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THE METHODOLOGY AND MYTHOLOGY OF COMPUTER SIMULATIONS

by

Robert L. Gordon

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INTRODUCTION

The use of general purpose computers for systems simulations will become more widespread because of increases in computational speed and new developments in high level languages. It is the intention of this paper to focus on some of the fundamental methods used in digital simulations and thereby expose some of the myths.

METHODS OF MODELING AND SIMULATION

Simulation and modeling as a means of problem solving have always been used by man. An early example is man's attempt to model the shape of the earth. Since he could only observe that the horizon appeared to be a straight line, one model for the earth's shape was that of a finite plane. Another model, not too popular at the time, was that of a sphere. These models were necessary to construct in order to project what might happen if one sailed farther than the eye could see. As we know, a voyage (or experiment) eventually had to be conducted in order to validate the model.

Today, simulation and modeling still involve those same basic concepts, although we have at our disposal a large array of technological innovations to help us in this job. Simulation, modeling, experimentation, and analysis are all dependent on each other, and we should keep uppermost in our mind that the proper mix is essential to any reasonable research and development program.

MODELING

In order to gain a clearer view of simulation and modeling, modeling will be defined as a subset of simulation. Modeling is then divided into the two broad categories of physical models and mathematical models:

a. Physical Models

Physical models are an attempt to reproduce the phenomenon of interest in an exact form to the same scale or some other scale. A couple of examples as shown in

Figure 1 should suffice.

A scale model submarine is subjected to flow studies in a water tank, data on drag and lift forces is collected, and empirical formulas are developed to aid in performance predictions. The physical model in this case is the scale model submarine.

A general purpose computer is used to simulate some special purpose digital hardware. Data is obtained on logic flow, register sizes, and truncation errors. The physical model in this case are the internal registers scaled to act as small registers.

b. Mathematical Models

Mathematical models will be further dissected into the two categories; deterministic and stochastic for illustrative purposes:

(1) Deterministic Mathematical Models

The average engineer is probably most aware of the deterministic model since these were used most extensively in his undergraduate training. One example should suffice. Consider the response of the RC circuit in Figure 2 to a voltage input. Here a differential equation for this circuit determines the exact voltage output at any point in time for a particular input. This equation then is a deterministic model of that circuit; insofar as the main voltage characteristics are concerned. The accuracy of the solutions are dependent on the computing machinery and the programming techniques.

(2) Stochastic Mathematical Models

The stochastic type of mathematical model is not so well known. Associated with this model is a name "Monte Carlo", due to the use of random sampling in these models. Two elementary examples will illustrate the two basic variations used.

In the first example we are required to evaluate the following definite integral:

$$y = \int_0^1 (x)dx \qquad (1)$$

The Monte Carlo method of solving this integral is to obtain an ordered pair of random samples[1] from a uniform distribution between 0 and 1. The first sample is considered to be the x (abscissa) value and the function of x is computed. If the second sample from the ordered pair is less than the computed value (less than x in this case) a success or Yes decision is indicated. If it is greater than x then a failure or No decision is indicated. The success and failure regions are indicated in Figure 2. The ratio of successes to total trials now gives us an estimate of the integral. Out of 100 tries we might have 51 successes, thus our answer would be 0.51. As we know, the correct answer is 0.5. However, we may increase our trials to further reduce the inaccuracy.

The second example is an illustration of the second variation of the "Monte Carlo" technique. Here the model is <u>event</u> oriented. Let us suppose we are studying the flow of people through a check-out counter at a super market. Figure 3 illustrates the process. We ask the question once every second if someone is waiting to be checked out. This is the first event. The answer is provided by the throw of a pair of dice (a random sampling technique) and some decision rules. When there is someone waiting, the checker will proceed to start checking the items. This is the second event. We now ask the question whether the customer is finished checking, (or the second event). Again the answer will be determined by the throw of the dice and some other decision rules. This process is repeated many times over and one can find answers to the questions, "How many people on the average are waiting?"; "How long does it take to get checked-out?". Of course our answers will be dependent on how many items we assume the customer has in the cart, (these are our decision rules in the checking process). How valid the model is, is dependent on the validity of the decision rules. Hence, we may study at will under what conditions it is wise to open up another counter.

The above examples are certainly not exhaustive. There are many good references available.[2.]

SIMULATION

Since models are a subset of simulations, any or all of the types of models described maybe used singularly or together, in a simulation. The way in which the models are interconnected with each other, and with humans, allows us to dissect simulations into the three main classes; fully automatic, semi-automatic, and integrated.

A fully automatic simulation is a hands-off type of simulation in which the process is under complete computer control. The simulation is left free to run for a period of time without human intervention and the results are then inspected. The study of a special purpose computing hardware previously mentioned is such an example.

In the semi-automatic type of simulation critical decisions on parameter values, or plain value judgements are entered directly into the simulation when needed. If in our super market example the decision to open up another counter was made by a human, and the process continued, such a simulation would be known as a semi-automatic simulation. The results of course are heavily dependent on the person engaged in the simulation.

The integrated type of simulation generally involves the computer control of special purpose devices or physical models and the interaction of humans. Such a simulation might involve the testing of a large system under controlled inputs. An example is a simulated Apollo count-down.

A variety of high level computer languages have been developed to aid in computer simulations by allowing one to easily specify models of various types in an easy fashion. A recent tabulation in the IEEE April Transaction on Computers, show 20 such translations in use.[3] One example of an event oriented language is "GPSS" or general purpose system simulator. An example of a digital hardware simulation language is "MIMIC", developed at Wright Patterson Air Force Base.

In summary, computer simulations are essentially a very special type of experiment in which the basic building blocks are models of small aspects of the total system. The attractiveness is that system performance may be observed as slight changes are made in the models.

CRITERIA FOR APPLICATION

"When should such a tool be used?", is a frequently asked question. The answer will be divided into three parts:

a. A simulation should be used if analytical methods fail to exist, or are not as efficient as a simulation, and all other approaches have been explored. Analytical methods and problems do not always exist side by side.

b. A simulation should be used if we have reasonable assurance that sufficient data exists to give realism to the built-in assumptions of our models and data basis.

c. A simulation should be used if the process of constructing and running the simulation can be a beneficial learning experience.

There are at least two applications to sonar technology that stand out as examples of a good application of simulation techniques.

a. The first example is the simulation of prospective digital hardware for sonar systems. The UNIVAC 1108 at NUSL has a powerful repertoire of machine instructions to be put to advantage. Such simulations allow one to gain confidence in the specification of reasonable experimental sea going hardware, by exercising a physical model. The adaptive beamforming algorithms have many questions concerning sensitivity to hardware implementation.

b. The second is the application of simulation to the sonar design problem. Characteristic of this problem is the interaction between many parameters, and the manipulation of large data bases. A semiautomatic simulation with the designer operating in an interactive environment would relieve the designer of the tedious bookkeeping that is a large part of the design job. Interactive, of course, implies some type of graphic computer terminal. Such a simulation would allow the design of sonar systems on more than a first order statistical basis.

Summarizing this section, one finds that the application of simulations to a specific job is really understanding the capability of the resources available, the problems at hand and then providing a heavy does of common sense to match the two.

THE ANALYSIS OF RESULTS AND THE MYTHS IN SIMULATIONS

No model, be it physical or mathematical, can accurately model all the effects or parameters of interest.

In the deterministic RC circuit equation of Figure 2, the thermal voltage generated by the resistor was ignored. Models must be validated against real data.

Our first example of modeling the earth in this paper pointed out this important fact. Eventually an experiment (voyage) had to be run in order to validate the two reasonable models of a flat world, and a round world. This aspect of model validation cannot be overemphasized.

Failure at model validation has generated a simulation mythology. A myth, as used here, is defined by Webster as a "belief given uncritical acceptance by the members of a group, expecially of existing or traditional practices and institutions." This will probably always arise in simulation work because of its very nature. Let us list a few reasons at why myths are developed.

First, a semi-automatic simulation invariably gives different answers depending on the value judgements and parameter values used by the operator. This is exactly what was intended, of course, but it generates the myth: "One never gets consistent results from a simulation."

Second, simulations that involve the stochastic event type model generate the same type of myth due to their nature of traveling different probability trees. However, this is what the designer intended. It is this aspect which is to be studied.

Third, and perhaps the most common error in simulation, is to use existing models to evaluate a different set of parameters than originally intended. This gives rise to the often heard myth: "Simulation results will never agree with any real life experience."

These and other myths in computer simulation work can be held to a minimum only if the results, assumptions, parameters, and judgements built into each and every model in the simulation is critically inspected for departures from real life experience, and such departures clearly documented. It is realized that it is not human nature to document the weaknesses of ones work. However, documentation has the important benefit of pointing up those areas where knowledge is lacking and more effort should be employed.

CONCLUSIONS

Since simulations are only limited by man's ingenuity in developing modeling techniques and systems of models, it has been difficult to treat adequately such a broad subject in so short a space. Successes at treating complex problems by simulation methods has opened up the danger of viewing simulation as a panacea for all complex problems. It is not. Only common sense and the proper mixture of analytical experimental and simulation work will result in a successful attack on tomorrow's problems.

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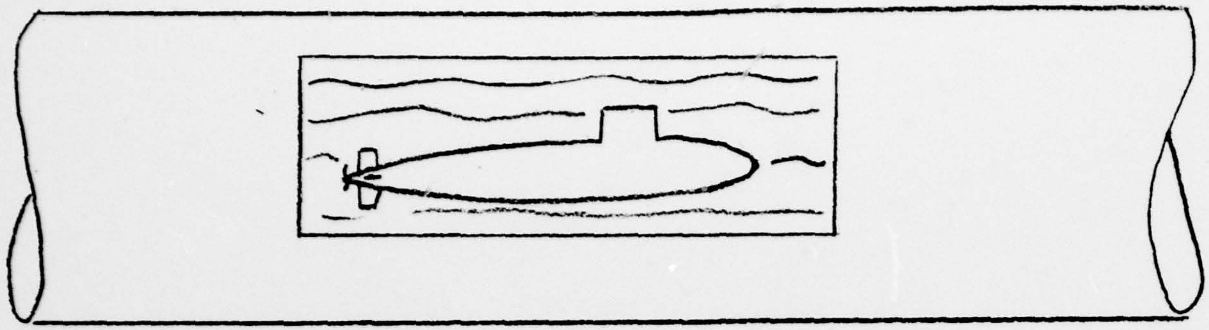
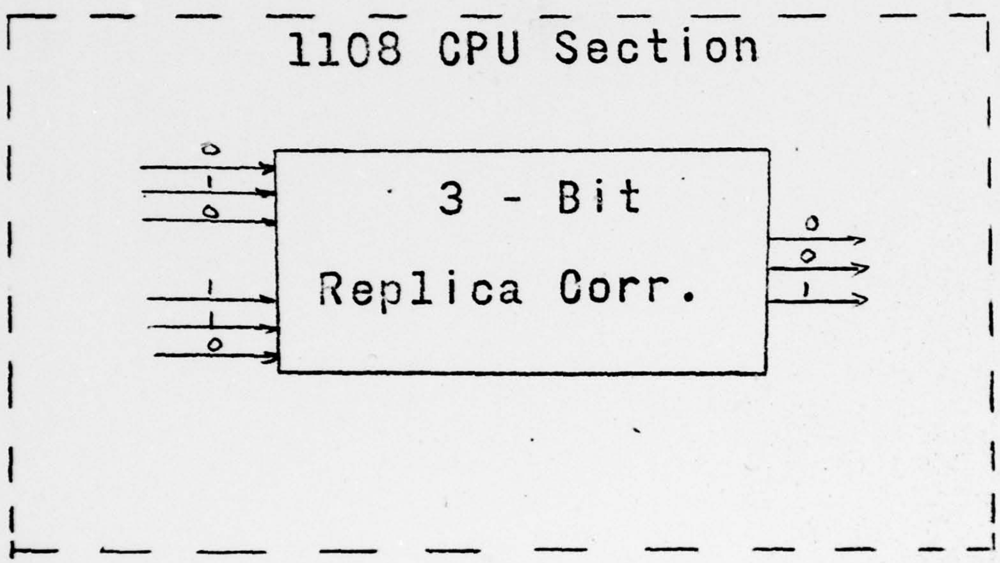
PHYSICAL MODELS



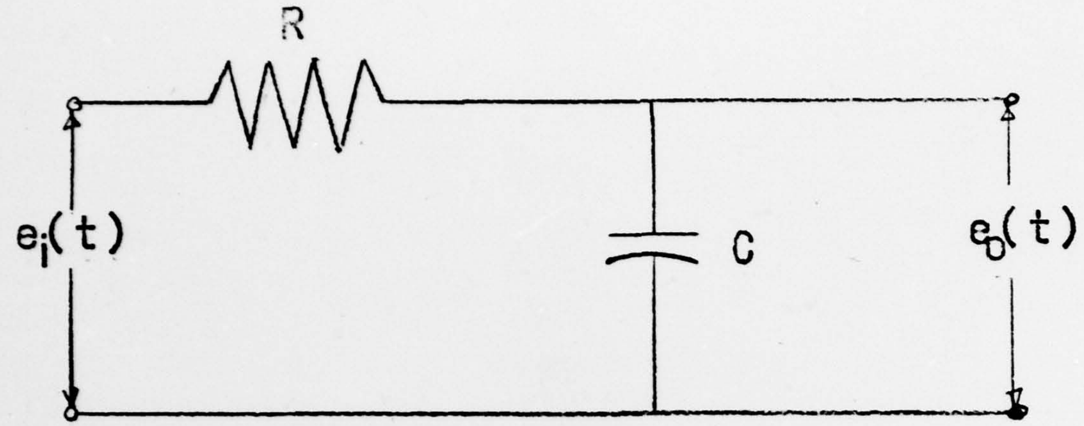
Scale Ship Studies



Scaled Digital Hardware Studies

FIGURE 1.

DETERMINISTIC MATHEMATICAL MODELS

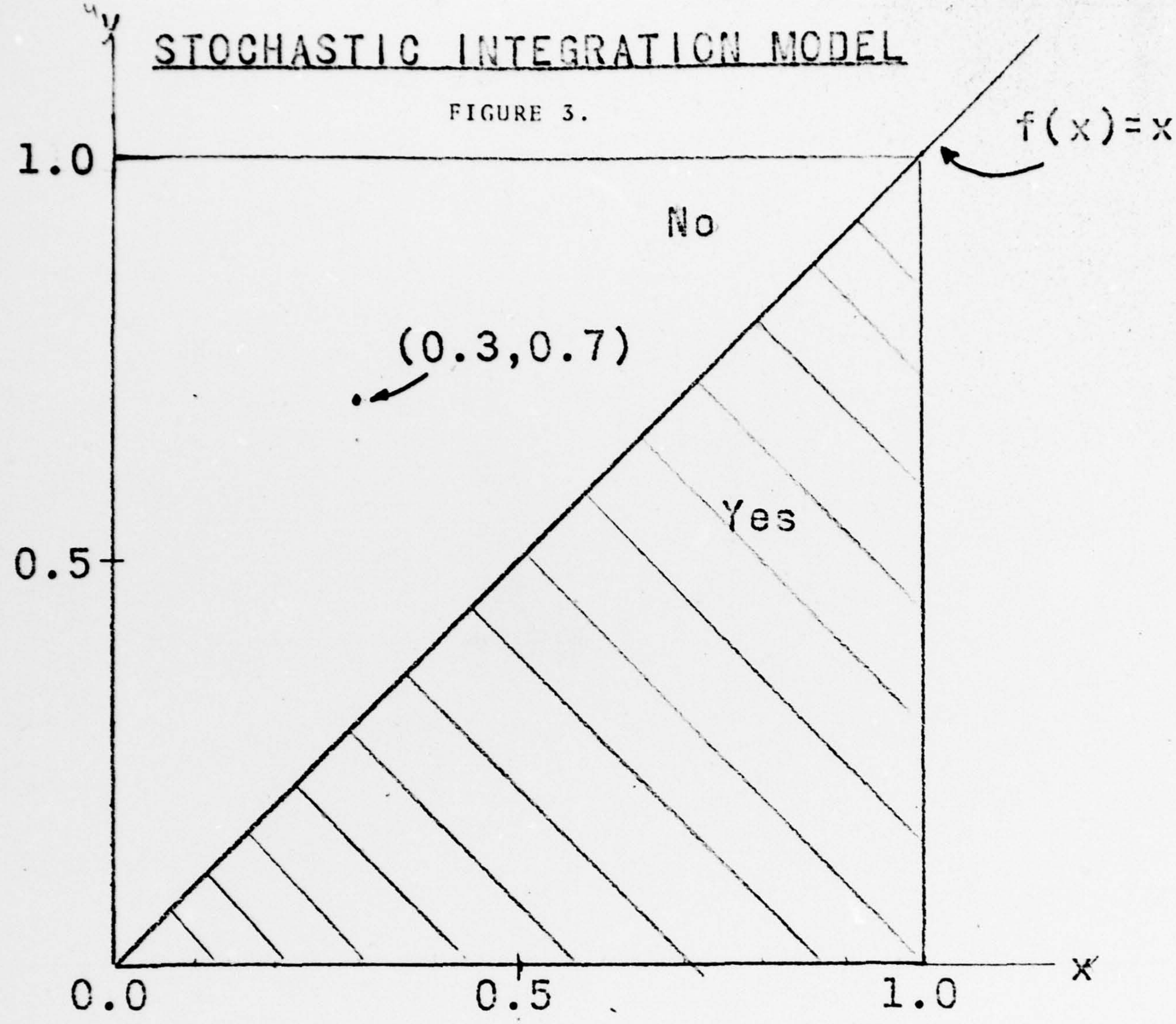


$$T \frac{de_o}{dt} + e_o = e_i \qquad T = RC$$

FIGURE 2.

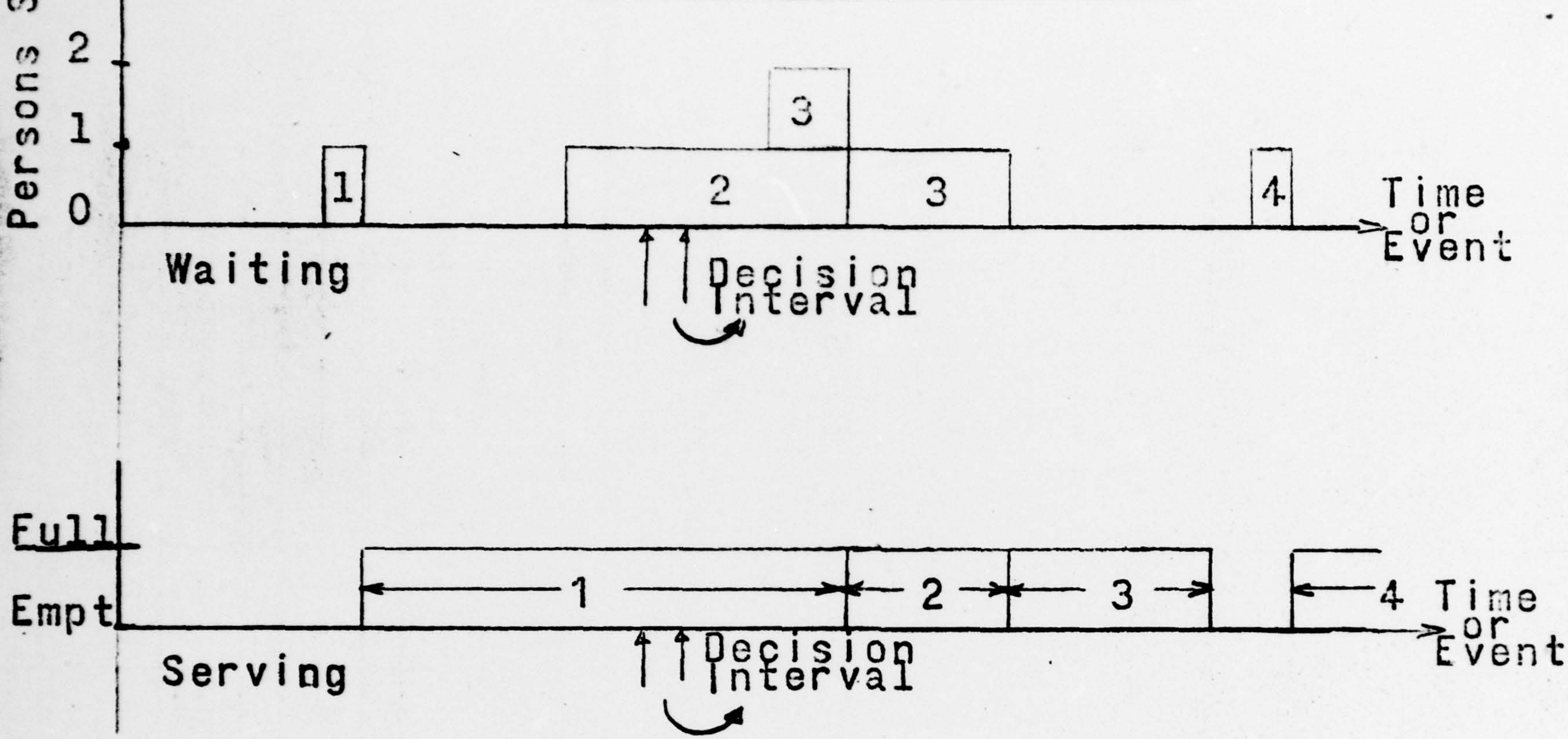
STOCHASTIC INTEGRATION MODEL

FIGURE 3.



$$\frac{\text{Yes}}{\text{Yes+No}} \approx \int_0^1 x\,dx$$

STOCHASTIC EVENT MODEL



Average Service Time?

Average Number Waiting?

FIGURE 4.