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PRINCIPLES AND TECHNIQUES OF SIMULATION VALIDATION, VERIFICATION, AND TESTING

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ABSTRACT

Sufficient experience has been gained over the last decade in simulation validation, verification, and testing (VV&T) to establish basic principles about its characteristics. This paper presents 15 principles of simulation VV&T. These principles help the researchers, practitioners and managers better understand what model VV&T is all about. They serve to provide the underpinnings for the VV&T techniques that can be used throughout the life cycle of a simulation study. This paper also surveys current software VV&T techniques and current simulation VV&T techniques. Understanding and applying these principles and employing proper testing techniques throughout the life cycle of a simulation study are key factors in increasing the probability of success in a simulation study.

1 INTRODUCTION

The U.S. General Accounting Office (GAO) prepared three reports due to concerns about the credibility of federally funded computerized models. The first report, presented to the U.S. congress in 1976, identified the need for improved management and model development activities (U.S. GAO 1976). The second one described the modeling process and presented a very high-level approach to model evaluation (U.S. GAO 1979). The third one, presented to the National Security Subcommittee of the House of Representatives, described improved assessment procedures for the credibility of Department of Defense simulation studies (U.S. GAO 1987). All three reports described simulation modeling problems that have emerged due to the lack of understanding the principles of simulation model validation, verification, and testing (VV&T).

Principles are important to understand the foundations of simulation model VV&T (Balci 1996). The principles help the researchers, practitioners and managers better comprehend what model VV&T is all about. They serve to provide the underpinnings for the 45 VV&T techniques, described by Balci (1994), that can be used throughout the life cycle of a simulation study. Understanding and applying these principles is crucially important for the success of a simulation study.

Simulation is the process of constructing a model of a system which contains a problem and conducting experiments with the model on a computer for a specific purpose of experimentation to solve the problem. Credibility of simulation results not only depends on model correctness, but also is significantly influenced by accurate formulation of the problem. Therefore, VV&T techniques must be employed throughout the life cycle of a simulation study.

Model Validation is substantiating that the model, within its domain of applicability, behaves with satisfactory accuracy consistent with the study objectives. In other words, in model validation, we substantiate that the input-output transformation of the model has sufficient accuracy in representing the input-output transformation of the system. Model validation deals with building the *right* model. It is conducted by running the model under the same input conditions that drive the system and by comparing model behavior with the corresponding system behavior.

Model Verification is substantiating that the model is transformed from one form into another, as intended, with sufficient accuracy. Model verification deals with building the model *right*. The accuracy of transforming a problem formulation into a model specification or the accuracy of converting a model representation in micro flowchart into an executable computer program is evaluated in model verification.

Model Testing is demonstrating that inaccuracies exist or revealing the existence of errors in the model. In model testing, we subject the model to test data or test cases to see if it functions properly. "Test failed" implies the failure of the model, not the test. Testing is conducted to perform validation and verification. Some tests are devised to evaluate the behavioral accuracy (i.e., validity) of the model, and some tests are intended to judge the accuracy of model transformation from one form into another (verification). We commonly refer to the whole process as *model VV&T* or *model testing.*

The purpose of this paper is to present discrete-event simulation model VV&T principles and to survey current software VV&T techniques and current model VV&T techniques. Although the principles are presented for discrete-event simulation studies, many of them are also applicable for continuous and combined simulation studies and for other types of modeling studies. Section 2 describes the principles. The VV&T techniques are surveyed in Section 3. Section 4 presents concluding remarks and research directions.

2 PRINCIPLES OF SIMULATION VV&T

The fifteen principles presented herein are established based on the experience described in the published literature and the author's experience during his research in simulation model VV&T since 1978. The principles are listed below in no particular order. For a more detailed description of the principles, see (Balci 1996).

2.1 Principle 1: The VV&T must be conducted throughout the entire life cycle of a simulation study

The VV&T is not a phase or step in the life cycle of a simulation study, but a continuous activity throughout the entire life cycle (Balci 1994, Nance 1994). The life cycle is composed of ten phases, ten processes, and 13 VV&T stages. Balci (1994) presents 45 VV&T techniques and describes how they can all be applied throughout the life cycle of a simulation study.

Conducting the VV&T for the first time in the life cycle when the experimental model is complete is analogous to the teacher who gives only a final examination (Hetzel 1984). No opportunity is provided throughout the semester to notify the student that he or she has serious deficiencies. Severe problems may go undetected until it is too late to do anything but fail the student. Frequent tests and homeworks throughout the semester are intended to inform the students about their deficiencies so that they can study more to improve their knowledge as the course progresses.

The situation in the VV&T is exactly analogous. The 13 VV&T activities throughout the entire life cycle are intended to reveal any quality deficiencies that might be present as the simulation study progresses from the communication of the problem until the implementation of the simulation results. This allows us to identify and rectify quality deficiencies during the life cycle phase in which they occur.

Every organization conducting a substantial simulation study should have a department or group called Simulation Quality Assurance (SQA). The SQA group is responsible for total quality management and closely works with the simulation project managers in planning, preparing test cases, and administering some of the VV&T activities throughout the simulation study. The SQA is a managerial approach which is critically essential for the success of a simulation study. Ören (1981, 1986, 1987) presents concepts, criteria, and paradigms which can be used in establishing an SQA program within an organization.

2.2 Principle 2: The outcome of simulation model VV&T should not be considered as a binary variable where the model is absolutely correct or absolutely incorrect

Since a model is an abstraction of a system, perfect representation is never expected. Shannon (1975) indicates that "it is not at all certain that it is ever theoretically possible to establish if we have an absolutely valid model; even if we could, few managers would be willing to pay the price."

The outcome of model VV&T should be considered as a degree of credibility on a scale from 0 to 100, where 0 represents absolutely incorrect and 100 represents absolutely correct. As the degree of model credibility increases, so will the model development cost. At the same time, the model utility will also increase, but most likely at a decreasing rate.

2.3 Principle 3: A simulation model is built with respect to the study objectives and its credibility is judged with respect to those objectives

The objectives of a simulation study are identified in the Formulated Problem phase, and explicitly and clearly specified in the System and Objectives Definition phase of the life cycle. Accurate specification of the study objectives is crucial for the success of a simulation study.

The study objectives dictate how representative the model should be. Sometimes, 60% representation accuracy may be sufficient; sometimes, 95% accuracy may be required depending on the importance of the decisions that will be made based on the simulation results. Therefore, model credibility must be judged with respect to the study objectives. The adjective "sufficient" must be used in front of the terms such as model credibility, model validity, and model accuracy to indicate that the judgment is made with respect to the study objectives. It is more appropriate to say "the model is sufficiently valid" than saying "the model is valid." Here "sufficiently valid" implies that the validity is judged with respect to the study objectives and found to be sufficient.

2.4 Principle 4: Simulation model VV&T requires independence to prevent developer's bias

The model testing is meaningful when conducted in an independent manner by an unbiased person. The model developer with the most knowledge of the model may be the least independent when it comes to testing. The developers are often biased because they fear that negative testing results may be used for their performance appraisal. Similarly, the organization which is contracted to conduct the simulation study is also often biased because negative testing results can damage the credibility of the organization and may lead to the loss of future contracts.

2.5 Principle 5: Simulation model VV&T is difficult and requires creativity and insight

One must thoroughly understand the whole simulation model so as to design and implement effective tests and identify adequate test cases. Knowledge of the problem domain, expertise in the modeling methodology, and prior modeling and VV&T experience are required for successful testing.

However, it is not possible for one person to fully understand all aspects of a large and complex model especially if the model is a stochastic one containing hundreds of concurrent activities.

The model developers are usually the most qualified to show the creativity and insight required for successful testing since they are intimately knowledgeable about the internals of a model. However, they are usually biased when it comes to model testing and they cannot be fully utilized. Therefore, the inability to use model developers effectively for testing increases the difficulty of testing.

2.6 Principle 6: Simulation model credibility can be claimed only for the prescribed conditions for which the model is tested

The accuracy of the input-output transformation of a simulation model is affected by the characteristics of the input conditions. The transformation that works for one set of input conditions may produce absurd output when conducted under another set of input conditions.

In the simulation of a traffic intersection, for example, a stationary simulation model can be built assuming constant arrival rate of vehicles during the evening rush hour and its credibility may be judged sufficient with respect to the evening rush hour input conditions. However, the simulation model will show invalid behavior when run under the input conditions of the same traffic intersection between 7:00 a.m. and 6:00 p.m. During this time period, the arrival rate of vehicles is not constant and a non-stationary simulation model is required. Hence, establishing sufficient model credibility for the evening rush hour conditions does not imply sufficient model credibility for input conditions during other times.

The prescribed conditions for which the model credibility has been established is called the *domain of applicability* of the experimental simulation model (Schlesinger *et al.* 1979). Model credibility can be claimed only for the domain of applicability of the model.

2.7 Principle 7: Complete simulation model testing is not possible

Exhaustive (complete) testing requires testing the model under *all* possible inputs. Combinations of feasible values of model input variables can generate millions of logical paths in the model execution. Due to time and budgetary constraints, it is impossible to test the accuracy of millions of logical paths. Therefore, in model testing, the purpose is to increase our confidence in model credibility as much as dictated by the study objectives rather than trying to test the model completely.

How much to test or when to stop testing is dependent on the desired domain of applicability of the experimental model. The larger the domain the more the testing is required. The domain of applicability is determined with respect to the study objectives.

In model testing using test data, it must be noted that the law of large numbers does simply not apply. The question is not how much test data is used, but what percentage of the valid input domain is covered by the test data. The higher the percentage of coverage the higher the confidence we can have in model credibility.

2.8 Principle 8: Simulation model VV&T must be planned and documented

Testing is not a phase or step in model development life cycle; it is a continuous activity *throughout* the entire life cycle. The tests should be identified, test data or cases should be prepared, tests should be scheduled, and the whole testing process should be documented.

Ad hoc or haphazard testing does not provide reasonable measurement of model accuracy. Hetzel (1984) points out that "such testing may even be harmful in leading us to a false sense of security." Careful planning is required for successful testing.

2.9 Principle 9: Type I, II, and III errors must be prevented

Three types of errors may be committed in conducting a simulation study (Balci and Nance 1985). *Type I Error* is committed when the simulation results are rejected when in fact they are sufficiently credible. *Type II Error* occurs when invalid simulation results are accepted as if they are sufficiently valid. *Type III Error* is the error of solving the wrong problem and committed when the formulated problem does not completely contain the actual problem.

Committing Type I Error unnecessarily increases the cost of model development. The consequences of Type II and Type III Errors can be catastrophic especially when critical decisions are made on the basis of simulation results. Type III Error implies the solution of the wrong problem and the simulation study results become irrelevant when it is committed.

The probability of committing Type I Error is called *Model Builder's Risk* and the probability of committing Type II Error is called *Model User's Risk* (Balci and Sargent 1981). The VV&T activities must focus on minimizing these risks as much as possible. Balci and Sargent (1981) show how to quantify these risks when using hypothesis testing for the validation of a simulation model with two or more output variables.

2.10 Principle 10: Errors should be detected as early as possible in the life cycle of a simulation study

A rush to model implementation is a common problem in simulation studies. Sometimes simulation models are built by direct implementation in a (simulation) programming language with no or very little formal model specification. As a result of this harmful build-and-fix approach, experimental model VV&T becomes the only main credibility assessment stage. On the other hand, detecting and correcting major modeling errors at this stage is very time consuming and expensive.

Detection and correction of errors as early as possible in the life cycle of a simulation study must be the primary objective. Sufficient time and energy must be expended for each of the 13 credibility assessment stages (Balci 1994). Correcting errors detected in later phases of the life cycle is much more time consuming and expensive. Some vital errors may not be detectable in later phases resulting in the occurrence of Type II or III error.

Nance and Overstreet (1987) advocate this principle and provide diagnostic testing techniques for models represented in the form of condition specification. A model analyzer software tool is included in the definition of a simulation model development environment so as to provide effective early detection of model specification errors (Balci and Nance 1992).

2.11 Principle 11: Multiple response problem must be recognized and resolved properly

Due to the multiple response problem described by Shannon (1975), the validity of a simulation model with two or more output variables cannot be tested by comparing the corresponding model and system output variables one at a time using a univariate statistical procedure. A multivariate statistical procedure must be used to incorporate the correlations among the output variables in the comparison.

2.12 Principle 12: Successfully testing each submodel does not imply overall model credibility

The credibility of each submodel is judged to be sufficient with some error that is acceptable with respect to the study objectives. We may find each submodel to be sufficiently credible, but this does not imply that the whole model is sufficiently credible. The allowable errors for the submodels may accumulate to be unacceptable for the whole model. Therefore, the whole model must be tested even if each submodel is found to be sufficiently credible.

2.13 Principle 13: Double validation problem must be recognized and resolved properly

If data can be collected on both system input and output, model validation can be conducted by comparing model and system outputs obtained by running the model with the "same" input data that drives the system. Determination of the "same" is yet another validation problem within model validation. Therefore, this is called the double validation problem.

This is an important problem often overlooked. It greatly affects the accuracy of model validation. If invalid input data models are used, we may still find the model and system outputs sufficiently matching each other and conclude incorrectly on the sufficient validity of the model.

The "same" is determined by validating the input data models. We must substantiate that the input data models have sufficient accuracy in representing the system input process. Input data modeling deals with characterization of the system input data (Johnson and Mollaghasemi 1994). Simulation models are categorized into two with respect to the way they are driven: trace-driven and self-driven. In trace-driven simulation, the system input is characterized by the trace data collected from the instrumented system. The trace data becomes the input data model which should be validated against the actual system input process.

In self-driven simulations, simulation model is driven by randomly sampling from the probabilistic models developed to represent the data collected on the system input process. Usually, input data modeling is achieved by fitting standard probability distributions to observed data. The input data models should be constructed using a multivariate statistical approach if the input variables are correlated. Individually building a probabilistic model for each input variable does not incorporate the correlations among the input variables; therefore, a multivariate probabilistic approach should be used.

2.14 Principle 14: Simulation model validity does not guarantee the credibility and acceptability of simulation results

Model validity is a necessary but not a sufficient condition for the credibility and acceptability of simulation results. We assess model validity with respect to the study objectives by comparing the model with the system as it is defined. If the study objectives are incorrectly identified and/or the system is improperly defined, the simulation results will be invalid; however, we may still find the model to be sufficiently valid by comparing it with the improperly defined system and with respect to the incorrectly identified objectives.

A distinct difference exists between the model credibility and the credibility of simulation results. Model credibility is judged with respect to the system definition and the study objectives, whereas the credibility of simulation results is judged with respect to the actual problem definition and involves the assessment of system definition and identification of study objectives. Therefore, model credibility assessment is a subset of credibility assessment of simulation results.

2.15 Principle 15: Formulated problem accuracy greatly affects the acceptability and credibility of simulation results

It has been said that a problem correctly formulated is half solved (Watson 1976). Albert Einstein once indicated that the correct formulation of a problem was even more crucial than its solution. The ultimate goal of a simulation study should not be just to produce a solution to a problem but to provide one that is sufficiently credible and accepted and implemented by the decision makers. We cannot claim that we conducted an excellent simulation study but the decision makers did not accept our results and we cannot do anything about it. Ultimately we are responsible for the acceptability and usability of our simulation solutions although in some cases we cannot affect or control the acceptability.

The accuracy of the formulated problem assessed by the Formulated Problem VV&T (Balci 1994) greatly affects the credibility and acceptability of simulation results. Insufficient problem definition and inadequate user participation in defining the problem are identified as two important problems in the management of computer-based models. The importance of the Formulated Problem VV&T has not been recognized sufficiently. The problem is mostly educational. In higher education, students are not trained on how to formulate a problem and how to assess its accuracy. Generally, the interest lies in solving problems; therefore, typically an instructor starts a lecture by saying "here is the problem, let's see how we can solve it." As a result, the students do not gain the much needed knowledge in problem formulation and its VV&T. Consequently, when a real-life problem is encountered, people usually jump into a solution based on the communicated problem without spending sufficient time and energy in properly formulating the problem.

It must be recognized that if the Formulated Problem VV&T is poorly conducted resulting in Type III error, no matter how fantastically we conduct the simulation study, the results will be irrelevant.

3 VALIDATION, VERIFICATION, AND TESTING TECHNIQUES

Figure 1 shows a taxonomy which categorizes the VV&T techniques into six distinct credibility assessment perspectives: informal, static, dynamic, symbolic, constraint, and formal. The level of mathematical formality of each category increases from very informal on the far left to very formal on the far right. Likewise, the complexity also increases as the category becomes more formal (Whitner and Balci 1989).

It should be noted that some of the categories presented in Figure 1 possess similar characteristics and in fact have techniques which overlap from one category to another. However, a distinct difference between each classification exists.

The techniques are described in (Balci 1994).

Informal VV&T techniques are among the most commonly used ones. They are called informal because the tools and approaches used rely heavily on human reasoning and subjectivity without stringent mathematical formalism. The "informal" label does not imply any lack of structure or formal guidelines for the use of the techniques.

Static VV&T techniques are concerned with accuracy assessment on the basis of characteristics of the static model source code. Static techniques do not require machine execution of the model, but mental execution may be used. The techniques are very popular and widely used, with many automated tools available to assist the VV&T. The simulation language compiler is itself a static VV&T tool.

Static VV&T techniques can obtain a variety of information about the structure of the model, coding techniques and practices employed, data and control flow within the model, syntactical accuracy, and internal as well as global consistency and completeness of implementation (Whitner and Balci 1989).

Dynamic VV&T techniques require model execution and are intended for evaluating the model based on its execution behavior. Most dynamic VV&T techniques require model instrumentation.

The insertion of additional code (probes) into the executable model for the purpose of collecting information about model behavior during execution is called *model instrumentation*. Probe locations are determined manually or automatically based on static analysis of model structure. Automated instrumentation is accomplished by a preprocessor which analyzes the model static structure (usually via graph-based analysis) and inserts probes at appropriate places.

Dynamic VV&T techniques are usually applied using the following three steps. In Step 1, the programmed or experimental model is instrumented. In Step 2, the instrumented model is executed, and in Step 3, the model output is analyzed and dynamic model behavior is evaluated.

Much research has been conducted in applying statistical techniques for dynamic VV&T. Balci (1994) presents the statistical techniques proposed for model validation and lists related references.

The statistical techniques generally require that the system being modeled is completely observable, i.e., all data required for model validation can be collected from the system. Model validation is conducted by using the statistical techniques to compare the model output data with the corresponding system output data when the model is run with the "same" input data that derive the real system. Due to the multiple response problem (Shannon 1975), the comparison of model and system outputs must be carried out by using a multivariate statistical technique to incorporate the correlations among the output variables.

A validation procedure based on the use of simultaneous confidence intervals is presented in (Balci 1994). Whenever possible, a multivariate statistical technique should be used to conduct model validation.

Symbolic VV&T techniques, like dynamic VV&T

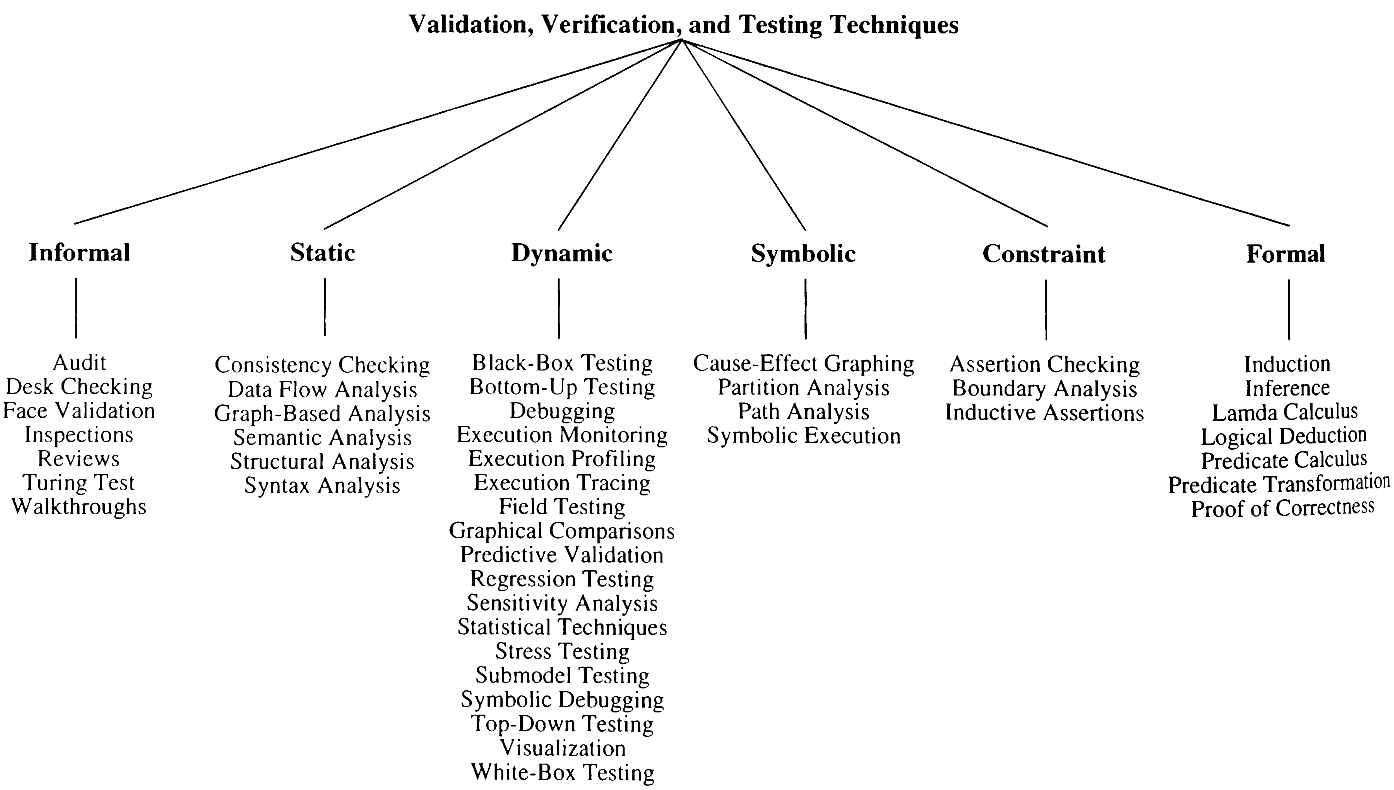

Figure 1: A Taxonomy of Validation, Verification, and Testing Techniques

techniques, are used to evaluate the dynamic behavior of the model during execution. In symbolic analysis, symbolic inputs are provided to a simulation model as input and expressions are produced as output which are drived from the transformation of the symbolic data along model execution paths.

Constraint VV&T techniques are employed to assess model correctness using assertion checking, boundary analysis, and inductive assertions.

Formal VV&T techniques are based on formal mathematical proof of correctness. If attainable, formal proof of correctness is the most effective means of model VV&T. Unfortunately, "if attainable" is the overriding point with regard to formal VV&T techniques. Current state-of-the-art formal proof of correctness techniques are simply not capable of being applied to even a reasonably complex simulation model. However, formal techniques serve as the foundation for other VV&T techniques.

4 CONCLUDING REMARKS AND RESEARCH DIRECTIONS

Assessing the acceptability and credibility of complex simulation study results poses significant technical challenges to researchers, practitioners, and managers. Nevertheless, we are confident that the challenge can be met by understanding and properly applying the principles of simulation model VV&T presented in this paper. Computer-aided assistance, visualization, knowledge-based approach, and an effective management style can contribute to meeting the challenge.

Automated support is essential to reduce the time and cost of testing since tests are repeatedly used during development and maintenance. Visualization or animation greatly facilitates model VV&T; however, seeing is *not* believing in visual simulation (Paul 1989). The use of a knowledge base may help improve the quality of testing and provides a means for automation. Management aspects of model VV&T are as important as its technical aspects. An effective SQA program within an organization can make a big difference for the success of simulation VV&T.

The life cycle application of VV&T is extremely important for successful completion of complex and large-scale simulation studies. This point must be clearly understood by the sponsor of the simulation study and the organization conducting the simulation study. The sponsor must furnish funds under the contractual agreement and require the contractor to apply VV&T throughout the entire life cycle.

Assessing credibility throughout the life cycle of a simulation study is an onerous task. Applying the VV&T techniques throughout the life cycle is time consuming and costly. In practice, under time pressure to complete a simulation study, the VV&T and documentation are sacrificed first. Computer-aided assistance for the VV&T is required to alleviate these problems. More research is needed to bring automation to the application of the VV&T techniques.

Integration of VV&T with model development is crucial. This integration is best achieved within a computer-aided simulation software engineering environment (Balci *et al.* 1995; Balci 1986; Balci and Nance 1987). More research is needed for this integration.

How much to test or when to stop testing depends on the study objectives. The testing should continue until we achieve sufficient confidence in credibility and acceptability of simulation results. The sufficiency of the confidence is dictated by the study objectives.

Establishing a simulation quality assurance (SQA) program within the organization conducting the simulation study is extremely important for successful credibility assessment. The SQA management structure goes beyond VV&T and is also responsible for assessing other model quality characteristics such as maintainability, reusability, and usability (human-computer interface). The management of the SQA program and the management of the simulation project must be independent of each other and neither should be able to overrule the other (Schach 1993).

Subjectivity is and will always be part of the credibility assessment for a reasonably complex simulation study. The reason for subjectivity is two-fold: modeling is an art and credibility assessment is situation dependent. A unifying approach based on the use of indicators measuring qualitative as well as quantitative aspects of a simulation study should be developed.

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