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SOME APPROACHES AND PARADIGMS FOR VERIFYING AND VALIDATING SIMULATION MODELS

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ABSTRACT

In this paper we discuss verification and validation of simulation models. The different approaches to deciding model validity are described, two different paradigms that relate verification and validation to the model development process are presented, the use of graphical data statistical references for operational validity is discussed, and a recommended procedure for model validation is given.

1 INTRODUCTION

Simulation models are increasingly being used in problem solving and in decision making. The developers and users of these models, the decision makers using information derived from the results of these models, and people affected by decisions based on such models are all rightly concerned with whether a model and its results are "correct". This concern is addressed through model verification and validation. Model verification is often defined as "ensuring that the computer program of the computerized model and its implementation are correct" and is the definition adopted here. Model validation is usually defined to mean "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesinger et al. 1979) and is the definition used here. A model sometimes becomes accredited through model accreditation. Model accreditation determines if a model satisfies specified model accreditation criteria according to a specified process. A related topic is model credibility. Model credibility is concerned with developing in (potential) users the confidence they require in order to use a model and in the information derived from that model.

A model should be developed for a specific purpose (or application) and its validity determined with respect to that purpose. If the purpose of a model is to answer a variety of questions, the validity of the model needs to be determined with respect to each question. Numerous sets of experimental conditions are usually required to define the domain of a model's intended applicability. A model may be valid for one set of experimental conditions and invalid in another. A model is considered valid for a set of experimental conditions if its accuracy is within its acceptable range, which is the amount of accuracy required for the model's intended purpose. This generally requires that the model's output variables of interest (i.e., the model variables used in answering the questions that the model is being developed to answer) be identified and that their required amount of accuracy be specified. The amount of accuracy required should be specified prior to starting the development of the model or very early in the model development process. If the variables of interest are random variables, then properties and functions of the random variables such as means and variances are usually what is of primary interest and are what is used in determining model validity. Several versions of a model are often developed prior to obtaining a satisfactory valid model. The substantiation that a model is valid, i.e., performing model verification and validation, is generally considered to be a process and is usually part of the model development process.

It is often too costly and time consuming to determine that a model is absolutely valid over the complete domain of its intended applicability. Instead, tests and evaluations are conducted until sufficient confidence is obtained that a model can be considered valid for its intended application (Sargent 1982, 1984 and Shannon 1975). If a test determines that a model does not have sufficient accuracy for a set of experimental conditions, then the model is invalid. However, determining that a model has sufficient accuracy for numerous experimental conditions does *not guarantee* that a model is valid everywhere in its applicable domain.

The primary purpose of this paper is to discuss the different basic approaches to verification and validation, to present two paradigms for relating verification and validation to the simulation model development process, and to describe the use of graphical data statistical references for comparison of model and system data in operational validation. See

Sargent (2000) for a general introduction to verification, validation, and accreditation of simulation models.

The remainder of this paper is organized as follows: Section 2 presents the basic approaches used in deciding model validity, Section 3 contains two different paradigms used in verification and validation of simulation models, Section 4 discusses operational validation, Section 5 gives a recommended validation procedure, and Section 6 has the summary.

2 BASIC APPROACHES

There are four basic approaches for deciding whether a simulation model is valid or invalid. Each of the approaches requires the model development team to conduct verification and validation as part of the model development process, which is discussed below. One approach, and a frequently used one, is for the model development team itself to make the decision as to whether a simulation model is valid. A subjective decision is made based on the results of the various tests and evaluations conducted as part of the model development process. However, it is usually better to use one of the next two approaches, depending on which situation applies.

If the size of the simulation team developing the model is not large, a better approach than the one above is to have the user(s) of the model heavily involved with the model development team in determining the validity of the simulation model. In this approach the focus of who determines the validity of the simulation model should move from the model developers to the model users. Also, this approach aids in model credibility.

Another approach, usually called "independent verification and validation" (IV&V), uses a third (independent) party to decide whether the simulation model is valid. The third party is independent of both the simulation development team(s) and the model sponsor/user(s). This approach should normally be used when developing large-scale simulation models, which usually have one large or several teams involved in developing the simulation model. Also, this approach is often used when a large cost is associated with the problem the simulation model is being developed for and/or to help in model credibility. In this approach the third party needs to have a *thorough* understanding of what the intended purpose of the simulation model is for. There are two common ways that IV&V is conducted by the third party. One way is to conduct IV&V concurrently with the development of the simulation model. The other way is to conduct IV&V after the simulation model has been developed.

In the concurrent way of conducting IV&V, the model development team(s) receives input from the IV&V team regarding verification and validation as the model is being developed. Thus, the development of a simulation model should not progress beyond each stage of development if the model is not satisfying the verification and validation requirements. It is the author's opinion that this is the better of the two ways. If the IV&V is conducted after the model has been completely developed, the evaluation performed can range from simply evaluating the verification and validation conducted by the model development team to performing a complete verification and validation effort. Wood (1986) describes experiences over this range of evaluation by a third party on energy models. One conclusion that Wood makes is that performing a complete IV&V effort is extremely costly and time consuming for what is obtained. This author's view is that if IV&V is going to be conducted on a completed simulation model then it is usually best to *only* evaluate the verification and validation that has already been performed.

The last approach for determining whether a model is valid is to use a scoring model (see, e.g., Balci (1989), Gass (1993), and Gass and Joel (1987)). Scores (or weights) are determined subjectively when conducting various aspects of the validation process and then combined to determine category scores and an overall score for the simulation model. A simulation model is considered valid if its overall and category scores are greater than some passing score(s). This approach is seldom used in practice.

This author does not believe in the use of scoring models for determining validity because (1) a model may receive a passing score and yet have a defect that needs to be corrected, (2) the subjectiveness of this approach tends to be hidden and thus this approach appears to be objective, (3) the passing scores must be decided in some (usually) subjective way, and (4) the score(s) may cause over confidence in a model or be used to argue that one model is better than another.

3 PARADIGMS

In this section we present and discuss paradigms that relate verification and validation to the model development process. There are two common ways to view this relationship. One way uses a simple view and the other uses a complex view. Banks et al. (1988) reviewed work using both of these ways and concluded that the simple way more clearly illuminates model verification and validation. We present a paradigm of each way that this author has developed. The paradigm of the simple way is presented first and this paradigm is the author's preferred one.

Consider the simplified version of the model development process shown in Figure 1. The *problem entity* is the system (real or proposed), idea, situation, policy, or phenomena to be modeled; the *conceptual model* is the mathematical/logical/verbal representation (mimic) of the problem entity developed for a particular study; and the *computerized model* is the conceptual model implemented on a computer. The conceptual model is developed through an *analysis and modeling phase*, the computerized model is developed through a *computer programming and implementation phase*, and inferences about the problem entity

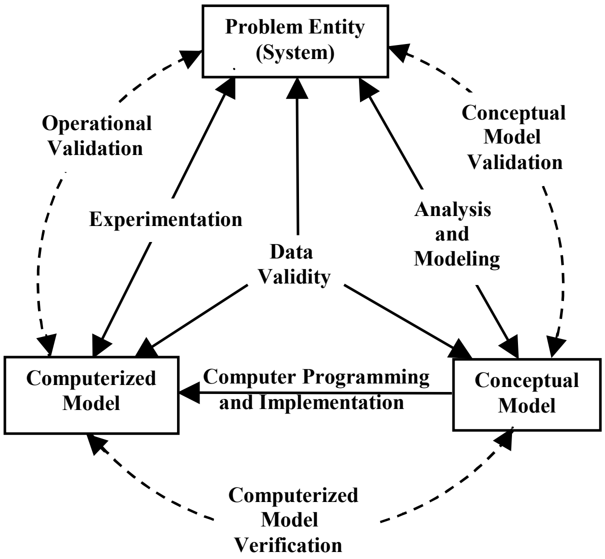

Figure 1: Simplified Version of the Modeling Process

are obtained by conducting computer experiments on the computerized model in the *experimentation phase*.

We now relate model validation and verification to this simplified version of the modeling process (see Figure 1). *Conceptual model validation* is defined as determining that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is "reasonable" for the intended purpose of the model. *Computerized model verification* is defined as assuring that the computer programming and implementation of the conceptual model is correct. *Operational validation* is defined as determining that the model's output behavior has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability. *Data validity* is defined as ensuring that the data necessary for model building, model evaluation and testing, and conducting the model experiments to solve the problem are adequate and correct.

In using this paradigm to develop a valid simulation model, several versions of a model are usually developed during the modeling process prior to obtaining a satisfactory valid model. During each model iteration, model verification and validation are performed (Sargent 1984). A variety of (validation) techniques are used. (See, e.g., Sargent (2000) for a set of validation techniques that are commonly used.) No algorithm or procedure exists to select which techniques to use. Some attributes that affect which techniques to use are discussed in Sargent (1984).

A detailed way of relating verification and validation to developing simulation models and system theories is shown in Figure 2. This paradigm was recently developed by this author at the suggestion of Dr. Dale K. Pace of The John Hopkins University Applied Physics Laboratory who believed there was a need for a such a paradigm. (Dr. Pace does considerable work in verification and validation for the U.S. Department of Defense. See Pace (2001a and 2001b) where he uses this paradigm.) This paradigm shows the processes of developing system theories and simulation models and relates verification and validation to both of these processes.

This paradigm shows a Real World and a Simulation World (See Figure 2.). We first discuss the Real World. There exist some *system or problem entity* in the real world of which an understanding of is desired. *System theories* describe the characteristics of the system (or problem entity) and possibility its behavior (including data). *System data and results* are obtained from conducting experiments (*experimenting*) on the system. System theories are developed by *abstracting* what has been observed from the system and by *hypothesizing* from the system data and results. If a simulation model exists of this system, then *hypothesizing* of system theories can also be done from simulation data and results. System theories are validated by performing *theory validation*. Theory validation involves the comparison of system theories against system data and results over the domain the theory is applicable for to determine that there is agreement. This process requires numerous experiments to be conducted on the real system.

We now discuss the Simulation World, which shows a (slightly) more complicated model development process than the other paradigm. A simulation model should only be developed for a set of well-defined objectives. The *conceptual model* is the mathematical/logical/verbal representation (mimic) of the system developed for the objectives of a particular study. The *simulation model specification* is a written detailed description of the software design and specification for programming and implementing the conceptual model on a particular computer system. The *simulation model* is the conceptual model running on a computer system such that experiments can be conducted on the model. The *simulation model data and results* are the data and results from experiments conducted (*experimenting*) on the simulation model. The conceptual model is developed by *modeling* the system, where the understanding of the system is contained in the system theories, for the objectives of the simulation study. The simulation model is obtained by *implementing* the model on the specified computer system, which includes programming the conceptual model whose specifications are contained in the simulation model specification. Inferences about the system are obtained by conducting computer experiments (*experimenting*) on the simulation model. *Conceptual model validation* is defined as determining that the theories and assumptions underlying the conceptual model are consistent with those in the system theories and that the model representation of the system is "reasonable" for the intended purpose of the simulation model. *Specification verification* is defined as assuring that the software design and the specification for programming and implementing the conceptual model on the

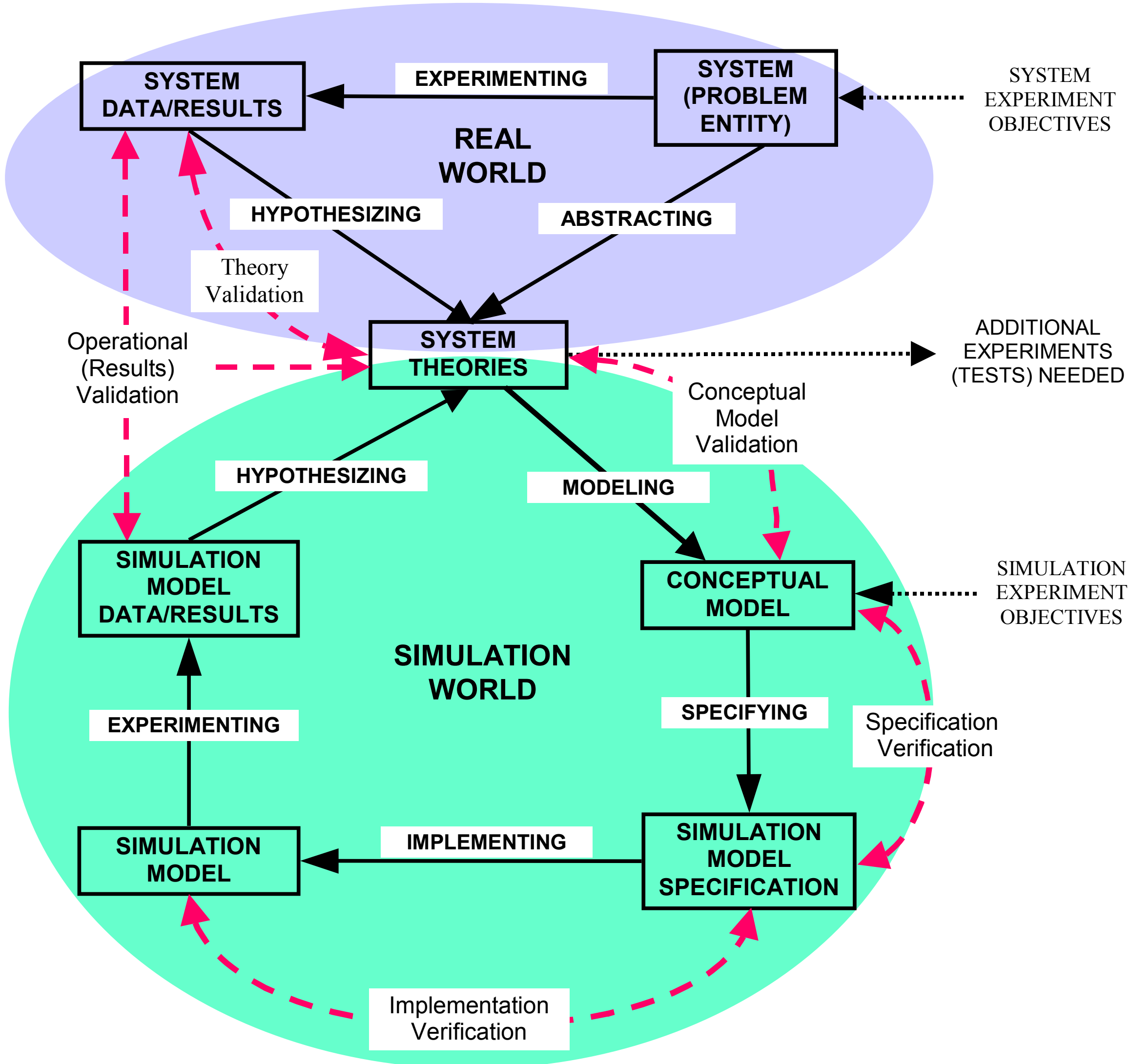

Figure 2: Real World and Simulation World Relationships with Verification and Validation

specified computer system is satisfactory. *Implementation verification* is defined as assuring that the simulation model has been implemented according to the simulation model specification. *Operational validation* is defined as determining that the model's output behavior has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability.

This paradigm shows processes for both developing valid system theories and valid simulation models. Both are accomplished through iterative processes. To develop valid system theories, which are usually for a specific purpose, the system is first observed and then abstraction is preformed from what has been observed to develop proposed system theories. These theories are tested for correctness by conducting experiments on the system to obtain data and results to compare against the proposed system theories. New proposed system theories may be hypothesized from the data and comparisons made, and also possibly from abstraction performed on additional system observation, and these new proposed theories will require new experiments to be conducted on the system to obtain data to evaluate the correctness of these proposed system theories. This process repeats itself until a satisfactory set of validated system theories has been obtained. To develop a valid simulation model, several versions of a model are usually developed prior to obtaining a satisfactory valid simulation model. During every model iteration, model verification and validation are performed. This process is similar to the one for the other paradigm except there is (slightly) more detail given in this paradigm.

4 OPERATIONAL VALIDATION

Operational validation is determining whether the simulation model's output behavior has the accuracy required for the model's intended purpose over the domain of the model's intended applicability. This is where much of the validation testing and evaluation take place. Since the simulation model is used in operational validation, any deficiencies found may be caused by what was developed in any of the steps that are involved in developing the simulation model including developing the systems theories or having invalid data. There are numerous validation techniques that are used in operational validation. See, e.g., Sargent (2000) for a discussion on these techniques.

The major attribute affecting operational validation is whether the system (or problem entity) is observable, where observable means it is possible to collect data on the operational behavior of the system. When a system is observable, it then is possible to compare the output behaviors of the system and simulation model to determine whether the simulation model has sufficient accuracy. If it is not possible to make these comparisons for several experimental conditions in the simulation model's domain of applicability, then it is not possible to obtain high confidence in the validity of a simulation model.

There are three basic approaches used in making these comparisons: (1) using graphs of the system and simulation model data to make a subjective decision, (2) using confidence intervals and (3) using formal hypothesis tests. It is preferable to use confidence intervals or hypothesis tests for the comparisons because these allow for objective decisions. However, it is frequently not possible in practice to use either of these approaches because (a) the statistical assumptions required cannot be satisfied or only with great difficulty (assumptions usually necessary are data independence and normality) and/or (b) there is insufficient quantity of system data available that causes the statistical results not to be "meaningful" (e.g., the length of a confidence interval developed in the comparison of the system and model means is to large for any practical usefulness). As a result, the use of graphs is the most commonly used approach for operational validity and a specific way of doing this is presented next. (For a general discussion and references on these three approaches, see Sargent (2000).)

We are going to discuss the use of graphical displays of simulation data as statistical references for operational validation. The idea of using graphical displays of data for operational validation was discussed in Sargent (1996). This idea of using simulation data as graphical data statistical references was further developed in Sargent (2001). We are going to discuss the use of three graphical displays of data as data statistical references: histograms, box (and whisker) plots, and scatter plots (scattergram or scatter diagram). (See, e.g., Johnson (1994) or Walpole and Myers (1993) for a discussion of histograms, box plots, and scatter plots.) The data for these graphical statistical references come from simulation models. We then compare the system data against these graphical data statistical references in performing operational validation.

4.1 Histograms and Box Plots

The data used in histograms and box plots need only to be identically distributed. The data does not need to be independent or have a specific statistical distribution. The data used may be the observations themselves or some function of subsets of the collected observations (e.g., the sample means from subsets of the collected observations). Usually a large number of data points are needed in histograms used as graphical data statistical references. The more variable the data and the higher the correlation among the data, the more data needed for the histogram. If the reference is a distribution of a variable, then the number of data points should usually be in the thousands, especially if the data have high correlation and extremely variability. If the reference is of sample means, then the number of data points should usually be in the hundreds. Box plots used as graphical data statistical references generally require less data points than histograms.

We present two histograms and two box plots developed from observations collected from a simulation model of a single server queueing model having an infinite allowable queue and a queue discipline of first-come first-served. The distribution of interarrival times is exponential with mean five and the service time is exponentially distribution with mean four. Figure 3 is a histogram of the times it took two thousand consecutive customers to go through the queueing model in steady state. These observations are highly correlated and quite variable. We know from queueing theory that the steady state distribution of these times is an exponential distribution with a mean of twenty. One can readily see that the histogram does not give a nice smooth curve. This indicates that more data points should probably be used depending on the accuracy needed for the graphical data statistical reference.

In Figure 4 we present a histogram containing one hundred steady state sample means. Each of these data points (sample means) are independent and identically distributed. They were obtained from one hundred separate independent simulation runs (or replications). The observations used for each sample mean were the times it took twenty consecutive customers to go through the queueing model in steady state. Recall that these times are exponentially distributed and highly correlated and thus each sample mean contains twenty correlated exponentially distributed observations. One can readily see from this histogram that the resulting sampling distribution is not a t (or normal) distribution. If a more accurate statistical reference is desired, then additional data points (sample means) should be added to the histogram.

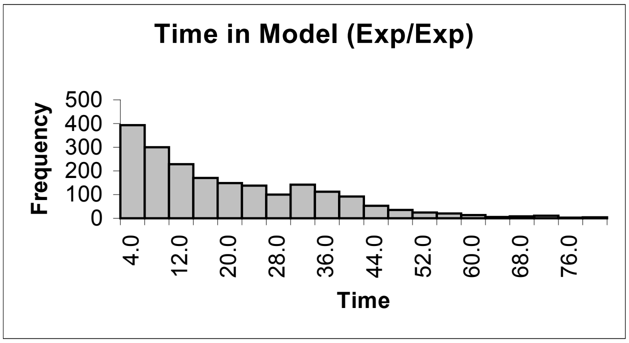

Figure 3: Histogram of Time in Model

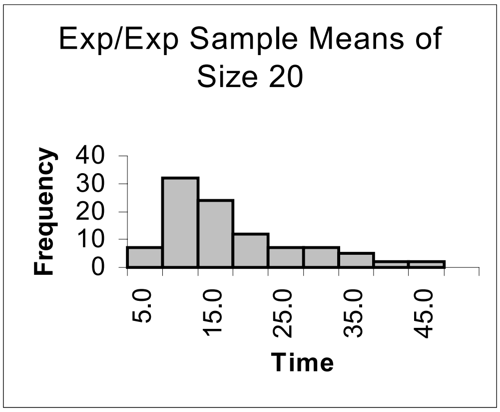

Figure 4: Histogram of Sample Means

Figure 5 contains box plots of the data contained in the histograms contained in Figures 3 and 4. Some software packages that create box plots show outliers as small circles and the software used here does that. One can readily see the skewness of each set of data by looking at the box, whiskers, and outliers in each box plot.

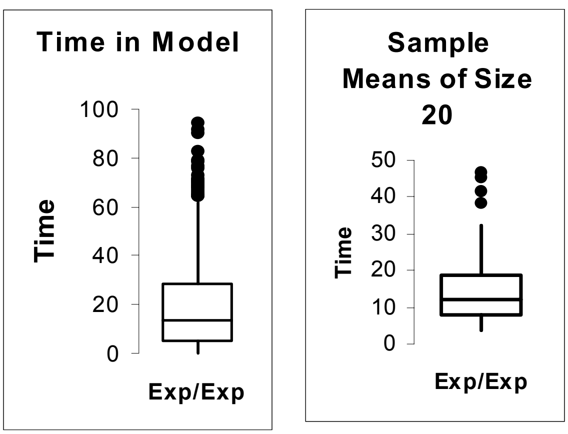

Figure 5: Box Plots of Queueing Model Data

As an example of the use of histograms and box plots in operational validation, we consider a simulation project by Lowery (1996). A simulation model was developed to predict the mean (average) number of beds used daily (census) in specific hospital units. Operational validation was performed to determine whether the simulation model's mean census (usage) of beds was within the required accuracy of four beds for large hospital units (i.e., units having a large number of beds). The data entries to be compared were determined. There was a day of week effect. Various histograms and box plots were used to validate this model. We will discuss one of the histograms and one of the box plots that were used. Figure 6 contains a histogram of sample means for census on Mondays of one of the hospital units. There were 24 system observations (weeks) available on this unit for Monday census and these observations are correlated. Thus, we use a 24-week average Monday census for our sample means. Observations were generated from the simulation model to obtain fifty independent 24-week average Monday census to be used as the data for a graphical data statistical reference, which is given in Figure 6. (This histogram is a sampling distribution of the 24-week average Monday census. Note that it is not shaped like a t distribution.) One can readily see that the system data point lies within the reference distribution.

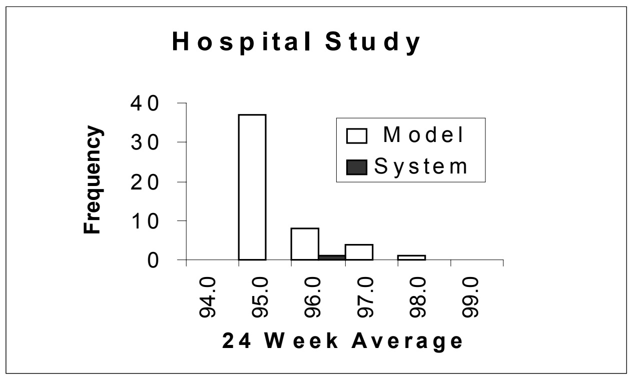

Figure 6: Histogram of Hospital Data

Figure 7 contains box plots of Sunday census observations for the same hospital unit discussed above. The model box plot, which is the graphical data statistical

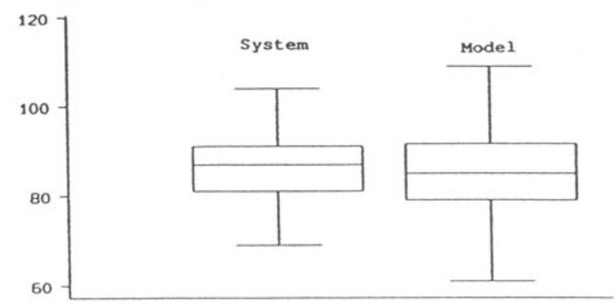

Figure 7: Box Plots of Sunday Census Data

reference, is developed from 100 observations (Sunday census) generated by the simulation model. The system box plot is developed from 24 observations (Sunday census) collected on the hospital unit. In comparing the two box plots, it appears that the model has more variability in its Sunday census than the hospital unit. It is this author's opinion that this pair of box plots has insufficient evidence to determine whether the model's mean census on Sunday is or is not within the four beds of the hospital's mean census desired. (Only two of the graphical comparisons used in performing operational validation on this model were presented here. It was concluded that this simulation model was valid based on the numerous comparisons made.)

4.2 Behavior Graphs

In operational validation, comparisons should be made between different behavior relationships occurring in the simulation model and those occurring in the system. These comparisons can be made by using behavior graphs (see Sargent (2000)). Behavior graphs use scatter plots to show the relationships between two entities such as parameters, variables, and functions of random variables by plotting paired data on the two entities. The data points plotted can be the observations themselves, which may be relatively few in number, or may be functions of subsets of the observations, which may be based on a large number of observations. There are no specific statistical assumptions required of the data used in behavior graphs. The data can be correlated, have any statistical distribution, and be nonstationary. Behavior graphs used as graphical data statistical references should have a sufficient number of data points in them to enable them to be well defined.

We suggest that behavior graphs be developed from simulation model observations to be used as graphical data statistical references. Then behavior graphs be developed from system observations for the same relationships and be compared against the graphical data statistical references to aid in making a subjective decision whether the simulation model has the accuracy needed for validity. It is important that appropriate measures and relationships be selected for the behavior graphs to ensure the simulation model isfor its intended purpose. Some different measures that can be used are means, variances, maximums, and time series of random variables. Relationships that can used are different measures on the same variable, the same measure on two different variables, or different measures on two different variables.

To illustrate the use of behavior graphs in model validation, we consider a simulation model of an interactive computer system in Anderson and Sargent (1974) where behavior graphs were used to validate the simulation model. Three of the behavior graphs that were used are presented in

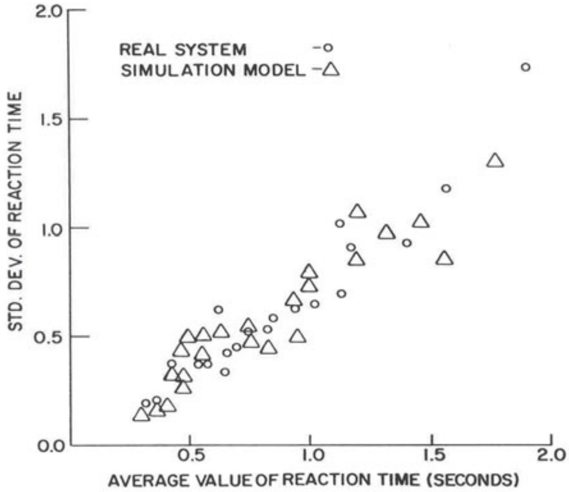

Figure 8: Reaction Time

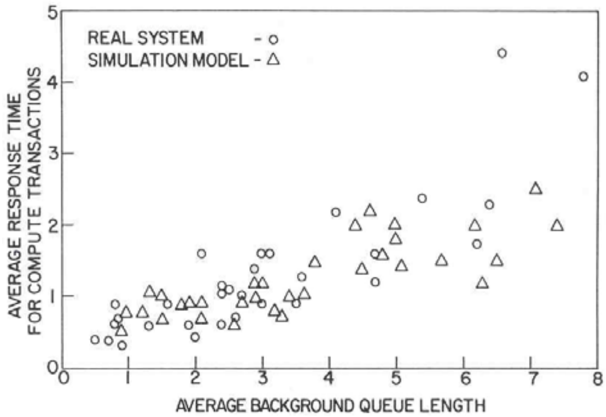

Figure 9: Response Time versus Queue Length

Figures 8, 9, and 10. The relationship between the mean and standard deviation of reaction time is shown in Figure 8. On can readily observe that the same linear relationship occurs in both the simulation model and the computer system. Figure 9 contains the relationship of average response time versus average background queue length. On can readily observe that these model and system relationships are similar except for two system points, which is important to determine why. Figure 10 contains relationships for both the average and maximum observed values of reaction time versus the total number of disk accesses. Each data point is from or represents five minutes of computer system time. We observe that these model and system relationships are similar with the exception that the system has more variability than the model. (For additional behavior graphs and details of the validation of this simulation model, see Anderson (1974) and Anderson and Sargent (1974).)

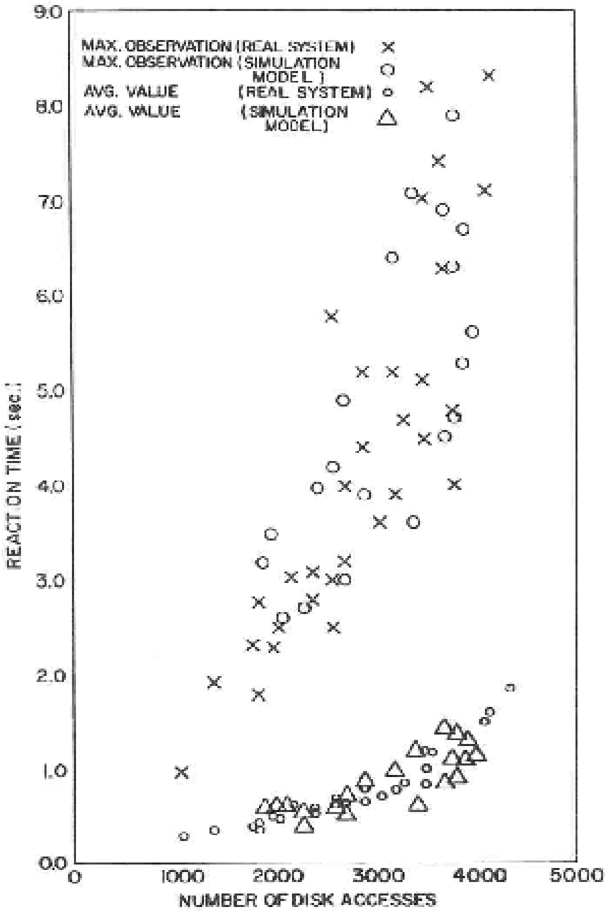

Figure 10: Reaction Time versus Disk Accesses

5 RECOMMENDED PROCEDURE

This author recommends that, as a minimum, the following steps be performed in model validation:

1. Have an agreement made prior to developing the model between (a) the model development team and (b) the model sponsors and (if possible) the users that specifies the basic validation approach and a minimum set of specific validation techniques to be used in the validation process.
2. Specify the amount of accuracy required of the model's output variables of interest for the model's intended application prior to starting the development of the model or very early in the model development process.
3. Test, wherever possible, the assumptions and theories underlying the model.
4. In each model iteration, perform at least face validity on the conceptual model.
5. In each model iteration, at least explore the model's behavior using the computerized model.
6. In at least the last model iteration, make comparisons, if possible, between the model and system behavior (output) data for at least two sets of experimental conditions.
7. Develop validation documentation for inclusion in the model documentation.
8. If the model is to be used over a period of time, develop a schedule for periodic review of the model's validity.

Some models are developed for repeated use. A procedure for reviewing the validity of these models over their life cycles needs to be developed, as specified in Step 8. No general procedure can be given, as each situation is different. For example, if no data were available on the system when a model was initially developed and validated, then revalidation of the model should take place prior to each usage of the model if new data or system understanding has occurred since the last validation.

6 SUMMARY

After giving an introduction to verification and validation of simulation models, we presented and discussed the four basic approaches used in deciding whether a simulation model is valid. Next we presented two paradigms, one simple and one detailed, that relate verification and validation to the model development process. Then we described in fair detail three types of graphical data statistical references and how to use them in operational validation. Lastly, we presented a recommend procedure to follow when conducting verification and validation of simulation models.

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