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KNOWLEDGE-BASED SIMULATION TO ASSIST IN SYSTEM DESIGN IDENTIFICATION

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ABSTRACT

A considerable amount of research in recent years has been conducted to explore the coupling of artificial intelligence concepts with simulation, some of it fruitful but much of it still in the prototype or developmental stage. In this paper we present a three dimensional perspective of the types of possible couplings of expert systems with simulation models. This perspective serves as a foundation for discussing a heuristic reverse simulation procedure developed by Wild and Pignatiello (1992). Reverse simulation employs an embedded expert system to adapt simulation model configurations to user-defined target performance requirements to identify initial feasible values for simulation system design variables. We discuss reverse simulation within the context of our three dimensional model and suggest several enhancements for improving and implementing the technique.

1 INTRODUCTION

Research efforts aimed at creating intelligent simulation environments and those combining artificial intelligence concepts with simulation techniques are in essence two sides of the same coin. The former focuses on conceptualization of characteristics that make a simulation environment an intelligent one, the latter on materialization of such characteristics. Among the various fields in artificial intelligence, expert systems has earned the most consideration from simulationists. Research efforts focused on using expert systems to enhance simulation studies have stimulated interest in recent years. This paper contributes to such efforts.

We first consider research efforts using expert systems to facilitate simulation studies. A three-dimensional perspective for such consideration is presented with a premise that such an extended perspective is needed to gain more insight into the problem and process of coupling expert systems with simulation. With this perspective in mind, a reverse simulation technique is discussed as a distinct approach for combining an expert system with a simulation program to find initial feasible values for simulation system design variables. Finally, we present our ongoing efforts to improve the proposed reverse simulation technique.

2 HISTORICAL PERSPECTIVE

In a landmark article, Henriksen (1983) proposed a direction for simulation environments of the 1990's. The central idea is to achieve an "integrated" environment in which all essential tasks in a simulation life cycle are concurrently supported, integrated basically by a common "knowledge base". Shannon (1986) addressed this issue of integration as "precisely the goal of AI based Expert Simulation systems, with the added goal of embedding within the software as much of the expertise as possible." Thus, the dual key concepts of intelligent simulation environments are brought together: integration and intelligence. The goal of injecting "intelligence" into a simulation environment is twofold: as a key to integration as well as a means to provide users with the expertise needed during the stages of a simulation study. Naturally, the field of artificial intelligence (AI) was considered to be an obvious candidate for achieving an intelligent simulation environment. Oren and Ziegler (1987), Reddy (1987), Rothenberg (1990), Nielsen (1991) and Rao et al. (1990) are among many researchers who have explored the challenge of applying AI philosophies, concepts, tools, and techniques to enhance simulation studies and environments.

Expert systems is one of the earlier fields in AI that has attracted and is still gaining the attention of simulationists. Shannon et al. (1985) discussed prominent characteristics of expert systems and lucrative possibilities to couple expert systems with simulation to make simulation a more useful and accessible tool for analysts. They indicated that "The goal for the development of expert simulation systems is to make it possible for engineers, scientists, and managers to do simulation studies correctly and easily without ... elaborate training." O'Keefe (1986) introduced a taxonomy for combining expert systems and simulation in which four possibilities of the coupling were presented: embedded, parallel, cooperative, and intelligent front-end.

3 A THREE DIMENSIONAL PERSPECTIVE FOR USING EXPERT SYSTEMS TO ENHANCE SIMULATION STUDIES

Although O'Keefe's taxonomy undoubtedly offers a useful view of research efforts in combining expert systems with simulations, it does not include two other dimensions that should be considered in the use of expert systems to enhance simulation studies. We propose that, together with O'Keefe's taxonomy, which is concerned primarily with the architecture of the link, two other dimensions should be included: those of a link dynamic and the simulation task. Figure 1 illustrates the proposed perspective.

The first dimension, O'Keefe's taxonomy, deals essentially with the architecture of the link between expert systems and simulation programs. It explores possible ways of achieving the coupling using the following categorization. An *embedded* link describes an architecture in which an expert system resides within a simulation environment or vice versa. As such, an "embedded" expert system is conceptually part of the execution of a simulation environment. A *parallel* link refers to an environment in which an expert system and a simulation model execute separately or in parallel, most likely while performing different tasks, but sharing results with each other. A *cooperative* link differs from a parallel link not only in terms of task but also in emphasis. In a cooperative link, the expert system and simulation model perform together on the same task. Also, while in a parallel link either the expert system or the simulation stands as the main tool—one to which users have access; in a cooperative link both tools are equally accessible to users. Finally, in an *intelligent front-end* link, the expert system is used as a tool to provide an intelligent interface between simulation software and users.

Although O'Keefe's discussion does explore possible areas of application for each architectural link, the main emphasis of the taxonomy is on the architecture of the link. Three application areas suggested in the discussion of this taxonomy are: 1) entirely new simulation tools developed by combining the two tools; 2) advice-giving systems for inexperienced users, especially in the areas of experimental design and output analysis; and 3) intelligent front-ends developed for existing simulation packages. O'Keefe's taxonomy offers a foundation for further consideration of combining expert systems with simulations.

Motivation for the second dimension in our perspective comes from a stream of research which attempts to materialize conceptual discussions in the area of intelligent simulation environments in general, and coupling expert systems with simulation in particular. Efforts aimed at building working simulation environments, in prototype form or otherwise, that link expert systems and simulation programs are becoming more abundant. As is evidenced in this stream of

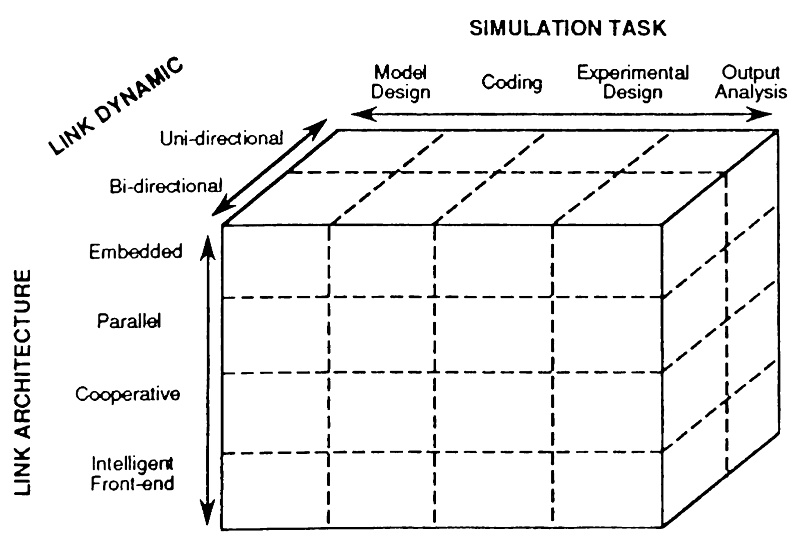

Figure 1: A Model for Using Expert Systems to Enhance Simulation Studies

research, most of the concrete systems that couple expert systems and simulations select to concentrate only on one particular task in a simulation study. As an example, Mellichamp and Park (1989) described a statistical expert system which offers assistance in statistical analysis needed during a simulation life-cycle. Their system—"Statistical Expert System for Simulation Analysis" (SESSA), was designed to address statistical analysis from a perspective specific to a simulation study. Deslandres and Pierreval (1991) described an expert system that also assists in the tasks of statistical analysis but only those pertaining to the statistical validation process. Hill and Roberts (1987) developed a prototype knowledge-based simulation support system which assists users in the task of debugging logical errors in simulation code. Murray and Sheppard (1988) developed a Knowledge-Based Model Construction (KBMG) which automates the model construction phase in a simulation life cycle. Coats (1990) used expert systems as an "intelligent front-end" to interface with users and assist them in the task of simulation model modification.

From the cited examples, it appears appropriate that research efforts in combining expert systems with simulations need to be considered in relation to the task or set of tasks such combined systems are intended to support. Our perspective proposes that four major phases in a simulation life-cycle lend themselves well to categories of simulation tasks, i.e., model design, coding, experimental design, and output analysis.

The third dimension originated from a distinct characteristic of the focus of this paper, that is, a reverse simulation technique. The dimension "link dynamic" refers to the actual interaction between an expert system and a simulation program, particularly to how results from one are transferred to be used by the other and how the transferred information affects the working of both the expert system and the simulation which are being combined. In most studies which combine expert systems with simulations, the dynamic of the link can be described as *uni-directional*, namely, results are transferred from one system to the other at some specified intervals, usually at the end of an execution. As an example of a uni-directional link dynamic, consider the statistical expert system developed by Mellichamp and Park (1989). Their expert system assists users at different intervals in a simulation study, although the intervals span throughout a simulation life cycle. Before an execution of a simulation model, users might access the expert system to help with such tasks as estimating parameters for input variables, identifying distributions for input variables, or determining the simulation run length and number of independent replications. After a pilot run, users might access the expert system again to seek help with such tasks as comparing model response estimates to system estimates or assessing the impact of initial conditions. Then again, after actual execution of a simulation, users may need help with tasks associated with output analysis such as constructing confidence intervals for estimates of output variables or comparing output from alternative designs. For all interactions, results are transferred in one direction at a time and only after a complete execution of a simulation model by having the expert system read a data file containing the simulation results or by having users input such data to the expert system.

In contrast to the above link dynamic, the actual transfer of results and its effect can be described as *bi-directional* in a coupling such as that employed in a reverse simulation technique . As will be more evident later, a reverse simulation technique introduced by Wild and Pignatiello (1992) employs a link dynamic between an expert system and a simulation model that is bi-directional in nature. In brief, throughout the execution of a reverse simulation, the expert system actually "supervises" the simulation model linked to it based on an ongoing transfer of simulation system state information and expert system recommendations. The link is "bi-directional" and the ongoing transfer of information affects the actual execution of both the expert system and the simulation model simultaneously. This will be made clearer in the following section on Wild and Pignatiello's reverse simulation technique.

As a final note on the perspective of using expert systems to enhance simulation studies as presented here, it is believed that the distinctions within each dimension should be considered along a continuum rather than in disjoint form, hence the lines with arrows at both ends in Figure 1. Especially in the simulation task dimension, a certain task domain, such as statistical analysis, can cover the entire continuum while another task domain, such as debugging, may well be mapped on the coding phase of a simulation study.

4 REVERSE SIMULATION

Simulation studies are conducted for a variety of objectives. Two of the more common objectives are to explore the behavior of a system given a specified system and its stochastic components and to optimize a system's response given the system, its stochastic components and the response to be optimized. Hunter and Naylor (1970) discussed appropriate experiment designs for both objectives.

The second objective, to identify a system whose response is optimized based on specified performance requirements, is known as *system design* or *system synthesis* (Gordon 1978). The simulation experimentation process generally involves a series of iterative simulation experiments in which a proposed system is modeled based on a pre-specified set of output performance objectives. The output objectives may be general, such as minimize the time customers spend in queue, or specific, such as no customer should wait in queue more than ten minutes. If the system's performance estimated by simulation experimentation compares favorably with the specified, desirable performance, the system is accepted. If not, the system is redesigned and the simulation experimentation process is repeated. The question an analyst faces initially is which system design should be used to start the system design process. Queueing theory may be applied in a limited, restricted set of cases, but in many instances, it is not appropriate and will provide only a "guesstimate" of the initial system design to be simulated. It is suggested in the simulation literature to determine the initial values for system design variables using intuition, cost constraints, or simple guesswork (Law and Kelton 1991).

System design identification can be a long and arduous process, especially for complex systems. The initial system specified may be far from optimal with respect to the performance objectives. In fact, a great deal of simulation experimentation may be required merely to find a stable, not necessarily optimal, system design. By a stable system design we mean one in which none of the queues is backing up and thus the throughput of the system approaches its expected value based on the arrival rate to the system.

Wild and Pignatiello (1992) introduced a technique they call reverse simulation as an initial step in system design identification. Reverse simulation is a heuristic procedure which attempts to find feasible values for system design variables which, in combination, produce a stable system design. A feasible value for a system design variable is a value for which a specific queue associated with that variable is not backing up. These feasible system design variable values, in combination, serve as a starting point for the system design process of further system evaluation and optimization. Thus, reverse simulation is employed in conjunction with, not instead of, system design identification.

As with system design, reverse simulation requires an analyst to state in advance desired system performance in the form of target values or ranges of values for system performance measures. Unlike system design, reverse simulation does not require the simulation analyst to identify a system design whose estimated performance will be compared to the desired performance specified. With the assistance of an expert system which contains system knowledge and rules regarding target performance, the system design variable values are adjusted dynamically as the simulation executes to satisfy performance criteria. Hence, the expert system is used to adapt model configurations to user-defined performance requirements to find feasible values for system design variables. The system design variable values produced by reverse simulation are used to construct appropriate experiment designs for subsequent simulation experimentation to search for and identify an optimal or "best" system design through statistical output analysis.

In summary, the objective of reverse simulation is to find feasible values for system design variables which, in combination, produce stable system designs that serve as initial systems in the process of identifying a "best" system design. The input is what is traditionally output (target performance measures) and the output is what is conventionally input (specified system designs that, in the case of reverse simulation, satisfy performance requirements).

Reverse simulation illustrates an alternative way in which an expert system and simulation can complement one another to enhance simulation as an analysis and design tool and can be viewed within our proposed three dimensional perspective as follows.

4.1 Task Dimension

To specify an experiment design (or data collection plan) for simulation experimentation such as a factorial or fractional factorial design, an initial set of values must be identified for the system design variables that will be manipulated during the simulation experimentation process. Reverse simulation provides an adaptive environment in which a system's design variable values adapt to user-defined performance requirements. The feasible values of system design variables produced through reverse simulation serve as the initial values to be used in the experiment design for subsequent system design identification. Thus, reverse simulation can be viewed as a sub-task within the experimental design phase of a simulation study.

4.2 Link Architecture

Essentially, the prototype system described by Wild and Pignatiello (1992) employs an embedded architecture. The concepts underlying the reverse simulation technique are implemented by augmenting the simulation program with an expert system. The simulation program executes with direct recommendations from the expert system; the recommendations guide the simulation execution in a dynamic manner. The simulation program captures the physical layout of the system being simulated, the logic associated with entity flow, and any parameters associated with a simulation run. The expert system is a rule-based system which employs constraint-directed reasoning. The problem-specific information that is needed to customize the expert system for a particular application is solicited from the analyst during an initial dialogue between the simulation analyst and the expert system. Figure 2 depicts a conceptual view of the architecture for the reverse simulation technique.

As an example, consider a simple queueing system. For such a system, system objectives may be to minimize total time an entity or a transaction (e.g., a customer, a part, etc.) spends in a system as well as to maximize throughput (e.g., the number of customers served in an hour, the number of jobs finished in a day, etc.). Given these system objectives, the overall goal is usually to find the optimal system configuration, one in which system design variable values in combination (e.g., the number of cashiers, the number of machines, etc.) yield an optimal performance at minimum cost.

Simulation experimentation can be used to determine the best system configuration among many options (e.g., among systems with 3, 5, and 7 cashiers or machines). However, before such determinations are made, the initial settings of the system design variables need to be identified. Reverse simulation attempts to find initial feasible values for system design variables which, in combination, produce a stable system design. This stable system design serves as a starting point for subsequent system performance analysis and optimization.

With reverse simulation, a simulation analyst specifies the system performance objectives, states desired target values or ranges of values for performance measures, and indicates a preference ranking for satisfying conflicting objectives. This specification is done through a dialogue between the analyst and the expert system. Once the information has been obtained and verified, the expert system selects the appropriate rules from its rule-base to be used during the reverse simulation process. For example, for a queueing system, target objectives might be to have no more than ten customers in a queue, and a throughput of thirty customers per hour. The expert system in the reverse simulation will convert these objectives (and their interrelationships) into a set of constraints. The

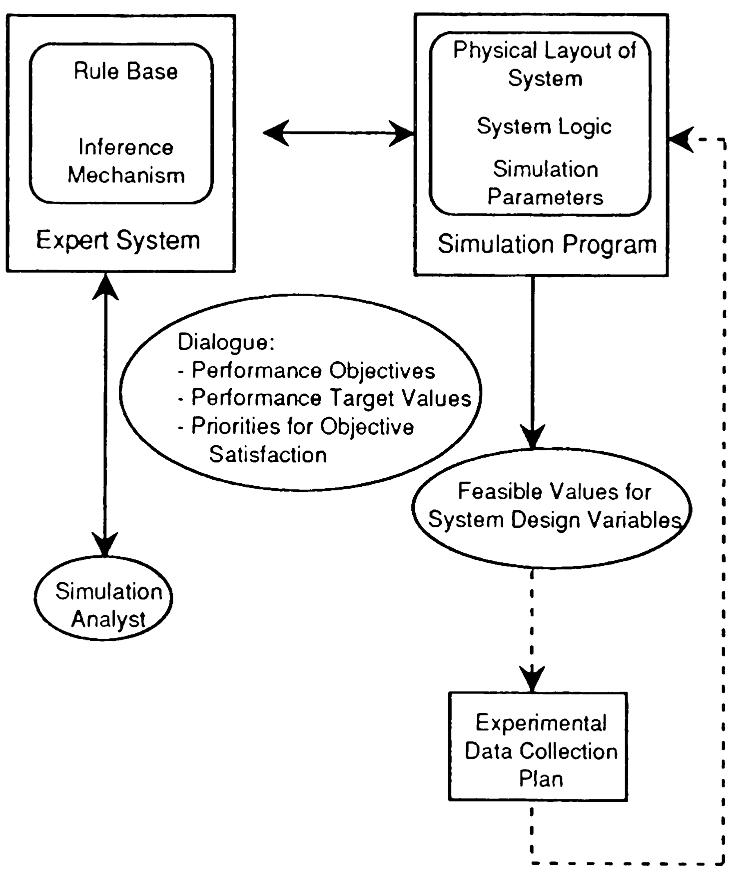

Figure 2: Reverse Simulation

constraints are represented in the expert system as rules. During the execution of the reverse simulation, the expert system will, in essence, "monitor" the values of system design variables by "firing" appropriate rules. The rules attempt to map target system performance onto the actual system state. Thus, for example, resource capacity may be altered dynamically to conform to target performance criteria. As a simple example, a rule associated with queue length might read: "if queue length is greater than or equal to 10, add another server to the system."

The output of the reverse simulation will be statistics associated with system design variables, including the average and the maximum values of each system design variable needed to satisfy system performance objectives. Using our simple example, the output might be that, given the two objectives, the average number of cashiers needed in the shop is nine cashiers with twelve as the maximum. Statistics other than the average and the maximum are also possible. For the prototype system, output are presented in simple tabular and graphical forms, in which a histogram is provided depicting the percentage of simulated time in which one through the maximum value assumed by a system design variable was required to satisfy system performance target criteria.

4.3 Link Dynamic

As is evident from the above description, the reverse simulation technique employs an expert system in a different manner than many other efforts in combining expert systems with simulations. First, the conclusions drawn by the expert system are not drawn from a direct consultation with the user. Rather, they are drawn from a direct "consultation" with the simulation program. The expert system is invoked by the simulation program as the simulation is executing, and the advice given by the expert system is given to the simulation program dynamically as the simulation executes. The bi-directional link dynamic is evident in this concurrent transferring of data and monitoring of the system state as the simulation program executes.

4.4 Areas for Enhancement

As developed by Wild and Pignatiello (1992), the embedded expert system was in a prototype form. Although the prototype well illustrates the concept of the reverse simulation technique, there are several areas where enhancement is needed before the system is ready for practical, functional use. Candidate areas for further enhancement are as follows.

- Viable communication link: To our knowledge, there is currently no commercial simulation software that is able to "communicate" directly with commercially available expert systems. In the prototype system, a "makeshift" link is achieved by building the expert system in a language (FORTRAN) that is able to communicate with the simulation environment (SIMAN). This lack of ready, direct communication links is a major issue, since the actual mechanics of the reverse simulation technique require a direct communication link between a simulation program and the embedded expert system. Research efforts to identify and explore possibilities of a feasible, efficient link will contribute to the enhancement of the reverse simulation technique. C++ is a candidate environment.
- User Interface Facilities: The prototype system does not have a built-in user interface to handle the needed dialogue between an analyst and the expert system. For an embedded expert system to be put into practical use, such an interface is obviously critical. Studies which explore how such facilities should be developed and implemented are therefore needed.
- Exhaustive Rule-Base / Knowledge-Base: The prototype system contains only specific sets of rules, adequate for illustrative and explorative purposes, but clearly insufficient for practical use. An exhaustive rule-base or knowledge-base needs to be compiled to handle systems with varying objectives. Also, because of the limitation put upon the prototype system by the communication link between the expert system and the simulation program, inference mechanisms are limited and inflexible. In a functional expert system, inference mechanisms should be more flexible and dynamic.
- Presentation Facilities: Output from the prototype system are presented in simple tabular or graphical forms. No mechanism for tracking the values assumed by the system design variables during an execution of a reverse simulation exists in the prototype. Such facilities will enhance the usefulness of the expert system. Also, exploration of other presentation techniques that might be useful for the analysis will also be of value.
- Output Analysis Facilities: Output from the prototype expert system are comparatively not richly descriptive. In the prototype system, statistics are given based on results compiled from a reverse simulation run. For a more meaningful analysis, explanation facilities are needed. Such facilities would provide a detailed description of the interaction between the expert system and the simulation such that insight into system performance can be gained. For example, queries into when, why and how often each rule is fired would give insight into the impact of its associated constraint. Such insight provides an analyst with more varied information to aid in subsequent decisions on the ultimate system

design. Research efforts in developing powerful explanation facilities will greatly enhance the usefulness of reverse simulation.

5 PROSPECTIVE DIRECTIONS

Given the above considerations on enhancement of an expert system for reverse simulation, prospective directions on the efforts are described here. Figure 3 provides an overview of these directions. The shaded areas in the figure represents three areas identified for further enhancement. Discussions of the three areas are as follows.

5.1 Intelligent Interface

Two levels of interface are being considered.

• User Interface: To facilitate the dialogue between an analyst and the expert system, a user-friendly interface needs to be developed. The interface is intended to intelligently manage the dialogue in two ways. First, it will provide users with an appropriate and inclusive menu of information needed for the expert system to proceed with a reverse simulation run. The dialogue should proceed naturally both at conceptual and interactive levels. Second, the interface and the dialogue it manages will be based on the knowledge residing in the rule-base or knowledge-base of the expert system.

• Viable Communication Link: Investigation into possible communication links will be made. A survey of currently available expert systems and simulation environments should provide insight into viable options for an efficient interface mechanism needed for a bi-directional dynamic link integral in a reverse simulation run. The final result of this investigation will be a set of efficient interface mechanisms, one of which will be chosen for a system we will develop for possible commercial viability.

5.2 Knowledge-Base for Reverse Simulation of Queueing Systems

The second major effort for enhancement will be the development of a comprehensive, general knowledge-base which contains all encompassing knowledge applicable to a study of any queueing type system. Three major sub-tasks to achieve this knowledge-base are in order.

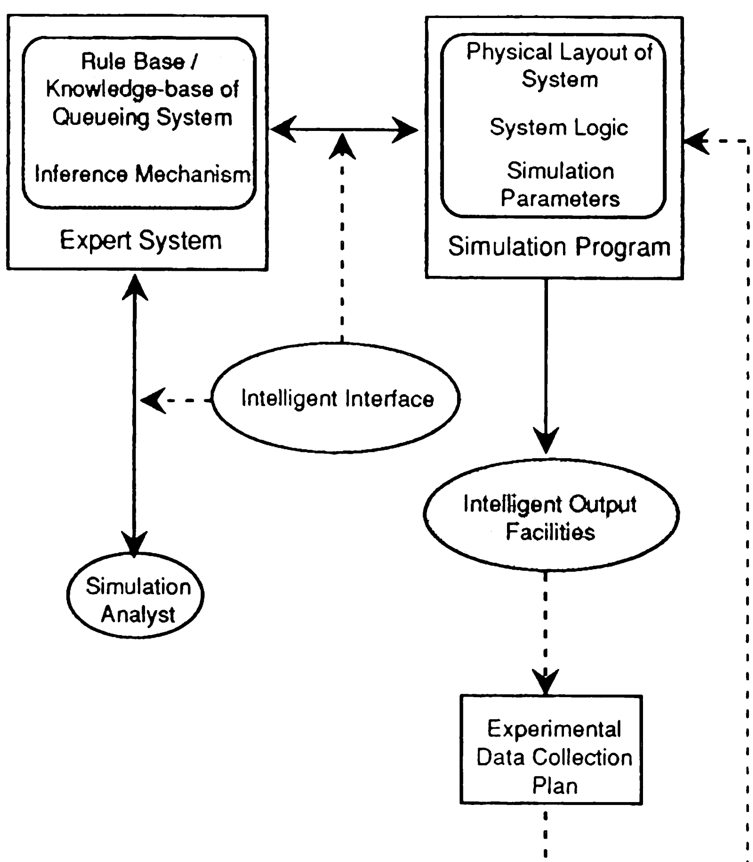

Figure 3: Prospective Enhancements of Reverse Simulation Technique

1) Compilation of Factors for Consideration in a Study of Queueing Systems: An integrated set of factors to be considered in a study of queueing systems will be compiled from a survey of simulation applications. Domains for this compilation include but are not limited to factors pertaining to the following:

- Possible goals of a study.
- System types and their associated factors.
- Possible candidates for assumptions made in a study together with their potential effects.
- Candidate factors for decision variables and the transformation of these factors into design variables.
- Candidate factors to be considered as performance measures.
- Possible factors to be treated as random components.

2) Integration of the Compiled Factors into a General Knowledge-Base Applicable to a Study of a Particular Queueing System: With the compiled factors from the first step, a general knowledge-base will be developed. A major issue to explore at this step will concern consideration of appropriate knowledge representation techniques for this knowledge-base. It is expected that a rule-based expert system may be a likely candidate since it appeared to work well in the prototype system. However, it is also possible that as the knowledge-base increases in size and complexity, some other knowledge representation techniques, such as frame-based or objected-oriented representations, may be more attractive. Exploration of this issue is expected to result in insight and rationale for an appropriate choice of a knowledge representation technique for our knowledge-base. The final result at this step will be an all encompassing knowledge-base, from which a set of necessary factors for a reverse simulation run of any queueing system can be customized, according to information gathered from a dialogue with an analyst.

3) Development of an Appropriate Inference Mechanism: An inference mechanism will be developed and applied for the working of the knowledge-base in (2). It is expected that a flexible and dynamic inference mechanism will better support the bi-directional nature of the link between the embedded expert system and a simulation program since data from an ongoing reverse simulation run will be applied more rigorously in the execution of the expert system. A major consideration to be resolved during this step is a management of conflicting goals, a common phenomenon in a simulation study. Conflicting goals result in conflicting constraints in a reverse simulation and hence conflicting rules in a knowledge-base. It is intended that a flexible general scheme to prioritize and compromise conflicting goals, constraints or rules will be developed such that an analyst is allowed to customize a prioritizing and compromising scheme for a particular study.

The final product of this second research effort will be a fully-functioning expert system which can be embedded in a simulation program to provide full and customized support for a reverse simulation run of any queueing system being studied.

5.3 Intelligent Output Facilities

The third and final research effort will concentrate on enhancement of the content and form of output from a reverse simulation. Intelligent output facilities will be developed along the following dimensions.

The first step in this effort is to identify a classification of the content of output from reverse simulation. In the prototype system, content of the output is essentially a set of static summary statistics. It is believed that a more dynamic output should also be made available given the potential provided by an expert system. The power of an expert system lies in its explanatory as well as prescriptive capacities. Output from a reverse simulation should also contain this explanatory descriptive content, which is lacking in the prototype system. Detailed behavior of a system during a reverse simulation run should be made possible. For example, explanation should be available as to when, why, how often, and to what effect certain rules have been fired. Also, a record of values assumed by the system design variables during a reverse simulation should be kept to present output which helps to ensure that the reverse simulation has been run long enough for the system to have settled down. Such dynamic output would provide more insight into the system and hence more meaningful information on which a final decision about initial feasible values for system design variables can be based. For instance, explanatory output is expected to provide useful qualitative information to the analyst as well as alert the analyst to constraints that may be too tight to find acceptable system design variable values.

Given a classification and specification of desirable content from the first step, the next step is to develop mechanisms by which necessary information can be gathered during a reverse simulation run such that the desired output can be produced. These mechanisms will then be incorporated in the embedded expert system.

The final step in the development of intelligent output facilities is to devise a set of more sophisticated output presentation formats. A guideline for this development is to match an appropriate format to a class of content. For example, it is possible that for dynamic output, such as a tracking of the values of system design variables, a graphical output will be more appropriate. Mechanisms to create several formats of output, either in tabular or graphical form, need to be devised and incorporated in the reverse simulation environment.

6 CONCLUSION

Research efforts in creating intelligent simulation environments in general, and combining expert systems and simulation in particular, have been underway long enough to expect results from such efforts which will materialize in viable and functional products for users. With this trend, users can expect to access a more powerful yet practical simulation environment. The reverse simulation technique discussed in this paper has potential to contribute to such a success. Prospective research efforts presented here have been devised with the goal of bringing such potential closer to reality.

REFERENCES

Coats, P. K. 1990. Combining an expert system with simulation to enhance planning for banking networks. *SIMULATION* 55: 253-264.

Deslandres, V. and H. Pierreval. 1991. An expert system prototype assisting the statistical validation of simulation models. *SIMULATION* 56: 79-89.

Gordon, G. 1978. *System simulation.* 2d ed. New Jersey: Prentice Hall.

Henriksen, J. O. 1983. The integrated simulation environment (simulation software of the 1990's). *Operations Research* 31: 1053-1074.

Hill, T. R. and S. D. Roberts. 1987. A prototype knowledge-based simulation support system. *SIMULATION* 48: 152-161.

Hunter, J. S. and T. H. Naylor. 1970. Experimental designs for computer simulation experiments. *Management Science* 16: 422-434.

Law, A. M. and W. D. Kelton. 1991. *Simulation modeling and analysis.* 2d ed. New York: McGraw-Hill.

Mellichamp, J. M. and Y. H. Park. 1989. A statistical expert system for simulation analysis. *SIMULATION* 50: 134-139.

Murray, K. J. and S. V. Sheppard. 1988. Knowledge-based simulation model specification. *SIMULATION* 50: 112-119.

Nielsen, N. R. 1991. Application of artificial intelligence techniques to simulation. In *Advances in simulation: vol. 4—knowledge-based simulation.*, ed. P. A. Fishwick and R. B. Modjeski, 1-19. New York: Springer-Verlag.

O'Keefe, R. 1986. Simulation and expert systems—a taxonomy and some examples. *SIMULATION* 46, 10-16.

Oren, T. I. and B. P. Ziegler. 1987. Artificial intelligence in modelling and simulation: directions to explore. *SIMULATION* 48: 131-134.

Rao, M, T-S. Jiang, and J. J-P.Tsai. 1990. Integrated intelligent simulation environment. *SIMULATION* 55: 291-295.

Reddy, R. 1987. Epistemology of knowledge based simulation. *SIMULATION* 48: 162-166.

Rothenberg, J. 1990. Artificial intelligence and simulation. In *Proceedings of the 1990 Winter Simulation Conference*, ed. O. Balci, R. P. Sadowski, and R. E. Nance, 22-24. Institute of Electrical and Electronics Engineers, New Orleans, Louisiana.

Shannon, R. E. 1986. Intelligent simulation environments. In *Proceedings of the Conference on Intelligent Simulation Environments*, ed. by P. A.Luker and H. H. Adelsberger,150-157. Society for Computer Simulation, Sandiago, California.

Shannon, R. E., R. Mayer and H. H. Adelsberger. 1985. Expert systems and simulation. *SIMULATION* 44: 275-284.

Wild, R. H. and J. J. Pignatiello. 1992. Finding stable system designs: a reverse simulation technique. To appear in *Communications of the ACM.*

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