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A General Framework for System Modelling and Simulation Types

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Abstract-* In this paper we are discussing about the concepts of simulation, how it is developed, different steps and processes for simulation. we have discussed about need of steady state simulation and methods used for this. Finally about the selection of simulation software and example software. The intension is for those unfamiliar with the area of discrete event simulation as well as beginners looking for an overview of the area. This includes anyone who is involved in system design and modification – system analysts, management personnel, engineers, military planners, economists, banking analysts, and computer scientists. Familiarity with probability and statistics is assumed.

Keywords: simulation, system analysts, discrete event simulation

I. Introduction

System Simulation is the mimicking of the operation of a real system, such as the day-to-day operation of a bank, or the value of a stock portfolio over a time period, or the running of an assembly line in a factory, or the staff assignment of a hospital or a security company, in a computer. Simulation in general is to pretend that one deals with a real thing while really working with an imitation. A flight simulator on a PC is also a computer model of some aspects of the flight: it shows on the screen the controls and what the "pilot" is supposed to see from the "cockpit" . Suppose we are interested in a gas station. We may describe the behavior of this system graphically by plotting the number of cars in the station; the state of the system. Every time a car arrives the graph increases by one unit while a departing car causes the graph to drop one unit. This graph could be obtained from observation of a real station, but could also be artificially constructed. Such artificial construction and the analysis of the resulting sample path consists of the simulation. Simulations may be performed manually. Most often, however, the system model is written either as a computer program or as some kind of input into simulator software.

II. Development Of System Simulation

Discrete event systems (DES) are dynamic systems which evolve in time by the occurrence of events at possibly irregular time intervals. DES abound in real-world applications. Examples include traffic systems, flexible manufacturing systems, computer-communications systems, production lines, coherent lifetime systems, and flow networks. Most of these systems can be modeled in terms of discrete events whose occurrence causes the system to change from one state to another. In designing, analyzing and operating such complex systems, one is interested not only in performance evaluation but also in sensitivity analysis and optimization. A typical stochastic system has a large number of control parameters that can have a significant impact on the performance of the system. To establish a basic knowledge of the behavior of a system under variation of input parameter values and to estimate the relative importance of the input parameters, sensitivity analysis applies small changes to the nominal values of input parameters as in fig 1. For systems simulation, variations of the input parameter values cannot be made infinitely small. The sensitivity of the performance measure with respect to an input parameter is therefore defined as (partial) derivative. Descriptive Analysis includes: Problem Identification & Formulation, Data Collection and Analysis, Computer Simulation Model Development, Validation, Verification and Calibration, and finally Performance Evaluation. Prescriptive Analysis: Optimization or Goal Seeking. These are necessary components for Post-prescriptive Analysis: Sensitivity, and What-If Analysis.

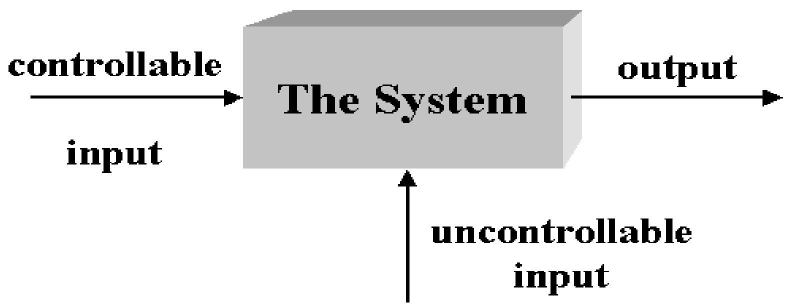


Fig1 General stochastic system

- **Problem Formulation**: Identify controllable and uncontrollable inputs. Identify constraints on the decision variables. Define measure of system performance and an objective function. Develop a preliminary model structure to interrelate the inputs and the measure of performance.
- **Data Collection and Analysis:** Regardless of the method used to collect the data, the decision of how much to collect is a trade-off between cost and accuracy.
- **Simulation Model Development:** Acquiring sufficient understanding of the system to develop an appropriate conceptual, logical and then simulation model is one of the most difficult tasks in simulation analysis.
- **Model Validation, Verification and Calibration:** Verification checks that the implementation of the simulation model (program) corresponds to the model. Validation checks that the model corresponds to reality. Calibration checks that the data generated by the simulation matches real (observed) data.
- **Input and Output Analysis:** Discrete-event simulation models typically have stochastic components that mimic the probabilistic nature of the system under consideration. The input data analysis is to model an element (e.g., arrival process, service times) in a discrete-event simulation given a data set collected on the element of interest.Careful planning, or designing, of simulation experiments is generally a great help, saving time and effort by providing efficient ways to estimate the effects of changes in the model's inputs on its outputs.
- **Performance Evaluation and What-If Analysis:** The `what-if' analysis is at the very heart of simulation models.
- **Sensitivity Estimation:** Users must be provided with affordable techniques for sensitivity analysis if they are to understand which relationships are meaningful in complicated models.
- **Optimization:** As with sensitivity analysis, the current approach for optimization requires intensive simulation to construct an approximate surface response function. I
- **Gradient Estimation Applications:** There are a number of applications which measure sensitivity information, Local information, Structural properties, Response surface generation, Goal-seeking problem, Optimization, What-if Problem, and Meta-modelling
- **Report Generating:** Report generation is a critical link in the communication process between the model and the end user.

III. Types Of Processes In Simulation

A stochastic process is a probabilistic model of a system that evolves randomly in time and space. Formally, a stochastic process is a collection of random variables {X(t), t □ T} all defined on a common sample (probability) space. The X(t) is the state while (time) t is the index that is a member of set T.

Examples are the delay {D(i), i = 1, 2, ...} of the ith customer and number of customers {Q(t), T □ 0} in the queue at time t in an M/M/1 queue. In the first example, we have a discrete- time, continuous state, while in the second example the state is discrete and time in continuous.

The following table 2 is a classification of various stochastic processes. The man made systems have mostly discrete state. Monte Carlo simulation deals with discrete time while in discrete even system simulation the time dimension is continuous, which is at the heart of this site.

Table I. A Classification of Stochastic Processes

		Change in the States of the System	
		Continuous	**Discrete**
Time	**Continuous**	Level of water behind a dam	Number of customers in a bank
	Discrete	Weekdays' range of temperature	Sales at the end of the day

A. Simulation Output Data And Stochastic Process

To perform statistical analysis of the simulation output we need to establish some conditions, e.g. output data must be a covariance stationary process (e.g. the data collected over n simulation runs).

- **Stationary Process (strictly stationary):** A stationary stochastic process is a stochastic process {X(t), t □ T} with the property that the joint distribution all vectors of h dimension remain the same for any fixed h.
- **First Order Stationary:** A stochastic process is a first order stationary if expected of X(t) remains the same for all t. For example in economic time series, a process is first order stationary when we remove any kinds of trend by some mechanisms such as differencing.
- **Second Order Stationary:** A stochastic process is a second order stationary if it is first order stationary and covariance between X(t) and X(s) is function of t-s only.

Again, in economic time series, a process is second order stationary when we stabilize also its variance by some kind of transformations such as taking square root.

Clearly, a stationary process is a second order stationary, however the reverse may not hold.
In simulation output analysis we are satisfied if the output is *covariance stationary*.

- **Covariance Stationary:** A covariance stationary process is a stochastic process {X(t), t □ T} having finite second moments, i.e. expected of $[X(t)]^2$ be finite.

Clearly, any stationary process with finite second moment is covariance stationary. A stationary process may have no finite moment whatsoever. Since a Gaussian process needs a mean and covariance matrix only, it is stationary (strictly) if it is covariance stationary.

IV. Steady State Simulation

Unlike in queuing theory where steady state results for some models are easily obtainable, the steady state simulation is not an easy task.

A. Techniques Used For Steady State Simulation

Regenerative Method: This method is used for its theoretical nice properties, however it is rarely applied in actual simulation for obtaining the steady state output numerical results.

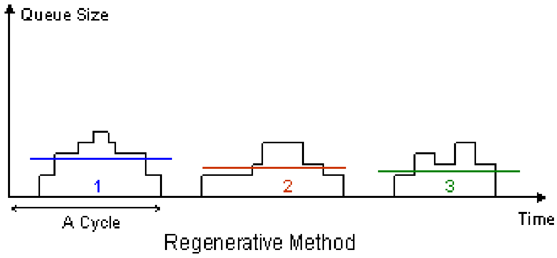


Fig 2: Regenerative method for steady state simulation

Suppose you have a regenerative simulation consisting of m cycles of size n_1, n_2,…n_m, respectively. The cycle sums is:
$y_i = x_{ij} / n_i$, the sum is over j=1, 2, ..,n_i
The overall estimate is:
Estimate = y_i / n_i, the sums are over i=1, 2, ..,m
The 100(1-Z/2)% confidence interval using the Z-table (or T-table, for m less than, say 30), is:
Estimate Z. S/ (n. $m^{½}$)
where,
n = ni /m, the sum is over i=1, 2, ..,m
and the variance is:

$$S^2 = (y_i - n_i \,.\, \text{Estimate})^2/(m-1), \text{ the sum is over i=1, 2, ..,m}$$

Method of Batch Means: This method involves only one very long simulation run which is suitably subdivided into an initial transient period and n batches. Each of the batch is then treated as an independent run of the simulation experiment while no observation are made during the transient period which is treated as warm-up interval. Choosing a large batch interval size would effectively lead to independent batches and hence, independent runs of the simulation, however since number of batches are few on cannot invoke the central limit theorem to construct the needed confidence interval. On the other hand, choosing a small batch interval size would effectively lead to significant correlation between successive batches therefore cannot apply the results in constructing an accurate confidence interval.

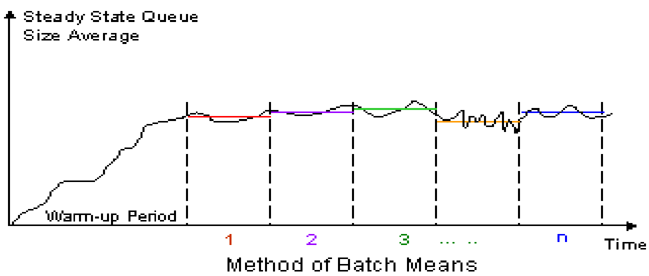
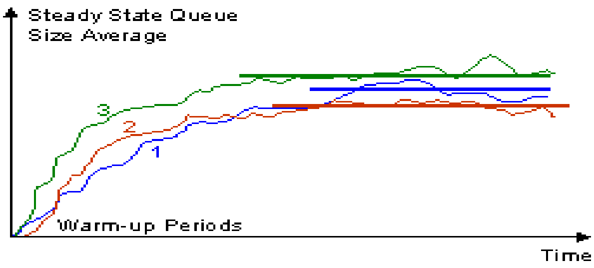


Fig 3: Method of batch means

Suppose you have n equal batches of m observations each. The means of each batch is:
$\text{mean}_i = x_{ij} / m$, the sum is over j=1, 2, ..,m
The overall estimate is:
Estimate = mean_i / n, the sum is over i=1, 2, ..,n
The 100(1-Z/2)% confidence interval using the Z-table (or T-table, for n less than, say 30), is:
Estimate Z. S ,where the variance is:

S^2 = Z($mean_i$ - Estimate)^2/(n-1), the sum is over i=1, 2, ..,n

Method of Independent Replications: This method is the most popularly used for systems with short transient period. This method requires independent runs of the simulation experiment different initial random seeds for the simulators' random number generator. For each independent replications of the simulation run it transient period is removed. For the observed intervals after the transient period data is collected and processed for the point estimates of the performance measure and for its subsequent confidence interval.



Method of Independent Replications

Fig 4:Independent replications

Suppose you have n replications with of m observations each. The means of each replication is:

$mean_i$ = x_{ij} / m, the sum is over j=1, 2, ..,m

The overall estimate is:

Estimate = $mean_i$ / n, the sum is over i=1, 2, ..,n

The 100(1-□/2)% confidence interval using the Z-table (or T-table, for n less than, say 30), is:

Estimate Z. S

where the variance is:

S^2 = ($mean_i$ - Estimate)^2/(n-1), the sum is over i=1, 2, ..,n

V. Simulation Software Selection

The vast amount of simulation software available can be overwhelming for the new users. The following are only a random sample of software in the market today:

ACSL, APROS, ARTIFEX, Arena, AutoMod, C++SIM, CSIM, Call$im, FluidFlow, GPSS, Gepasi, JavSim, MJX, MedModel, Mesquite, Multiverse, NETWORK, OPNET Modeler, POSES++, Simulat8, Powersim, QUEST, REAL, SHIFT, SIMPLE++, SIMSCRIPT, SLAM, SMPL, SimBank, SimPlusPlus, TIERRA, Witness, SIMNON, VISSIM, and javasim.

There are several things that make an ideal simulation package. Some are properties of the package, such as support, reactivity to bug notification, interface, etc. Some are properties of the user, such as their needs, their level of expertise, etc. For these reasons asking which package is best is a sudden failure of judgment. The first question to ask is for what purpose you need the software? Is it for education, teaching, student-projects or research?

The main question is: What are the important aspects to look for in a package? The answer depends on specific applications. However some general criteria are: Input facilities, Processing that allows some programming, Optimization capability, Output facilities, Environment including training and support services, Input-output statistical data analysis capability, and certainly the Cost factor.

A. SIMSCRIPT II.5

Without computer one cannot perform any realistic dynamic systems simulation.

SIMSCRIPT II.5 is a powerful, free-format, English-like simulation language designed to greatly simplify writing programs for simulation modelling. Programs written in SIMSCRIPT II.5 are easily read and maintained. They are accurate, efficient, and generate results which are acceptable to users. Unlike other simulation programming languages, SIMSCRIPT II.5 requires no coding in other languages. SIMSCRIPT II.5 has been fully supported for over 33 years. Contributing to the wide acceptance and success of SIMSCRIPT II.5 modelling are:

- **Design:** A powerful worldview, consisting of Entities and Processes, provides a natural conceptual framework with which to relate real objects to the model.
- **Programming:** SIMSCRIPT II.5 is a modern, free-form language with structured programming constructs and all the built-in facilities needed for model development. Model components can be programmed so they clearly reflect the organization and logic of the modeled system. The amount of program needed to model a system is typically 75% less than its FORTRAN or C counterpart.
- **Debugger:** A well designed package of program debug facilities is provided. The required tools are available to detect errors in a complex computer program without resorting an error. Simulation status information is provided, and control is optionally transferred to a user program for additional analysis and output.
- **Evolution:** This structure allows the model to evolve easily and naturally from simple to detailed formulation as data becomes available. Many modifications, such as the choice of set disciplines and statistics are simply

specified in the Preamble.

- **Documentation:** You get a powerful, English-like language supporting a modular implementation. Because each model component is readable and self-contained, the model documentation is the model listing; it is never obsolete or inaccurate.

VI. Types Of Simulations

1.Social Simulation:

The field of 'social simulation' seems to be following an interesting line of inquiry. Artificial Life is an interdisciplinary study enterprise aimed at understanding life-as-it-is and life-as-it-could-be, and at synthesizing life-like phenomena in chemical, electronic, software, and other artificial media. Artificial Life redefines the concepts of artificial and natural, blurring the borders between traditional disciplines and providing new media and new insights into the origin and principles of life. Simulation allows the social scientist to experiment with 'artificial societies' and explore the implications of theories in ways not otherwise possible.

2.Web-based Simulation

Web-based simulation is quickly emerging as an area of significant interest for both simulation researchers and simulation practitioners. This interest in web-based simulation is a natural outgrowth of the proliferation of the World-Wide Web and its attendant technologies, e.g. HTML, HTTP, CGI, etc. Also the surging popularity of, and reliance upon, computer simulation as a problem solving and decision support systems tools. Currently, the researchers in the field of web-based simulation are interested in dealing with topics such as methodologies for web-based model development, collaborative model development over the Internet, Java-based modeling and simulation, distributed modeling and simulation using web technologies, and new applications.

3.Parallel and Distributed Simulation

System modeling for parallel simulation, specification, re-use of models/code, and parallelizing existing simulations. Language and implementation issues, models of parallel simulation, execution environments, and libraries. Web based distributed simulation such as multimedia and real time applications, fault tolerance, implementation issues, use of Java, and CORBA.

VII. Conclusion

Simulation modeling and analysis makes it possible to Obtain a better understanding of the system by developing a mathematical model of a system of interest, and observing the system's operation in detail over long periods of time.Test hypotheses about the system for feasibility. Compress time to observe certain phenomena over long periods or expand time to observe a complex phenomenon in detail.

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