introduction

In practical activities, simulation as an effective working technology is used to solve a wide group of management problems: production management, industry projects, information business systems, optimization of control modes for technological (logistic, communication) systems, state and territorial administration [1].

Simulation, as a research method, is based on the fact that the analyzed dynamic system is replaced by a simulator, and experiments are performed with it to obtain information about the system under study. The role of the simulator is often performed by a computer program.

Before a modeling object is displayed by a software simulation model, a conceptual

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model and a formalized representation of the object in the form of an adequate mathematical scheme are formed for it.

The use of various mathematical schemes at the formalization stage has led to the fact that four paradigms are covered by modern simulation technologies – four self-sufficient approaches [2]:

- discrete-event modeling,
- dynamic modeling,
- system dynamics in the sense of Forrester and
- multi-agent approach.

2 Simulation Paradigms and its Unity

In discrete event modeling, the functioning of the system is presented as a chronological sequence of events. An event occurs at a certain point in time and marks a change in the state of the system. Advancement of system time is realized through programming a simulator - “mover”. Simulation is reduced to setting the initial state of the system, starting the simulator, and observing the reproduction of the trajectory of the “movement” of the simulated object in the space of changing its states [2].

Dynamic modeling is used to simulate processes described by differential equations presented in Cauchy form, which are solved by numerical methods with automatic selection of time steps [3].

In computer simulations, symbolic infinitesimal increments are replaced by numerical finite increments, and a system simulation is performed in discrete time. The choice of the value of the advancement step is not related to the principle of imitation and is due to the dynamics of the simulated processes.

The logic of "continuous" dynamic modeling in terms of the mechanism of advancement in time coincides with the logic of discrete-event modeling [1].

In system dynamics, the structural elements of the model are levels and rates. The interaction in the model is displayed by continuous processes, presented in the form of equations in finite differences. A step in the system of difference equations of levels can be considered as a step of changing values of levels and flows over time.

Multi-agent modeling examines the behavior of decentralized agents and how their behavior determines the behavior of the entire system as a whole. The behavior of agents is determined on an individual level, and global behavior arises as a result of the activities of many agents (bottom-up modeling). The actions of agents are imitated in the model in the same way as any other events - as direct consequences from the achieved state of the system. And the model time advances the simulator strictly forward, in exact accordance with the mechanism of cause and effect.

In all four considered versions of simulation modeling, the simulator advances the system time and creates a current time layer of the system at each next step. This layer contains information about possible upcoming and recent changes that have occurred and for recurring recalculation of indicators. This principle of modeling is the essence of computer simulation.

Therefore, all four paradigms, are simply different approaches to constructing trajectories of state transitions. All of its use a causal mechanism for advancing processes over time. The differences relate only to the choice of a particular set of basic mathematical and program objects. The logic of process simulation is the same.

3 The Principles of Promoting System Time

In the communication technology, the correspondence between continuous and discrete signals is based on the Nyquist – Kotelnikov theorem, which justifies the representation (transmission) of analog signals by separate sample values through the step

$$\Delta t = 1/2F_l,$$

where F_l is the cutoff frequency – frequency limiting the effective spectrum bandwidth of the analog signal from above. Frequency response is a hallmark of any dynamic system.

In this regard, this approach to the assignment of the step применяетсяt is also used for SM dynamic systems. Since the fraction of the frequency spectrum adjacent to this cutoff frequency is very small compared to the lower frequency region of this limited spectrum, there are many sections in the discrete interpretation of the analog signal in which consecutive sampled values are practically indistinguishable from each other. For this reason, for example, in the communication technique, from cyclic discretization with a step Δt, we switched to adaptive discretization with a random step.

In adaptive sampling, a certain zone (aperture) is set relative to the presented (transmitted) value, and the next sampled value is taken (transmitted) through the time interval when this value deviates from the previous presented (transmitted) up or down, by an amount exceeding the value apertures. This sets a random step between the represented (transmitted) values (events) of the analog signal. We have such a connection between continuous and discrete in all four “paradigms” of simulation. And if a fixed step is used in dynamic modeling, system dynamics, then in discrete-event and agent modeling both fixed and random steps are used to advance the system time.

When constructing the “mover” of system time, two main schemes for constructing modeling algorithms are used - the event diagram and the process diagram. The event diagram is used in discrete-event modeling, and the process diagram is used in multi-agent modeling. And in that, and in another scheme for the advancement of system time, the principle of “special” moments is applied. So that the computer can calculate the next “special” moment, a calendar is used in which for each type of event the nearest moment is specified when such an event will occur. According to the calendar, the next special moment is determined as the smallest of the moments recorded in the calendar.

Let us compare the scheme of events and the scheme of processes.

The scheme of events is more coherent: events do not intersect, one event is simulated in one step, events are simulated in chronological order, the step algorithm is divided into stages with a clear functional purpose (event simulation, updating statistics, scheduling new events). The main difficulty in developing a model according to the scheme of events – in difficult situations it is quite difficult to create a list of types of events and correctly develop the corresponding parts of the algorithm so as not to miss any necessary elementary events and correctly take into account the relationships.

The process diagram does not require, when developing an algorithm, to take into account immediately everything that can happen in the system, but allows separate development of individual processes. The development of simulation models is especially simplified when using a ready-made simulation system when the user only needs to describe the sequence of events and work in the processes, and the simulation system takes care of the interaction of processes, statistics, and controls the order of simulation of processes. However, the process diagram does not allow us to distinguish functionally different parts of the algorithm: statistics replenishment and event planning are investigated with state change operations within one phase of the process. This is fraught with omissions in the development of the algorithm.

At the stage of the initial training in modeling and in modeling simple systems, it is advisable to apply an event scheme, and when modeling complex systems using universal tools, a process scheme is preferable.

4 Versatility Modeling

When stochastic systems are being simulated, the paradigm of simulation includes two components: a simulator that implements the advancement of system time, and the Monte Carlo method, which ensures the playing of "events". Both components are present in all four approaches to simulation [4].

4.1 Random Modeling

Simulation, taking into account the influence of random factors, is associated with multiple reproductions of possible options for the development of processes. Repeatability allows you to get a strip of the most probable trajectories for statistical estimates of the desired indicators. The accuracy of the estimates characterizes the accuracy of simulation, as a measure of the correspondence of the numerical solution obtained by modeling, the exact solution of the mathematical problem. A well-known drawback of the Monte Carlo method is its slow convergence, which is especially evident in the modeling of rare events and problems of large dimensions. And here the problem of accelerating simulation using the Monte Carlo method becomes particularly relevant due to the reduction in the number of numerical experiments. A common strategy for reducing the price of accuracy is to accelerate the convergence of calculated estimates.

4.2 Simulation Acceleration

Acceleration can be achieved:

1. due to the corresponding analytical transformation of the problem being solved;
2. by organizing parallel computing and distributed modeling.

The greatest effect can be achieved when the acceleration methods take into account the specifics of the modeled objects, the tasks being solved, and the algorithms for solving them. So, for example, in [5] both of these approaches to simulation acceleration are developed and described concerning the tasks of modeling information and communication networks. The theoretical basis of accelerated modeling of networks is the methods of layered sampling, equal-weighted modeling, elements of the theory of extreme statistics.

4.3 Simulation is Versatile.

However, ready-made simulation models cost a lot of money and require a powerful computer, which often delays the practical use of a software product. There is a need to build a complex of inter-industry models since quite often the tasks of various applied areas in the formulation and results have much in common.

For example, in structural and functional terms there is an almost complete coincidence in the purpose of the elements of telecommunication networks and transport networks: unified units of transportation of both messages (packet, frame) and material flows (packet, container, road trailer), virtual channels of telecommunication networks with transport corridors, buffer storage in telecommunication network nodes and warehouses in transport nodes. And the tasks solved on the networks during macro modeling coincide in a statement, the models for many objects are similar. The working simulation model is close to physical simulation, visually reflects the process of functioning of a real system. The practice of simulation modeling is inextricably linked with system analysis. Training with a line of simulation models is the most obvious way to train system architects and analysts [3].

Conclusion

Indeed, imitation modeling, as high technology, contribute to the realization of the principle of consciousness and activity of students. Active methods involve the use of problem-based learning. A suitable form of such training is the simulation. It contributes to the development of students 'self-search and decision-making skills, students' independent development of "specifics", and the acquisition of new knowledge ("from knowledge problem"). The problematic approach, implemented through imitation, allows you to force students into specific conditions of their future professional activity.

Simulation modeling provides the ability to most fully take into account the relationships existing in the system; mapping the influence of internal structure on the nature of the functioning of the model; the possibility of implicit assignment of the objective function and constraints for a complex system, which contributes to the education of students in a systematic approach.

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