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An Empirical Assessment Of Three Types Of Simulation Models Used In Developing Decision Support Systems

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AN EMPIRICAL ASSESSMENT OF THREE TYPES OF SIMULATION MODELS USED IN DEVELOPING DECISION SUPPORT SYSTEMS

by

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ABSTRACT

Visual interactive simulation (VIS) was first developed in the mid-1970s and has been claimed to be a better type of simulation model than traditional simulation for supporting decision making. VIS models which compare two simulated systems using paired-difference statistics have been claimed to be a more powerful decision-support tool than viewing animated simulation model output or steady state statistics. Since simulation is one of the most frequently used techniques in decision support systems (DSS), an examination of which type of simulation model is better for developing DSS is of vital importance. This dissertation focuses on examining and comparing the relative effectiveness and efficiency of three types of simulation models: traditional simulation models, conventional VIS models, and VIS models with paired-systems and paired-difference statistics.

The research was done through a laboratory experiment in which seventy-one second-year Masters' students in Business Administration at the Western Business School participated and were randomly assigned to one of the three experimental groups. Three DSS (one based on a traditional simulation model, one on a conventional VIS model, and one on a VIS model with paired-systems and paired-difference statistics) were developed and each was assigned to one of the three experimental groups. Subjects were asked to solve a production problem presented as a case using the DSS provided.

The results of the experiment indicated that of the three types of DSS, the one based on a VIS model with paired-systems and paired-difference statistics was the most effective and efficient. The DSS based on a conventional VIS model was the second most effective, while the traditional simulation was the least effective. In particular, the DSS based on a VIS model with paired-systems and paired-difference statistics significantly outperformed traditional simulation on all five evaluation criteria defined and used in this study.

This research made three important contributions: first, the work provided management science/operations research (MS/OR) researchers with the first empirical comparison of three different types of simulation-based DSS, and the results of the study provided the first strong empirical case for the use of VIS. Second, the research rigorously tested two claims in the literature by proponents of VIS. Third, the results of this research provided MS/OR practitioners with new insight on the development of simulation-based DSS.

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CHAPTER 1

INTRODUCTION

1.1 Research Objectives

The goal of this thesis was to investigate and compare the effectiveness of a relatively new type of simulation model with the traditional simulation model. Simulation was one of the most popular MS/OR techniques used in decision support for managerial decision making [Eom and Lee, 1990a]. Visual interactive simulation (VIS) was pioneered by R D Hurrion in the mid-1970s [Hurrion, 1976] and was then claimed to be a more effective type of simulation model for use in developing decision support systems for solving semi-structured problems [Hurrion, 1985]. Understanding the effectiveness of this type of "non-traditional" simulation model was of vital importance to both academic researchers and MS/OR practitioners. The focus of this thesis was on comparing the decisions generated by visual interactive simulation and traditional simulation models. Data employed for this research goal were collected via an experiment designed for this study.

A second and equally important research objective was to evaluate the usefulness of paired-difference statistics (in contrast to traditional individual-sample statistics) in visual interactive simulation. A number of studies such as Hoffman and Earle [1981] and Dos Santios and Bariff [1988] had proved the usefulness of presenting difference statistics in improving decision making. Bell [1989] suggested the use of a "paired-difference" approach in visual interactive simulation; a new type of simulation model which combined visual interactive simulation and paired-difference statistics was proposed. This type of simulation model ran and displayed two alternative simulated systems on screen simultaneously and produced paired-difference statistics instead of traditional individual-sample statistics. The experiment designed for the first research goal also collected data for measuring the usefulness of this type of "paired-simulation" model (i.e., paired-simulated systems and paired-difference statistics). The focus was on evaluating the benefits of using visual interactive simulation and paired-difference statistics together in supporting decision making.

This thesis made contributions in three major areas. First, it provided MS/OR researchers with an empirical evaluation of three types of simulation models. Individual or separate successful cases of visual interactive simulation and paired-difference statistics had been found and reported in the literature. Both Parker [1986] and O'Keefe and Pitt [1991] suggested evaluating the effectiveness of visual interactive simulation in an experimental mode, where teams with identical problems could be provided with different decision support systems. This study provided such an evaluation by comparing three different types of simulation models in a common experimental setting.

Second, it rigorously tested two allegations existing in the simulation literature: that visual interactive simulation was more effective than traditional simulation, and that visual interactive simulation with paired-systems and paired-difference statistics was better than conventional visual interactive simulation. This research provided an evaluation of these two allegations.

The third contribution, which may be even more important, was to provide some insights and evidence to MS/OR practitioners on which type of simulation model was more effective in developing decision support systems to help solve managerial decision problems.

1.2 The Problem

Simulation had long been an important tool used by management scientists and operations researchers. The recent development of visual interactive simulation (VIS) models had made simulation more "accessible" by managers. Moreover, the statistics literature had often suggested that paired-difference statistics were more powerful than traditional individual-sample statistics in comparing two systems. The question here was: "Are visual interactive simulation (with or without paired-difference statistics) models really better than traditional simulation models displaying individual-sample statistics?" In particular,

1. could visual interactive simulation models help users to understand better and more quickly the underlying interrelationship among variables, that, in turn, could help obtain better results in managerial decision making than the traditional simulation models?

2. could visual interactive simulation with paired-systems and paired-difference statistics as the statistical outputs help users compare two similar systems more easily and more effectively than conventional visual interactive simulation displaying individual-sample statistics, that, again, could help achieve better performance in solving managerial problems?

Although there was a growing body of mainly anecdotal evidence presenting individual success stories using visual interactive simulation in decision support systems and paired-difference statistics in comparing two alternative simulated systems, more rigorous empirical studies were needed to compare these two types of simulation models with traditional simulation models in an identical setting. The present study was an attempt to conduct this empirical assessment.

1.3 Overview of Chapters

Chapter 2 provides an overview of decision support using traditional simulation and visual interactive simulation. The development, usefulness, and problems of traditional simulation are first discussed, followed by a discussion of visual interactive simulation and its differences from traditional simulation. Issues, including methodological, technical, statistical and behavioral aspects, on decision support using simulation are described and the chapter concludes with a discussion of the potential benefits of using visual interactive simulation and paired-difference statistics for decision support.

Chapter 3 reviews the previous literature in four related areas: simulation model validation; decision support system/simulation model implementation; visual interactive simulation and the usefulness of graphics in decision support systems; and analyzing and comparing alternative simulated systems. The review concludes with the expressed need for an empirical test on the usefulness of visual interactive simulation and paired-difference statistics.

Chapter 4 presents details of the research methodology adopted in this study. Major research questions in the study are first presented, followed by a detailed description of the experiment framework. Research hypotheses and experimental measures are discussed. Finally, the pilot study is described.

Chapter 5 presents an analysis of the data collected from the experiment and discusses the results obtained. Hypothesis tests and regression are performed to compare results generated from the three experimental groups.

Chapter 6 contains conclusions and implications from the research findings. A summary of the research project and its conclusions are presented, followed by the limitations of the study. Finally, research contributions and future research issues are discussed.

CHAPTER 2

DECISION SUPPORT USING TRADITIONAL SIMULATION AND VISUAL INTERACTIVE SIMULATION

2.1 Decision Support Systems (DSS) and Simulation

Decision support systems (DSS) have been around for more than twenty years. More than two hundred applications in many different fields have appeared in the literature [Eom and Lee, 1990a, 1990b]. Decision support examples in different corporate functional areas range from marketing to finance, production and human resources management, and cover industries in commerce, agriculture, education, government, hospital and health care, military, natural resources and urban and community planning. Their impact on both the research and practice of management decision making has been great.

The term decision support systems was first coined by Keen and Scott-Morton [1978]. Although there was no accepted definition of decision support systems [Keen, 1987], most people agreed that a decision support system had the following characteristics [Parker and Al-Utaibi, 1986]:

- it assisted users in their decision process in semi-structured tasks;
- it supported and enhanced, rather than replaced, managerial judgement;
- it improved the effectiveness of decision making rather than its efficiency;

- it attempted to <u>combine the use of models or analytical techniques with traditional data access and retrieval functions</u>;
- its focused on features which made it <u>easy to use by non-computer people in an interactive mode</u>; and
- it emphasized <u>flexibility and adaptability to accommodate changes</u> in the environment and the decision-making approach of the user.

These distinct features (those underlined above) separated decision support systems from traditional management science/operations research (MS/OR) models which looked for optimal (analytical) solutions to (mostly) structured and operational problems, and earlier management information systems (MIS) which focused on data processing. In Ackoff's terms, a decision support system mainly supported "a decision for which adequate models can be constructed but from which optimal solutions cannot be extracted" [Ackoff, 1967, p.154].

The basic framework for a decision support system consisted of three major components: model base, data base, and dialog system [Sprague and Carlson, 1982]. Each of these three components interacted with the others and with the user to support decision making. Because of its "support" nature, involving the end-user in the decision support system building process was a key characteristic of the decision support system modelling methodology. The prototyping (also called adaptive design or middle-out design) approach, which basically involved frequent communication and many short feedback loops between the system builder and end-user during the whole model building process, was considered the most popular approach to decision support system design and development [Huff, 1985].

Because a decision support system usually aimed at tackling semi-structured problems, building an analytical (MS/OR) model (which aimed at getting the optimal solution) to help solve the problem might not always be possible. Simulation was thus a natural and logical choice. This aspect was reflected in the results of a survey conducted by Eom and Lee [1990a]. Of the twenty modelling techniques surveyed in the study, simulation was the second most frequently used technique in DSS building (the most frequent technique was graphics). About 20% (41 of 203) of the decision support system applications used simulation as their core model base.

Simulation has a much longer history than the decision support systems. Since Tocher built the first simulation language, General Simulation Program (G.S.P.), in the 1960s [Hollocks, 1983], simulation has developed as one of the most popular modelling tools used by management scientists/operations researchers. Surveys concerning the practical applications of MS/OR models always reached a conclusion that simulation was one of the top three most frequently used techniques (for example, Thomas and Dacosta [1979], Lee [1983], Forgionne [1983], Beasley and Whitchurch [1984], Eiselt, Eiselt and Sandblom [1986], Carter [1987], Harpell, Lane and Mansour [1989], Eom and Lee [1990a], and Cornford and Doukidis [1991]). It was used in areas such as production, corporate planning, engineering, finance, research and development, marketing and personnel management (Christy and Watson [1983], Ford et al. [1987] and Er [1988]).

Based on Naylor et al. [1966], Hoover and Perry [1989, p.5] defined simulation as

> "the process of designing a mathematical or logical model of a real system and then conducting computer-based experiments with the model to describe, explain, and predict the behaviour of the real system."

Therefore, simulation always involved experimentation, usually on a computer-based model of some system. The model was used as a vehicle for experimentation [Pidd, 1984]. This "trial and error" and "learning" method of experimentation helped support management decision making on some semi-structured problems, which was the main purpose of decision support systems.

Gray and Borovits [1986] investigated the roles of Monte Carlo simulation and computer-based management games (which could be considered as another type of simulation) in decision support systems. They concluded that both tools were good for developing decision support systems. Monte Carlo simulation was preferred for comparative studies while a management game was better for exploratory studies.

In the context of supporting decision making, Davies and O'Keefe [1989] suggested that simulation could have three main purposes:

- to <u>compare</u> alternative systems or the effect of changing a decision variable;
- to <u>predict</u> what would happen to the state of the system at some future point in time; and

- to investigate how the system would behave and react to normal and abnormal stimuli; to give insight into the behaviour of the system.

Broadly speaking, these three purposes fitted with the three major categories of DSS suggested by Finlay and Martin [1989]. Based on Thompson and Tuden's [1959] framework, Finlay and Martin developed a matrix of decision support systems as shown in Figure 2.1. Matching the three purposes of simulation discussed above with the matrix, it seemed that "to compare" could be used for "extrapolatory systems", "to predict" for "decision insight systems", and "to investigate" for "scenario development systems". This matching might explain why DSS using simulation was so popular in real-world applications. Simulation was more than the last resort in modelling and was not used only when all else failed, as suggested by Wagner [1970].

		Uncertainty about outcomes: Low	Uncertainty about outcomes: High
Uncertainty about cause and effect	Low	Data Processing Systems	Decisions Insight Systems
	High	Extrapolatory Systems	Scenario Development Systems

Figure 2.1: A matrix of decision support systems (after Finlay and Martin [1989])

2.2 Traditional Simulation: Its Development, Usefulness and Problems[1]

"There is now a clear recognition of the value of simulation by most medium and large organizations in the UK" [Blightman, 1987, p.769].

The growth of simulation (and its usefulness) accompanied the advancement of computer technology. The development of simulation had been basically technology-driven, rather than research-driven. Before the widespread use of commercial computing, most simulation models were designed and built expensively by hand. They were mainly found in defence establishments or in research laboratories and relatively few were found in the commercial world. Pidd [1987] called this period the first generation of simulation and used the word "scarcity" to describe this generation. This scarcity constraint led to the development of a three-phase simulation modelling approach by Tocher [1963] which was designed to make efficient use of the scarce computing resources.

The significant advancement of computer technology in the late 1960s and early 1970s strongly fostered the growth of simulation. The modular design of the computer invented by IBM led to substantial production cost reductions and the proliferation of commercial computers. With the widespread use of standard

[1]In this thesis, "traditional" simulation is defined as those models built by conventional simulation methodology (as described, for example, in Naylor et al. [1966]), particularly in contrast with the new type of simulation models such as visual interactive simulation (VIS). A detailed comparison between visual interactive simulation and traditional simulation is discussed in Section 2.3.3.

hardware, software portability was promoted. Special-purpose simulation languages, rather than general-purpose languages such as FORTRAN and PASCAL, were developed by simulationists and management scientists/operations researchers. Important ones were GPSS, SIMSCRIPT, SIMULA, CSL, HOCUS and GASP. Also, more simulation application areas were exploited. In the UK, simulation went into coal and steel industries. In the US, it expanded to the analysis of telecommunications networks [Pidd, 1987].

The replacement of solid-state electronics by micro-electronics in the 1970s made computers more powerful and faster; this led to more simulations being run. The technology of multi-user access via time-sharing gave rise to the possibility of interactive computing, which made simulation program development easier. Moreover, better software was developed, for example, with SIMSCRIPT becoming SIMSCRIPT II, CSL becoming ECSL, GASP becoming SLAM.

In the 1980s, micro-computers and work-stations entered into the work place. Simulation was no longer restricted to mainframe use. Simulation languages in a micro-computer version were developed, such as GPSS/PC and PC SIMSCRIPT II.5. In a recent issue of the magazine "OR/MS Today" (October 1991), Swain [1991] provided a detailed survey of 48 commercially available simulation software packages. The use of simulation is ubiquitous.

Simulation was useful, as reflected in the quotation cited at the beginning of this Section and shown in the results of surveys done by Christy and Watson [1983], and Ford et al. [1987]. The rapid advancement of computer technology, including faster computers, improved computer graphics in micro-computers, and powerful networks and work-stations, had relaxed the "technology" constraint of simulation growth. The problem of simulation growth became not a question of technology, but how to put this MS/OR tool into the actual work place. Previous research on simulation had concentrated on the technical/statistical side and neglected other important issues such as model implementation and the evaluation of the need to develop new methodology to improve the power of simulation. For example, a special issue on simulation appeared in 1983 in the journal "Operations Research," consisting of nine articles. Seven of them were about statistical issues, but none addressed the issue of model implementation or methodology. "Journal of the Operational Research Society" also produced a special issue on current simulation research in 1987. Of the ten articles included in the special issue, however, none was about model implementation. "Management Science" published a special issue on simulation in November 1989, focusing on the issue of variance reduction methods in simulation.

Nevertheless, the implementation issue was critical to the success of simulation. Finlay and Martin [1989, p.530] commented on the future of decision support systems (an observation which was believed equally applicable to simulation):

> "It is no longer possible to make significant progress by producing more mathematically complex or more technically sophisticated systems. For a substantial breakthrough, the behavioral, political and organizational aspects of decision-making need to be more forcibly addressed by practitioners, and the results taken up by both software suppliers and consultants in the field."

Several groups of researchers in the UK and Canada, aiming to tackle these non-technical issues in modelling, and to make use of the recent advancement of computer technology, especially the advancement of high quality computer graphics in micro-computers, developed a new type of simulation model called visual interactive simulation (VIS).

2.3 Visual Interactive Simulation (VIS)

The term visual interactive simulation (VIS) was first used by Hurr [1976] while he was working on job shop scheduling problems in manufacturing. It belonged to a broader problem-solving approach called visual interactive problem-solving (VIPS) [Bell, Parker and Kirkpatrick, 1984] or visual interactive modelling (VIM) [Bell, 1985a].

2.3.1 Visual Interactive Modelling (VIM)

"Visual interactive modelling (VIM) is not a single technique, but rather is a generic term for a range of interactive, graphical model-building methods" [Bell, 1985b, p. 975]. It was a process of building and using a visual interactive (VI) model to investigate issues important to decision makers [Bell, 1986]. A visual interactive model usually consisted of three main components:

- a visual model of a problem or system;
- one or more algorithms that derived a "good" solution to be displayed using the visual model; and
- a user-friendly interactive component to allow the user to run the model and display the results.

Visual interactive modelling researchers emphasized that the visual model was different from high quality presentation graphics because it was used as an integral part of problem-solving [Bell, Parker and Kirkpatrick, 1984]. Coupled with the interactive interface, a visual interactive model user could work with the model interactively (such as changing the values of some decision variable on screen during the model run) and examine the effect of different decisions in graphic form on the computer screen. "The power of VIPS (visual interactive problem-solving) as a decision-making tool comes from the confidence in the model that grows as the manager sees the model confirm his understanding of the real system" [Bell, Parker and Kirkpatrick, 1984].

The roots of visual interactive modelling stemmed from research into the use of graphic presentations to communicate status indicators in MS/OR modelling [Parker, 1986]. Examples of this research include Miller [1969], Shostack and Eddy [1971], Sulonen [1972], Palme [1977] and Janson [1980]. Graphic models in these studies were mostly representational graphics, i.e., bar charts, line plots, pie charts, or other forms of data representation. Early visual interactive models were mainly applied to geographically-oriented problems (such as facilities location, the travelling salesman problem, urban transportation system planning and truck routing) and project scheduling (including critical path analysis and PERT) which usually consisted of a map or chart in the problem-solving process. Later visual interactive models (mostly visual interactive simulation models) began to use iconic graphics to represent the dynamics of the operation/system under study, for example, an automatic assembly line with chassis and bodies moving from station to station. Bell [1986] provided more than a dozen references for these early applications. With the help of commercial visual interactive modelling/visual interactive simulation packages such as GENETIK, WITNESS, CINEMA and SIMFACTORY, available in the market beginning in the 1980s, visual interactive modelling had expanded its applications to many other areas such as timber processing [Garbini et al., 1984], corporate cash management [Bell and Parker, 1985, and Parker and Bell, 1989], financial planning [Jack, 1985], workforce (nurse) scheduling [Bell, Hay and Liang, 1986], hospital management [Jones and Hirst, 1986], manpower planning in banks [Billington, 1987], profit model/diagnosis [Pracht, 1990], production plant design [Bell and Chau, 1991], and waterfront management [Danielsen, Eldridge and Brown, 1991]. Kirkpatrick and Bell [1989a] gave results of a recent survey of visual interactive modelling in industry.

A significant methodological difference between visual interactive modelling and traditional MS/OR models was that, like decision support systems, visual interactive modelling used the prototyping approach and emphasized the importance of user involvement in the model development process. Also called the "evolutionary" approach [Keen, 1980] and "iterative" approach [Sprague and Carlson, 1982], prototyping referred to a process of building a "quick and dirty" version of system that performed only the most important functions. This "working prototype" was then tested and evaluated by user and builder together. System needs were redefined and the system was improved. The "test-evaluate-improve" process was repeated several times until a system satisfactory to both the user and the builder evolved. Turban [1988] emphasized the importance of user involvement in the prototyping approach. He said [Turban, 1988, p.152],

> "Involvement of users is a very important feature. Prototyping assumes that the user may actively participate in and direct the design. The requirement stems from a need for user expertise in the design effort, and also recognizes that successful implementation will be more easily achieved with active involvement."

Visual interactive modelling also saw model building and implementation as closely integrated activities. Parker [1986] proposed a four-phase visual interactive model-building approach consisting of:

1. visual model development;
2. interface development;
3. formal model building; and
4. data collection and model programming.

Parker associated this approach with the "soft systems" approach proposed by Checkland [1981]. During the entire model development process, the user was required to participate and give inputs, comments and recommendations on the visual interactive model. Bell [1986, 1987] called this approach "active VIM". It differed from the "passive VIM" approach which basically saw the visual interactive modelling as "not a new MS/OR method, but an implementation vehicle that increases the likelihood that the underlying MS/OR model or algorithm will be used" [Lembersky and Chi, 1984]. Hurrion [1980, p.87] described the benefits of the active visual interactive modelling as follows:

> "If the model progresses as the manager expects, then credibility in its use is increased. If, however, the model diverges from the expectations of the manager then this leads to direct communications between the analyst and the manager. Either the model is correct, in which case the manager learns from the situation, or the model is logically incorrect. If the latter is true then the manager can usually state the logical inconsistency in the model, since he is watching the dynamic visual representation. At the next interactive session with the inconsistencies rectified, the model soon ceases to become the analyst's model and becomes the manager's own management model. This observation has occurred on all management visual simulations developed to date."

2.3.2 Software Development for Visual Interactive Simulation

The software development of visual interactive simulation in the U.K. differed from its development in North America. In Britain, the first commercially available visual interactive simulation software package was SEE-WHY in 1979. Before that, visual interactive simulation model builders wrote programs in BASIC for the Apple II. Developed by the Operational Research Group at British Leyland in the U.K., SEE-WHY was a FORTRAN-based software and consisted of a Cromomco 8-bit microcomputer (Z80A microprocessor) which transmitted ASCII character strings to a linked Intecolor 8080 microprocessor-based microcomputer which converted the characters into graphics. It used Tocher's three-phase approach, in which a simulation was programmed as a number of bound and conditional events [Tocher, 1963].

In 1981, the OR group of the British Steel Corporation released a second visual interactive simulation package called FORSSIGHT (which was also marketed in the U.S. under the name WITNESS). FORSSIGHT was quite similar to SEE-WHY, also FORTRAN-based and using similar hardware. It offered improved visual facilities and incorporated a separate program to enable the model builder to create highly graphic visual displays using cursor movement and color keys. One important difference between FORSSIGHT and SEE-WHY was that in FORSSIGHT the background displays were saved on disk and recalled at run-time, while in SEE-WHY, the displays were entirely generated at run-time.

The third visual interactive simulation package was OPTIK, developed by Insight International Limited in 1982. It was basically a family of related products. OPTIK-1, the heart of the package, consisted of a set of general interactive graphics routines that allowed the model builder to build and display pictures of almost infinite size. The OPTIK-11 module included the facilities to construct visual interactive simulation models while the OPTIK-2 module was a relational data base. In 1986, Insight International Limited launched a new VIS package called GENETIK which used a more modular software design and had more general capabilities than OPTIK.

In April 1991, the company released the GENETIK version 8.50, with a simulation extension and a planning board extension.

Developments in North America had been heavily influenced by the popularity of two simulation packages: GPSS and SIMSCRIPT. The main difference between these North American products and the British ones was that they leaned more on "play-back type of animations" with relatively less interactive graphics capability.

GPSS was a simulation language developed by IBM in 1961. Important versions of GPSS developed by various software houses included GPSS/PC and GPSS/H. GPSS/PC included a number of graphics features and allowed movement of objects in two dimensions, animation of transaction movement in block diagrams, and dynamic statistical displays. TESS was an environment having graphics and animation features for GPSS/H simulations. AUTOGRAM postprocessed GPSS/H output to display animations of the modelled system [Bell,1991].

SIMSCRIPT was created by the RAND Corporation in the early 1960s as a discrete-event simulation language written in FORTRAN. The current PC version, SIMSCRIPT II.5, consisted of several additions for enhancing its graphics and animation capabilities. For example, SIMFACTORY was a factory modelling system with animation and interactive model development; SIMANIMATION was for moving pictures and charts; and COMNET provided a telecommunications modelling system with animation.

A more "VIS-like" package developed in North America was SIMAN/CINEMA. SIMAN was a combined discrete-continuous SIMulation ANalysis program which included an interactive graphics capability for model construction, output display and run-time interaction (through using a special release). CINEMA was a system which could provide a mouse/menu interface to design the animation display required in the SIMAN models. Therefore, when incorporated with the CINEMA system, SIMAN models could generate high resolution color graphics animation with considerable interactivity.

Another visual interactive simulation software package was XCELL+ developed by Conway, Maxwell, McClain and Worona in 1986 [Conway et al., 1990]. It was basically a factory modelling system which, Bell [1991] commented, was "the closest approach to end-user VIS software available". It was very easy to use but limited in its scope of applications.

Finally, the growth of object-oriented programming systems offered an interactive graphic development and processing environment for the development of visual interactive simulation models. Object-oriented languages, such as SMALLTALK and object-oriented packages such as AUDITION, provided a graphical design interface that evolved into the interpretive end-user's model. Parker [1991, p.4] argued that "this offers enhanced flexibility to modify parameters or attributes of the model at run-time, but at the potential expense of auditability of model integrity".

2.3.3 Comparing Visual Interactive Simulation with Traditional Simulation

Bell and O'Keefe [1987] stated that visual interactive simulation was the most important development in the practice of discrete-event simulation since the introduction of the first simulation language in the late 1950s. It was the one format of visual interactive modelling that had by far the greatest impact on MS/OR [Bell, 1986]. In short, visual interactive simulation was the development and application of simulations which produced a dynamic display of the system model, and allowed the user to interact with the running simulation.

Visual interactive simulation differed from traditional simulation in a number of ways. Broadly speaking, however, they could be grouped into two: technical and methodological differences.

Technical differences

1. Visual interactive simulation was usually coded in specialized visual interactive modelling/visual interactive simulation software packages such as WITNESS, GENETIK and CINEMA in order to ease the programming of dynamic graphical computer displays and the handling of a broad range of interactions with the model. Traditional simulation, on the other hand, was still mainly programmed in general purpose programming languages such as FORTRAN and PASCAL [Paul, 1991]. Respondents to a recent visual interactive

modelling survey reported that their visual interactive modelling software was more difficult to code, but simpler to debug and easier in on-going use than other software packages they had used [Kirkpatrick and Bell, 1989a].

2. Because the visual model and the interface had to be coded into the model, the program was generally much bigger and more complex than the simulation built in a traditional non-visual and non-interactive mode [Kirkpatrick and Bell, 1989b]. Also, because of the dynamic visual displays during the simulation model run, the speed of execution was much slower than its traditional counterpart.

3. Since visual interactive simulation emphasized both visual and interactive, its output was different from traditional simulation models with "animated" output which was often programmed and produced by a post-processor that developed the graphics from the output of a batch simulation [Kirkpatrick and Bell, 1989b].

Methodological Differences

1. The most important difference between visual interactive simulation and traditional simulation was the modelling approach that was adopted. As discussed in Section 2.3.1, visual interactive simulation adopted an active visual interactive modelling approach that was very different from the traditional one

that mainly relied on the traditional OR methodology (see, for example Wagner [1970]). In active visual interactive modelling, model validation was basically an on-going process throughout the whole model-building exercise. In the traditional OR methodology, the validation step usually started after the model was programmed and verified.

2. In traditional simulation model development, the model was verified by checking the program codes and validated by testing the model with real data, mainly performed by professional simulation specialists. In visual interactive simulation, however, a large part of model verification and validation was done by the model user, rather than the technical model builder, by running the model and observing the displays of the visual model. Bell [1985a] claimed that it could help confirm the "conceptual" and "experimental" validity [Landry, Malouin and Oral, 1983] of the model.

3. Another difference of visual interactive simulation from traditional simulation models was that, in visual interactive simulation, the process of problem definition and formulation was done through the design of the visual model, in which the user was highly involved. Pictures were used to represent detailed problem statements in words.

4. Finally, visual interactive simulation differed from simulation with animation because the primary objective of the former was user interaction with the

running simulation, while the latter was basically a portrayal of the simulation [Bell and O'Keefe, 1987]. Model interaction was neither common nor considered as important in simulation with animation.

2.4 Issues on Decision Support Using Simulation

A number of important issues had to be resolved when using simulation in decision support systems; these included methodological, technical, statistical, and behavioral issues.

2.4.1 Methodological Issues

An important question in decision support using simulation was the role of simulation in the system. Paul [1991] argued that simulation modelling was mainly used as a vehicle for understanding a problem rather than for problem solving. "The tendency is to use simulation modelling as a vehicle for debating about the problem" [Paul, 1991, p.220]. In other words, it played only a small, though very important, part in the process of decision support. Bell, Taseen and Kirkpatrick [1990] stated that some animated simulation models were not very helpful to a decision maker facing the analysis of a complex problem. Hurrion [1978] and Bowen et al. [1979], however, claimed that visual interactive simulation could help the user not just understand, but also analyze, the problem through watching the progress of a simulation model in an animated form and interacting by using different decision strategies with the model. To what extent a simulation model in general, and visual interactive simulation in particular, could help in a decision support role was thus an important issue. Its usefulness affected and was closely related to the question of what kind of modelling approach should be adopted.

In visual interactive simulation, an important methodological issue was the debate between the "passive visual interactive modelling" approach and the "active visual interactive modelling" approach [Bell, 1987]. The passive visual interactive modelling approach could be seen as an extension of the traditional simulation approach and was technology-led. The simulation model was built first and then the animation portion was added onto the original model. The active visual interactive modelling approach, however, was basically a novel approach which attempted to "revolutionize" the old simulation methodology. The building of the visual model in a visual interactive model was a key and the first part of the modelling process. The development of the formal mathematical model was not begun until a satisfactory visual model evolved. Although some claimed it was better than the passive visual interactive modelling [Bell, Taseen and Kirkpatrick, 1990], other researchers had advocated a more "passive" approach [Lembersky and Chi, 1984].

2.4.2 Technical Issues

Since simulation had been (and is still) technology-driven, Paul [1991, p.218] raised a question: "Will we be able to develop our ability to use the available power as fast as the available power is increasing?" Many researchers were attempting to develop automatic simulation modelling environments in order to enable the analyst to spend more time on the problem-solving aspect of the modelling task. Two prominent groups in this area were the CASM project group at the LSE in London, England and the SMDE group at Virginia Tech in the United States [Chau, 1990]. The use of artificial intelligence in simulation was an important issue in extending the power of simulation for decision support. Moser [1986], O'Keefe [1986] and Paul [1989] discussed the idea of integration of artificial intelligence and simulation.

Another major technical issue in visual interactive simulation was whether or not the visual interactive simulation modeller needed access to "the code" [Bell, 1991]. A visual interactive simulation package such as GENETIK provided an interactive environment where the user could build, edit, and run visual interactive simulation models using GENETIK functions, commands and statements. The view was that because of the interactive environment, code generation was not necessary. Another visual interactive simulation package, VS6, also provided an interactive environment for model specification but, unlike GENETIK, this could be used to generate a PASCAL source code for the model. The user could edit this code to accommodate problem features that could not be handled by the VS6 interface. Proponents of these code-generating visual interactive simulation packages claimed that access to the code provided complete flexibility. This issue determined the approach to future VIS software package development.

2.4.3 Statistical Issues

Statistical issues in simulation formed by far the most extensive area of research. Reviews of simulation usually had a substantial proportion of pages devoted to statistical analysis of simulation. Statistical issues in simulation included:

- how to validate the simulation statistically;
- how to reduce variances from the sample run; and
- how to analyze the simulation output statistically.

Statistical Validation of Simulation Models[2]

A simulation model was always only an approximation of the actual system. Therefore, trying to determine whether or not the simulation model was an accurate representation of the actual system was one of the most important issues facing any simulation builder/user. The key question was to determine how statistically representative were the simulation output data. A number of statistical approaches had been suggested for comparing the output data from a simulation model with those from the corresponding real-world system. Law and Kelton [1982a] reviewed four major approaches, namely classical statistical tests, inspection approach, confidence-interval approach, and spectral-analysis (time-series) approach. Balci and Sargent [1982] discussed validation using Hotelling's two-sample T^2 test. Torn [1985]

[2]This section mainly covers the statistical aspect of model validation. A broader discussion of simulation model validation, including both quantitative and qualitative analysis, appears in Chapter 3, Section 3.1.

proposed the use of simulation nets. Friedman and Friedman [1985a] suggested the use of a holdout sample and double cross-validation. Velayas and Levary [1987] proposed a procedure using decision theory in the validation of simulation models.

Variance Reduction

Simulations driven by random inputs produce random outputs. A number of methods, collectively called variance-reduction techniques (VRT), had been proposed to reduce the variances of an output variable from a simulation without disturbing its expected value. The goal was to obtain greater precision, that is smaller confidence intervals for the same time length of simulation, or, alternatively, to achieve a pre-specified precision with shorter simulation. Major variance-reduction techniques included common random numbers, antithetic variates, control variates, indirect estimation, conditional expectations, stratified sampling, systematic sampling, importance sampling, and jack-knifing. Law and Kelton [1982a], Bratley, Fox and Schrage [1985], James [1985], Ripley [1987] and Davies and O'Keefe [1989] each provided thorough discussion on several of the different variance-reduction techniques listed above. When the simulation model was used for comparing alternative systems, the common random numbers method was recommended by many researchers (Kleijnen [1976], Heikes, Montgomery and Rardin [1976], Law and Kelton [1982], Friedman and Friedman [1986] and Sloan and Unwin [1990]). In essence, statistical validation concerned the statistical "effectiveness" of a simulation model and variance reduction referred to the statistical "efficiency".

Output Analysis

Output analysis concerned how to use the simulation output to analyze/solve the problem. A key issue in output analysis was how to handle the "start-up" problem. "Start-up" problems occurred because many simulation studies aimed to deduce the steady-state results of output variables. A simulation run usually passed through a transient period before it reached the steady-state. This transient period was referred to as the "start-up" period. Since a simulation run had to end somewhere, determining the length of this period and then removing the data obtained during this period were important for obtaining good estimates of output variables in the steady-state. Wilson and Pritsker [1978a, 1978b], Schruben [1982] and Kelton and Law [1985] provided overviews of research on the simulation start-up problem. The methods suggested broadly included

1. starting the simulation with values of variables as close to the steady-state mode as possible;
2. running the simulation a sufficient length of time; and
3. truncating some data generated in the early simulation run according to some kind of truncation rules.

Bell [1989] suggested using visual interactive simulation and a paired-difference experiment to detect the length of the transient period.

Analyzing simulation output included variable estimation and alternative system comparison. Variable estimation essentially required replicated runs (with different streams of random numbers) to obtain a confidence interval for the estimate. Another method was to make a single extremely long run, throw away the initial part of that single run (due to the start-up problem), and then divide the remaining large part into a number of batches. These batches were then treated as separate runs for confidence interval construction. Law and Kelton [1982b], Schmeiser [1982], Adam [1983], Kleijnen [1984], Kelton and Law [1984], and Law and Kelton [1984] surveyed methods which produced confidence intervals for variables estimated by simulation. Approaches included replication, batch means, autoregressive representation, spectrum analysis and regeneration cycles.

Comparing alternative simulated systems was another important task in output analysis. It could be even more important than variable estimation since the aim of many simulation studies was to compare alternative solutions to a problem and then choose the best one [Amer, 1982]. Comparison might take place

1. between the means and variances of a certain variable of one system and those of another system [Kleijnen, 1976]; or
2. between the probability distributions of the interested variable [Friedman and Friedman, 1985b].

Various methods, including both parametric and non-parametric, had been proposed. For example, regression analysis was suggested by Kleijnen [1981]; a distribution-free statistic with blocking by random number stream by Friedman and Friedman [1986]; multivariate statistical methods by Friedman [1986]; and two-way analysis of variance by Balmer [1987].

For the first type of comparison (which was much more common than the second type), many studies suggested the use of paired-difference statistics in comparing alternative simulated systems (for example, Kleijnen [1976], Heikes, Montgomery and Rardin [1976], Law and Kelton [1982], Balmer [1987], Hoover and Perry [1989], and Sloan and Uniwin [1990]). Paired-difference statistics could be sample mean or variance of differences of paired samples. The paired samples might be throughput/unit time, mean time-in-system, operating cost/unit time, or contribution/unit time. By independently running two alternative simulated systems many times and computing the differences of interesting variables, paired-difference statistics were obtained. A major benefit of paired-difference statistics was that they were independent and identically distributed random variables. Standard parametric statistical tests could then be used for output analysis.

The above studies used paired-difference statistics mainly for comparing interesting variables in the steady-state. Bell [1989] suggested that analysis of the transient state was also important in comparing two alternative simulated systems. He further proposed using paired-difference statistics together with paired-systems (in visual interactive simulation). By running two alternative simulated systems simultaneously and displaying run-to-date statistics on screen, the sensitivity of the statistics to run-times could be investigated directly. Bell [1989] used a "hub" service system as an example to illustrate the benefits of using paired-systems and paired-difference statistics in visual interactive simulation.

Finally, simulation specialists such as Kleijnen [1976], Heikes, Montgomery and Rardin [1976], Law and Kelton [1982], Friedman and Friedman [1986] and Sloan and Unwin [1990] suggested the use of the common random numbers method as the variance reduction technique in evaluating alternative simulated systems. Kleijnen [1988, p.65] stated that "not only academic researchers had advocated common random numbers, but practitioners also applied this technique". Law and Kelton [1982a, pp. 352-354] provided an example showing the power of using common random numbers in variance reduction. In the example, the variance was reduced by approximately 96%. Bell suggested that by coupling paired-difference statistics with the common random numbers method; "different control rules for the same system can be used to plan management of a proposed system" [Bell, 1989, p.622].

2.4.4 Behavioral Issues

Statistical validity was a necessary condition for a simulation model to be useful for decision support. A sufficient condition was that the user had confidence in the system, accepted it and knew how to use it. It was related to the issue of implementation, a topic which was (and still is) discussed by management scientists/operations researchers as early as 1965 [Churchman and Schainblatt, 1965].

Model Confidence and User's Acceptance

"Model confidence is not an attribute of a model, but of the model user" [Gass and Joel, 1981]. The usefulness of a decision support system as an aid in resolving a specific problem depended on the extent to which the user accepted the model output as an active part of the decision-information set. In other words, model confidence could be defined as and expressed by the degree of willingness that the user had in employing the model output in making decisions.

The role of the model output in the decision process was based on the user's understanding and evaluation of the total modelling process that had produced the output. Early research such as Churchman and Schainblatt [1965] had pointed out the gap between the user's problem and the researcher's problem. Recent studies by O'Keefe [1989] stated the importance of understanding the user's cognitive style in order to get MS/OR used and accepted. Favreau [1979, p.103] said that "the cornerstone for establishing the credibility of a computer simulation is effective communication between the model builder and the model user". Balci and Nance [1985] and Bryant [1988] expressed similar views.

The traditional MS/OR (including simulation) modelling approach did not emphasize the importance of builder-user communication. Checkland's [1981] soft systems methodology included a line separating the "real world" from the "world of system thinking". The "real world" was the tangible set of objects and interactions which made up the physical, intellectual and social environments of the system under scrutiny, while the "world of systems thinking" was an abstract set of ideas and concepts which enabled the analyst to develop new insights into the "real world" [Pidd, 1988]. The traditional approach, however, seemed to spend too much time in the abstract world of models, computer programs, mathematics and statistics. The visual interactive modelling approach, especially the active VIM, might, however, be able to overcome the problem that the traditional approach had. The visual interactive modelling approach encouraged and asked for frequent communication between the builder and the user. Its visual model building process enabled the user to think over what he/she actually wanted and to understand the meaning of the model output. It provided an opportunity to close the gap between the user and the researcher. Also, its top-down approach, in which the problem was formulated and appropriate screens and interactions were designed prior to the choice of any model to aid the user, helped to overcome the barrier created by cognitive style and biases to the use and acceptance of the model [O'Keefe, 1989].

Output Interpretation

Another issue affecting the success of a decision support system was the ability of the user to interpret the output correctly. It related to the statistical issue of output analysis. Interpretation of numerical statistical output correctly by a user without sufficient training in simulation and statistics was not easy. Providing output results in a graphical form as in many visual interactive simulation applications might, on the one hand, ease the user in and provide a learning mechanism for understanding the results, but could, on the other hand, create the danger of interpreting and accepting the results too early and too easily.

> "Because the user thinks he can see what the simulation model does, he might think that he understands the system it is trying to emulate. Snapshots of a running visual simulation model are a dangerous yardstick to determine what is going on in the system over time" [Paul, 1991, 224].

Another potential problem in visual interactive simulation arose because values of decision variables were usually allowed to alter interactively in the middle of a simulation run at the user's will; statistical analysis afterwards might, therefore, become invalid. In this case, the output interpretation would have to be carefully done.

2.5 Potentials of Visual Interactive Simulation and Paired-Difference Statistics

2.5.1 Plausible Benefits to Decision Support

Bell [1989, p.624] said, "The simultaneous display of long-run and transient system behaviour, and the use of visual paired-difference experiments appear to be useful modelling approaches to help both modeller and manager validate and use a stochastic visual interactive simulation model". Based on the discussion from previous sections, it seemed that the above quotation was likely to be true. Visual interactive simulation and paired-difference statistics (with the common random numbers method) seemed to provide a number of benefits for decision support. Visual interactive simulation might:

- be more effective than traditional simulation in providing decision support to the user in terms of, for example, shorter decision time and better decision outputs such as higher contribution or lower production cost;
- provide the user with an opportunity to understand and learn about the underlying mechanism of the system being studied;
- help validate the simulation model and, by displaying the simulation run dynamically, the user might detect any modelling or logical errors through observing the displays;
- help detect the length of the transient period (with paired-difference experiments);
- help build the model confidence and the user's acceptance of the system; and
- help ease the interpretation of simulation outputs.

Paired-difference statistics (used in visual interactive simulation and in combination with the common random numbers variance reduction method) might:

- make comparison of two alternative systems easier than running and comparing two separate systems, by sharpening the differences between the two systems.
- allow two alternative systems to be compared not only at the steady-state, but also at any time during the simulation run.

2.5.2 Needs for Empirical Research

Although real-life applications such as Danielsen, Eldridge and Brown [1991] and Bell and Chau [1991] had demonstrated the power of using visual interactive simulation in decision support, evidence to support the claims of superiority of visual interactive simulation remained anecdotal [Kirkpatrick and Bell, 1989a]. Parker [1991] conducted an experiment to evaluate the effectiveness of a visual interactive financial model with 33 senior undergraduate students and 16 executive MBA students. His results offered support for the benefits of computer graphics. O'Keefe and Pitt [1991] conducted an experiment which examined user interaction with a visual interactive simulation model. Twenty-five Masters' students in either Business Administration, Industrial Engineering or Operations Research were recruited as subjects. Their results showed that performance with the visual interactive simulation model was "mediocre" [O'Keefe and Pitt, 1991, p.344]. However, in their conclusion, they suggested future experimental work which compared

> "the use of a visual interactive simulation to other methods...... the specification and testing of more formal hypotheses is a necessary follow-up to the general analysis conducted here" [O'Keefe and Pitt, 1991, p.347].

The benefits of paired-difference statistics with the common random number method had also been illustrated in several books on simulation (for example, Law and Kelton [1982]). Therefore, the "combined" power of using both visual interactive simulation and paired-difference statistics (with the common random numbers method) together in a single decision support system seemed to be worth researching.

An empirical investigation of the power of a visual interactive simulation with paired-systems (i.e., both alternative simulated systems were displayed on the same screen simultaneously) and paired-difference statistics was recommended. In particular, the empirical study should try to test whether or not this type of visual interactive simulation model was better than a "conventional" visual interactive simulation model and a traditional simulation model in terms of decision quality, decision speed, learning about the system being studied, and decision confidence.

CHAPTER 3

RELATED LITERATURE

Chapter 2 concluded with a recommendation for developing an empirical research project to investigate the usefulness of two types of visual interactive simulation models, conventional visual interactive simulation models and visual interactive simulation models with paired-systems and paired-difference statistics. In order to evaluate further the research need for this topic and to strengthen the foundation of the research design to be presented in Chapter 4, this chapter provices a comprehensive review of the literature on the issues related to the proposed project.

From the managerial decision support perspective, Liang [1986] reviewed about 120 previous studies relating to critical success factors of decision support systems. In essence, the literature suggested that an effective decision support system must satisfy the following conditions:

- the model must be verified and validated by the user;
- the system must be accepted, used and implemented by the user;
- the results produced must be better, in terms of decision quality and decision speed, than other decision support aids available to the user;
- the appropriate tools/techniques must be available (i.e., already incorporated in the decision support system) for comparing alternative systems.

The first condition related to the simulation model validation issue, while the second condition concerned model implementation. The third condition required the study of the overall usefulness of graphics in general, and visual interactive simulation, in particular, in decision support systems. The final issue related to the tools/techniques available for comparing alternative simulated systems. The following sections review the studies on these four issues.

3.1 Simulation Model Validation

Model validation has long been an important research topic in the MS/OR literature. It was different from model verification which was basically the process of ensuring that the computer code was a correct implementation of the conceptual model. Also, the validity of a model was essentially a matter of degree, and not a determination of whether the model had or did not have validity [Shannon, 1975].

Landry et al. [1983], combining and incorporating previous work on model validation such as Naylor and Finger [1967] and Majone [1980], provided a comprehensive view of model validation. They suggested that there were five different validation activities (Figure 3.1):

- conceptual validation,
- logical validation,
- experimental validation,
- operational validation, and

- data validation.

Conceptual validation was mainly concerned with the problem formulation process. Logical validation examined the capacity of the simulation model to describe correctly the problem formulated. Experimental validation looked into the quality and efficiency of the solution mechanism. Operational validation considered whether the solutions and recommendations were operationally useful and usable which, in turn, indicated whether or not there was justification in running the model and implementing the recommendations in terms of the time, efforts and costs. Finally, data validation was concerned with the sufficiency, accuracy, appropriateness, and availability of the data within acceptable cost limits (Landry et al. [1983]).

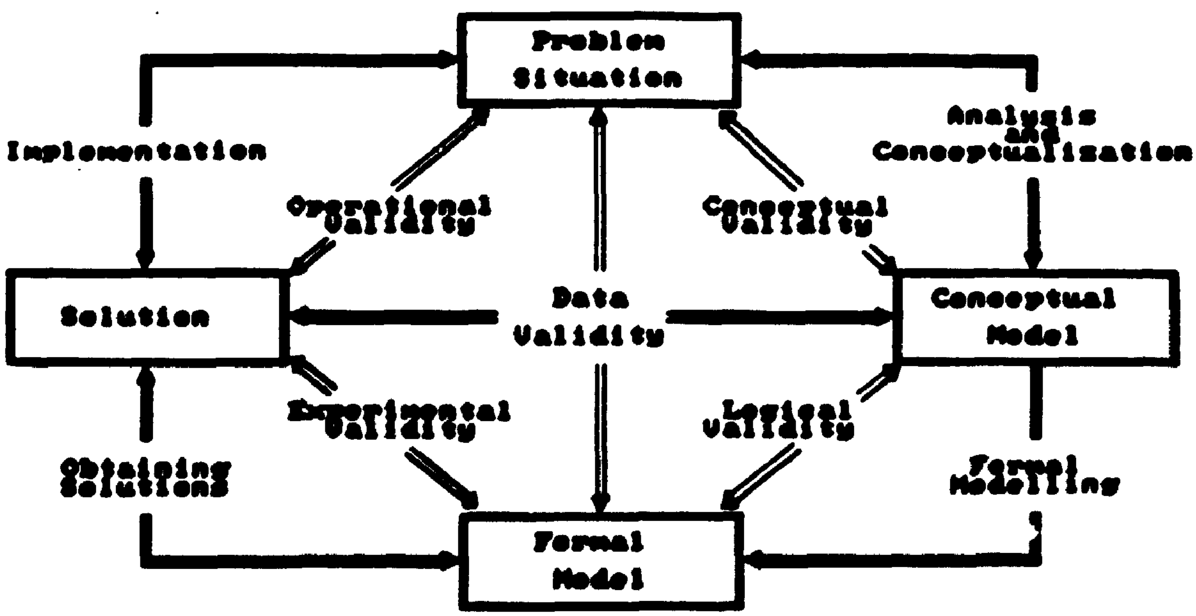


Figure 3.1 Five different activities of model validation (after Landry et al., 1983)

Various statistical procedures for validating a simulation model had been proposed by MS/OR researchers, for example, Stafford [1976], Balci and Sargent [1980 and 1982], Torn [1985], Freidman and Freidman [1985a] and Velayas and Levary [1987]. Simulation texts such as Ziegler [1976], Law and Kelton [1982a] and Hoover and Perry [1989] also described standard statistical procedures for validating a simulation model. These procedures included tests of means, analysis of variance or covariance, goodness of fit tests, regression and correlation analysis, spectral analysis and confidence intervals. The process of validation might conclude that the model was one of the following three types: replicatively valid, predictively valid and structurally valid [Gass, 1983]. A model was replicatively valid if it matched data already acquired from the real system. It was predictively valid when it could match data before the data were acquired from the real system. It was structurally valid if it not only reproduced the observed real system behaviour, but also accurately reflected the way in which the real system operated to produce this behaviour.

A major weakness of these traditional statistical procedures for simulation model validation was that they mainly concentrated their efforts on the activities shown in the lower half of Figure 3.1, namely logical validation and experimental validation. Conceptual validation (which was mainly concerned with problem understanding and problem structuring) and operational validation (which related to the issue of model implementation) were neglected. In terms of Checkland's [1981] soft system methodology, traditional procedures spent much of their time in the "world of systems thinking".

Gass [1983] also argued that most statistical procedures for simulation model validation were too technical. For a decision-aiding model, "validation tends to be the over-riding concern of the analyst......the process of validating a model must go beyond applicable statistical tests" [Gass, 1983, p.609 and p.612]. He proposed a more general validation framework consisting of three types of validation activities: technical validity, operational validity and dynamic validity.

Another major weakness of the statistical validation methods was that they were basically "post-modelling" and "post-simulation" procedures. The validation process was separate from the simulation model development process and from the running of the simulation. It could be argued that this separation between the model validation process and the model development process (and the model run) would lower the chance of subsequently implementing the simulation model.

Hurrion and Secker [1978] acknowledged the weakness of the statistical validation procedures and argued that visual interactive simulation was a better approach for modelling simulation systems because the visual model development process allowed the user to start the validation process as soon as the visual interactive simulation project started. Model confidence by the user was built up along with the model development process and the issues of both conceptual validation and operational validation were addressed. Bell [1985a], Bell and O'Keefe [1987], Kirkpatrick and Bell [1989] also suggested that visual interactive simulation could at least help to improve the conceptual validity, logical validity and experimental validity of a simulation system. Johnson and Loucks [1980] argued for the usefulness of interactive graphics in data validation. The use of interactive graphics "greatly reduces the programming effort required to input new data or modify existing data associated with optimizing or simulation models" [Johnson and Loucks, 1980, p. 96].

Balci and Nance [1985] pointed out the importance of conceptual validity and argued that an explicit requirement of model credibility (validity) was "formulated problem verification". They first suggested a procedure which guided the modeller to formulate problems and then proposed some indicators to check the formulated problem verification. They emphasized that correct problem formulation was extremely important for the successful conclusion of a simulation project.

In summary, the literature suggested that the traditional simulation model did not provide an environment for developing the five types of model validation activities suggested by Landry et al. [1983]. The visual interactive modelling approach seemed to be better in terms of its power to facilitate and improve the simulation model validation process.

3.2 Decision Support System/Simulation Model Implementation

The goal of a decision support system/simulation project is certainly not the modelling itself. Modelling is just the means of achieving a goal. Whether or not the model is subsequently implemented and used by the intended user is a key and fundamental criterion for judging the success of the decision support system/simulation project. Schultz, Slevin and Pinto [1987] described a valid but unused model as a project which had committed the "Type IV" error. The main problem was low user acceptance of the model.

The issue (and problem) of model implementation is an old one. The seminal work by Churchman and Schainblatt [1965] resolved that "the problem of implementation is the problem of determining what activities of the scientist and the manager are most appropriate to bring about an effective relationship between the two" [Chu.chman and Schainblatt, 1965, p.B-69]. Schultz and Slevin [1975] (cited in Hilberbrant [1980]) complained that

> "despite the promise of OR as a problem-solving discipline, the current situation reveals a significant gap between theory and managerial applications....... It appears that we have a real problem. Our ability to provide managers and user organizations with a system they will find useful and will adopt has not kept pace with our growing technical capacity" [Hilderbrant, 1980, p.4].

Pidd [1988] also urged MS/OR practitioners to take seriously the notion that the implementation of their work deserved as much attention as did the technical aspects that underlined their recommendations.

Implementation always involves changes of existing operations and/or people's working habits, and people resist change. Therefore, the issue of implementation practice is to look for ways to overcome resistance and to ensure a smooth transition of the changes. Hilderbrant [1980], Ginzberg and Schultz [1987] and Pidd [1988] were three recent studies which reviewed the research on implementation of MS/OR done since the mid-1960s. From a practical/managerial point of view, three main themes emerged:

- the roles of modeller/management/user to improve the chance of implementation success,
- the effects of changing technology on implementation practice, and
- the implementation strategy and model-building approach.

Roles of Modeller/Management/User

Churchman and Schainblatt [1965] stated the importance of closing the gap between the analyst and management for successful implementation of MS/OR and of encouraging frequent communication between the two. Malcolm [1965] suggested that in order to achieve a greater percentage of projects that would produce meaningful results, the analyst should try his best to secure management's continuing review and participation in defining and supporting the modelling project. Batson [1987] said that the modeller should play a key role as a communication facilitator, to explain to management the research methodology used and the research results obtained. Another task of the facilitator was to seek methods for overcoming resistance to change, altering managerial attitudes and gaining managerial acceptance of recommendations.

A number of researchers have used the factor approach to study the key factors to achieving a more effective implementation of MS and MIS (for example, Ginzberg [1978]). Three consistent findings were:

1. user-modeller interaction was key,
2. user involvement in the design of the alternative was necessary, and
3. management support was required for implementation success.

In simulation projects, Annino and Russell [1981] also argued that an inadequate level of user participation was one of the main reasons for simulation project failure. They suggested that the development plan should provide regularly scheduled briefings, progress reports, and technical discussions with expected users of the model.

Therefore, based on the above studies, implementation success seemed to depend upon three groups of people: modeller(s), user(s) and management. Each party should ensure sufficient communication with and support from the other two parties.

Changing Technology

The rapid advancement of computer technology, especially micro-computers and computer graphics, has had a great impact on the issue of simulation modelling and implementation.

McAulay [1987] examined the impact of modern software development tools and methodologies and found that these tools and techniques shifted the emphasis (and the bulk of the effort) in software development and implementation from the "back end" (detail design and coding) to the "front end" (planning and information specification). This change gave management a greater opportunity to participate in the development process. McAulay also stressed that management had a central role to play in successful system implementation, and that the new software tools enabled management to play that role better.

The Lewin-Schein model of change (Lewin [1947] and Schein [1969]) described any change process in terms of three sequential stages: unfreezing, moving and refreezing. The unfreezing stage dealt with activities that helped to create an awareness of the need to change. The moving stage involved lea ning new attitudes and methods. The refreezing stage consisted of activities that helped to reinforce the changes and stabilize the new situation. Bell [1987] argued that visual interactive simulation, using state-of-the-art computer technology in graphics and interface, contributed to the process of successful implementation. With the visual and interactive components, the visual interactive simulation could illustrate why the existing system (or method of operations) was inadequate and could create an awareness of the need for change. The visual interactive simulation could also help to facilitate and reinforce the change by demonstrating, visually and interactively, how the new system could solve the problem present in the existing system. Porter [1991] described a case study which highlighted the benefits of using visual interactive simulation as a communication tool during the whole project.

Implementation Strategy and Model-Building Approach

The traditional model-building approach adopted a process model which characterized the modelling process in terms of generic phases that had to be managed sequentially for the system to be eventually successful. The model was created independently of the user and the organization, and implementation was usually the final step of the modelling process. This separation led to many failures of model implementation and Bonder [1977] complained that "the results of OR practice, especially in long-range planning studies, are often not well regarded or used by the decision maker" (cited in Hilderbrant [1980], p.4).

The development of the prototyping approach in decision support systems and the visual interactive modelling approach changed the view of implementation in the model-building process. Implementation was not considered as a distinct step but it started early in the model development project and continued throughout the entire model-building process [Alter, 1980]. By dividing the project into manageable pieces and using prototypes, the model was implemented bit by bit until it became a full-fledged version. Hilderbrant [1980] and Pidd [1988] discussed in detail how the evolutionary or exploration approach affected the implementation strategy by viewing it as a "continued" step throughout the entire model-building process.

In conclusion, successful DSS/simulation implementation required a modelling approach which could:

- provide adequate user-modeller interaction,
- secure user involvement and management support easily,
- pass through the three main phases of change, and
- allow implementation to be carried out continuously throughout the entire model development process.

Visual interactive simulation seemed to be a plausible modelling approach satisfying these requirements.

3.3 Visual Interactive Simulation and the Usefulness of Graphics in Decision Support Systems

The value of computer-generated graphics as aids to decision making has long been an important research topic in the MS/OR/MIS literature. DeSanctis [1984] conducted a detailed review of the topic. With 116 references, she concluded that "despite claims on the part of vendors that the use of graphics will improve decision speed and quality over traditional methods of data display, the available evidence is far from supportive" [DeSanctis, 1984, p.463]. Subsequent studies reported both positive and negative results.

Benbasat and Dexter [1984] conducted an experimental evaluation of graphical and color-enhanced information presentation. The experiment was designed to investigate the main and interactive effects of report format, color and individual differences among the subjects. Their conclusions suggested that there were no performance differences due to tabular versus graphical format differences. However, color did improve decision quality, especially for subjects who were field-dependents and for subjects using graphical reports.

Remus [1984], reporting on an empirical investigation of the impact of graphical and tabular data presentations on decision making, concluded that the tabular aids outperformed the graphical aids.

Benbasat and Dexter [1986] investigated the effectiveness of color and graphical information presentation under varying time constraints (also reported in Benbasat, Dexter and Todd [1986]), and found that tabular reports led to better decision making whereas graphical reports led to faster decision making. Also, color led to improvements in decision making.

Liang [1986] studied the effect of the presentation format on decision performance and user satisfaction. He found that the presentation format was the main contributor to user attitudes towards DSS and that tabular reports were superior to graphs. Benbasat and Nault [1990], however, commented that this outcome was a consequence of the nature of the task; accurate numbers, rather than trend information, were required.

Dickson, DeSanctis and McBride [1986] conducted three laboratory experiments investigating the effectiveness of different formats. The overall conclusion they reached was that task environment (content, complexity and structure) modified the effectiveness of a given presentation and this influence seemed to be based on the volume of data and the precision required. Line plots outperformed tables in the task with higher levels of complexity and structure. Graphics were superior when large amounts of information were presented and whenever time dependent patterns or recall of specific facts were required.

MacKay and Villarreal [1987] examined the performance differences in the use of graphic and tabular displays of multivariate data. The study compared judgments made from Chernoff's faces (a multivariate display technique, Chernoff [1973]) with judgments made from traditional tabular displays of financial figures. The results showed that the relative contribution of graphical displays to decision making might vary considerably from situation to situation.

Montazemi and Wang [1989] performed a meta-analysis on the effects of modes of information presentation on decision making. They reviewed twenty-four published studies and cumulated the results of sixteen of these by the application of the meta-analysis technique. Their study concluded that the bar presentation format was slightly better than the tabular one in terms of information precision, while multi-color presentation was superior to the tabular format in terms of information relevancy.

A major weakness of these various studies was that they basically investigated the effectiveness of static, representational, and output graphics of decision support. Graphics could be static or dynamic, representational or iconic, and could show model output or model running (Figure 3.2).

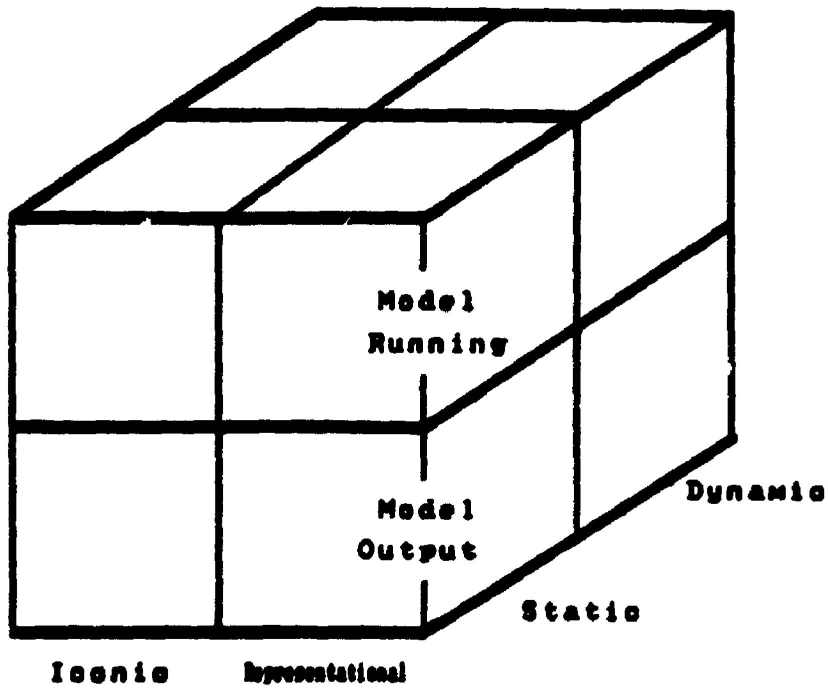


Figure 3.2 Different types of graphics

Static, representational and output graphics may be said to be the "most primitive" ones, while dynamic, iconic and model running graphics are the "more advanced" types of graphics which visual interactive simulation models usually provide. This type of visual interactive simulation graphics could be used not only for output analysis (the usual use of "most primitive" graphics) but also for problem analysis, problem understanding and even problem structuring. Many MS/OR researchers have discussed the usefulness of this type of graphics in supporting decision making. Crookes [1982. p.5] discussed its benefits in building model confidence and said,

> "it (the dynamic pictorial display) aids the analyst's client in enabling him to have grounds other than faith for believing the computer program to be a fair representation of his real world and a reasonable repository for his trust in making serious decisions....... a credibility gap has been closed in one stroke".

Aiding communication between the model user and the analyst was another important advantage of graphical displays which many visual interactive modelling researchers had claimed, for example, Withers and Hurrion [1982], Smith and Platt [1987], and Bell [1987]. Danielsen, Eldridge and Brown [1991] used a visual interactive simulation model to plan a waterfront rationalization project and concluded that "the visually-interactive aspect of the simulation was invaluable. It provided a common focus which all parties could understand, and so gave a credibility to the model without which the study would have faltered" [Danielsen, Eldridge and Brown, 1991, p.13].

Pracht and Courtney [1988] examined the effects of an interactive graphics-based DSS to support problem structuring. An experiment was designed to determine whether use of a graphical, interactive, problem-structuring tool led to a better understanding of problem structure. Their results showed a statistically significant effect between cognitive ability and the use of the interactive graphics-based DSS.

Kirkpatrick and Bell [1989] conducted a survey of visual interactive model builders and reported that 14 percent of the respondents said that the graphics component enhanced their understanding of various aspects of the problem or the mathematical techniques "incredibly", while 43 percent reported "greatly" and 33 percent reported "moderately".

Pracht [1990] discussed the need for graphics support in business problem modelling and problem structuring. He proposed a decision support system modelling framework based on a concept of "model visualization" that was, in principle, parallel to the visual interactive simulation approach. A "Profit model" was built using an object-oriented language called SMALLTALK/V. It was demonstrated that the model led to a greater level of support in problem structuring and provided a qualitative understanding of the dynamics of the system not available through typical quantitative analysis.

Angehrn and Luthi [1990] also supported the importance of model visualization. Combining this concept with AI techniques, they built a system called "Tolomeo", used in planning and analyzing a communication network. They concluded that

> "it (the visual interactive model) can be crucial in supporting DSS users in:
>
> (1) gaining new insights into the structure of their problems by generating different views of the decision situation, and
>
> (2) exploiting their own visual skills so that they can recognize meaningful alternatives and strategies during the problem-solving process" [Angehrn and Luthi, 1990, p.23].

Bell [1991] argued that the usefulness of graphics in decision support had been demonstrated by the strong preference for graphics options in the marketplace. The basic problem was that "the existence of dynamic iconic displays has not yet been recognized by MIS researchers" [Bell, 1991, p.275]. More empirical research on the effectiveness of dynamic iconic displays was needed.

3.4 Analyzing and Comparing Alternative Simulated Systems

Decision making always involves analyzing and comparing alternative options. A key function of the successful decision support system is thus to help the user compare different alternatives. Different alternatives may mean two systems with alternative designs or different operating rules or assumptions of certain inputs within one single system. The comparison consists of three main issues: what is to be compared, when it is to be compared, and how it is to be compared.

What is to be Compared

From a decision support point of view, what is to be compared in alternative simulated systems may include the following three dimensions: steady-state comparison, transient-state comparison and comparison of "crisis" and/or "unexpected" situations. The steady-state comparison may help the decision maker observe the long-run behaviour of the simulated system under study, while the transient-state comparison may appeal to a managerial user who is more familiar with day-to-day system performance than with steady-state behaviour [Bell, 1989]. The comparison of crisis or unexpected situations is important in decision support where the consideration of their occurrence, in terms of both frequency and impact on the system, should be included.

Kleijnen [1976, 1981], Amer [1982], Law and Kelton [1982a], Freidman and Freidman [1985b, 1986], Balmer [1987] and Sloan and Unwin [1990] developed statistical procedures for comparing alternative simulated systems. These procedures mainly concentrated on the steady-state comparison. The general steps were first to develop long-run point or interval estimates (confidence intervals) for certain important model parameters of alternative systems, and then to conduct statistical tests to determine if one system was significantly different from the other. The common random numbers method was always used as the variance reduction technique. The transient state was treated as a problem (start-up problem) and its importance was neglected. The comparison of crisis and unexpected situations was difficult because of the long-run averaging effect in the steady-state. Therefore, from the perspective of decision support, the usefulness of statistical procedures was limited.

Bell [1989] suggested the use of visual interactive simulation to help decision support and to conduct analysis in a comparative performance of two simulated systems. In addition to the traditional steady-state statistical comparison, transient-state comparison and crisis situation analysis were done through inspection of appropriate visual displays. Using a "hub" service system as an example, he discussed how to compare two alternative systems (or the same system with different parameters) and how to provide links between long-run average performance measures and the transient behaviour of the model. Bell also suggested using distinct visual color displays to cue unusual random inputs and/or outputs. With the interactive capability in visual interactive simulation, "the decision maker can judge the need for, and form ot, (managerial) intervention by observing "crises" precipitated by combinations of particular stochastic events" [Bell, 1989, p.620].

Bell, Taseen and Kirkpatrick [1990] provided another example of using visual interactive simulation to analyze the steady-state, transient-state and crisis situations of a simulation system. By using a single evolving display of key parameters, the transient state of the system was linked to the steady state without any interruptions during the model run. Also, the visual interactive simulation was able to provide the necessary interactions to allow a user to identify the cause of a crisis, or to simulate management of the system through periods of unacceptable transient behaviour.

When it is to be Compared

Most previous research on the comparison of alternative simulated systems was conducted after the steady-state had been achieved. They were basically "posterior" analyses. Recent studies in visual interactive simulation, such as Hurrion [1985] and Angehrn and Luthi [1990], suggested that the comparison and analysis of alternatives should be done during the entire simulation run. By displaying both alternative systems (or key parameters of alternative systems) on screen simultaneously [Bell, 1989], comparison could be done visually at any time during the simulation run. Therefore, it seems that visual interactive simulation can expand the time horizon of simulation model comparison.

How it is to be Compared

Decision making based on comparing alternative simulated systems required both summary and holistic information obtained from the simulation results. Alternative simulated systems were traditionally compared numerically, for example, mean waiting time, mean throughput rate or mean queue length. Recent examples included Philipoom and Fry [1990] and Morris and Tersine [1990]. Numerical average information, however, only provided a summary, not a holistic, perception of the simulation results obtained. Miller [1969], Sulonen [1972] and Janson [1980] suggested the use of standard representational graphics such as bar charts and line plots. When presented on a time-series basis, these graphics could provide some holistic view of the results of the simulation.

Several researchers developed tools/techniques for visual paired comparison of different alternatives, for example, Andrews' curves [Andrews, 1972], Chernoff's faces ([Chernoff, 1973], MacKay and Villarreal [1987]), and recently harmonious houses by Korhonen [1991]. Their aim was to provide a decision maker with a holistic perception of the information under study and a more natural (though not necessarily better) way of comparing two alternatives. The problem with these techniques was that evaluation became subjective and might not be sensitive enough; different people have different definitions of beautiful faces and harmonious houses and it might not be easy to compare two similar faces or houses and judge which was better.

O'Keefe [1986] proposed the idea of "intelligent front ends" (IFEs) for using simulation in decision support. Making use of an expert system sitting between a simulation model and a user, an IFE asked questions and gave necessary instructions to the user for decision analysis and decision making, such as comparing alternative simulated systems. It could also explain and help the user to interpret the simulation results. Several examples of IFEs were given in O'Keefe [1986].

Pounds [1969] conducted a study on the process of problem finding and found that the identification of differences was a key determinant in decision making. Sheridan and Stassen [1976] argued that model results should be presented to users as differences from some familiar base case, such as the current plan, to reduce mental workload. Also, in a multiple-cue probability learning task environment, Hoffman and Earle [1981] demonstrated that presentation of differences improved learning. Dos Santos and Bariff [1988] conducted an experiment to investigate the different effects of a display of incremental changes versus actual outcomes on strategy formulation and found that the display of incremental changes significantly improved performance.

Bell [1989] recommended using paired-difference statistics in visual interactive simulation to compare alternative simulated systems. It was essentially a combination of the benefits of visual display and "differences" display. Through the dynamic displays and continuous updates of both simulation runs and key difference statistics, the comparative performances of alternative systems could be observed visually.

3.5 The Present Study

The above literature review suggests that visual interactive simulation may be a promising, or even a more effective type of simulation model than traditional simulation in a simulation-based decision support system. It could be postulated that:

P1: Through watching the displays and interacting with the model, dynamic, iconic visual displays can be more useful for a decision maker to learn the system than traditional numerical, representational graphic displays.

P2: With paired-systems and paired-difference statistics in a visual interactive simulation model, the model can provide a decision maker with better support in comparing alternative simulated systems than a "conventional" visual interactive simulation model, which, in turn, is better than a traditional simulation model.

The above postulates need to be tested empirically. The test results are important because, from a research perspective, they would provide evidence, or even a solution, to the methodological issue of whether or not the visual interactive simulation model with paired-systems and paired-difference statistics is better than the "conventional" visual interactive simulation model, which, in turn, is better than the traditional simulation model. From a practical perspective, the test results would give insights into providing better decision support for the decision maker when using simulation in a decision support system.

Therefore, the main objective of the present study is to design and conduct an empirical experiment to examine the above postulates, in essence, to compare the effectiveness of the three types of simulation models discussed above: traditional simulation models, conventional visual interactive simulation models and visual interactive simulation models with paired-systems and paired-difference statistics. Chapter 4 discusses the research design in detail.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Research Questions

Chapter 3 concluded with two postulates:

1. dynamic, iconic visual displays can be more useful in decision support than traditional static, representational visual displays;
2. a visual interactive simulation model with paired-systems and paired-difference statistics can provide more effective support in comparing alternative simulated systems than a conventional visual interactive simulation model.

Following these two postulates, the major research questions in this study were whether:

1. visual interactive simulation models (a) could help users to understand better and more quickly the underlying interrelationship among variables that, in turn, (b) could help obtain better results for managerial decision making than traditional simulation models.
2. visual interactive simulation models with paired-systems and paired-difference statistics could help users to compare two similar systems more easily and more effectively than conventional visual interactive simulation

models displaying "individual-sample statistics", that again, could help achieve better performance in solving managerial problems.

An experiment was designed to answer the above two questions. The following sections provide details of the experiment.

4.2 The Experimental Framework

4.2.1 The Experimental Task

The task setting used in the experiment was an equipment scheduling problem presented as a case (Appendix 1). Briefly, the case concerned the production of a chemical product which required two types of chemical solutions mixed together. Both types of solutions were first produced (in batches) separately in another production area. One unit of the final product required one batch of each type of solution. Before mixing the solutions, all batches had to pass a chemical test. Production processes of both types of solution were subject to random failures. Any defective batches had to be eliminated before the final chemical product could be produced. The test device was perfect. Batches of solution arrived at the testing centre at random following a uniform distribution. Having passed the chemical test, the batch would be put immediately into an inventory storage area maintained at a suitable temperature. The failed batches were discarded. High demand for the final product led to the objective to produce as many units as possible.

The testing centre had a single piece of equipment to test both types of solution, i.e., both tests shared the same equipment. Switching the equipment from testing one type of solution to testing the other incurred a setup cost. There was separate, but limited, storage provided for arriving batches (of both types of solution) which could not be tested immediately. When the storage area in the testing centre was full, the arriving batch had to be temporarily stored in a refrigeration compartment located adjacent to the testing centre. As soon as storage space in the testing centre became available, batches would be transferred to the testing centre. Due to different temperature requirements, each type of solution had its own refrigeration compartment.

The managerial task in this case was to develop a control rule for when the equipment should test which type of solution with the objective of maximizing the average net contribution per time unit. The net contribution of the production was the gross contribution minus storage costs and equipment switching costs.

This task seemed appropriate for the experiment for four reasons:

1. It was not just a number-crunching exercise. A thoughtful subject performing the experiment could learn the underlying relationship among key variables through using the simulation system.
2. It was rich enough that, after some analysis, the subject might come up with a number of approaches to tackle the problem in the case.

3. It was reasonably realistic but not too complex for the subject to comprehend in a time limited experimental setting.
4. The difficulty in reaching the optimal solution within the time allowed prevented information leakage from early participants of the experiment to later participants.

4.2.2 Strategies for Resolving the Task

In order to control the experiment and help subjects to develop the control rule, four different scheduling strategies (specific to the task concerned) were provided and coded into the decision support system given to each subject. Therefore, subjects could develop the control rules by first choosing one of the four strategies provided and then determining the key parameters required in that strategy.

The four strategies were developed based on different key components of the production system, and a brief description of each follows:

1. Inventory difference method This strategy was based on the inventory difference of "after test and passed" batches of the two types of solution. The main idea was to maintain a good one-to-one inventory ratio at all times since producing one unit of the final product required one batch of each type of solution.

2. Fixed interval method This strategy concerned the input rate. The key idea was to allocate the time for testing either type of solution according to the ratio of arrival rates of both types of solution. Fixed intervals of time were assigned alternatively to testing the two types of solution.

3. Queue length method This strategy looked at the lengths of waiting batches in the storage areas of the testing centre. Once the length of a waiting queue reached a certain predetermined number, the equipment switched to test this type of solution. The main idea was to avoid using the refrigeration compartment which was required when the storage was full.

4. Queue difference method Instead of looking at the absolute length of each of the two queues, this strategy concerned the difference of the lengths of two waiting queues. Its key purpose was also to avoid using the refrigeration compartments.

4.2.3 Decision Support Systems

Developing the Systems

The experiment required three different decision support systems, DSS 1, DSS 2 and DSS 3. (Detailed description of the experimental design and procedures appears in Section 4.2.4). DSS 1 was a traditional simulation model; DSS 2 was a visual interactive simulation model; and DSS 3 was a visual interactive simulation model with paired-systems and paired-difference statistics.

The development process of the systems began in mid-March 1991. The first system built was DSS 2, the visual interactive simulation model, using the simulation package GENETIK version 8.50 as the modelling environment. GENETIK was chosen because it was a simulation software specially designed for building visual interactive simulation models and the researcher had one year's actual hands-on experience with the software. The machine used was a 386/25MHz IBM-PC compatible. Based on the case to be used in the experiment (Appendix 1), a simple prototype (on paper) was first developed in about two weeks. The contents of both the opening screen and the model running screen were drawn and the information (both what and how) to be presented in the output screens was sketched. Ways for model interaction (including model input, running and output) were also tentatively determined. The idea of this "visual model" was then presented to and discussed with two fellow PhD students in the Western Business School after they had read the case. The feedback was encouraging and positive. They both believed that the proposed system should help resolve the task in the case and volunteered to test the system once it was built.

The model building process of the first prototype of DSS 2 using GENETIK began in late March 1991. At the beginning, the programming process was quite smooth; it took about two weeks to complete the system. A number of simulation runs were performed and the simulation seemed to behave as expected. All numbers, icons and graphs in the system were dynamically displayed and updated as planned in the "paper prototype". At this stage, the system was mainly function-key controlled, i.e., model interaction was mainly through pressing appropriate function keys. However, one of the PhD students mentioned above suggested that the system would be easier to use if it could be built to be mouse-controlled; it was, therefore, decided to modify the model to be mouse-controlled. A comparison was then made to decide which kind of model interaction should be used. Another ten days were spent doing this modification but the result was poor: "pure" mouse-control could not be achieved because pausing the simulation run had to be done through function key. Therefore, it was decided to keep the system as function-key controlled. A more "refined" version of DSS 2, completed near the end of April 1991, was then tested again by a professor at the Western Business School. The comments once more were positive.

Based on DSS 2, DSS 1 was then built using much the same code. This could be achieved because both systems used the same methods of model interaction and displayed the same types of output information. However, all visual displays of numbers and icons in the opening and model running screens of DSS 2 were erased and replaced by a text-based screen listing the four strategies described in the case. DSS 1 took two weeks to program, test, refine and complete.

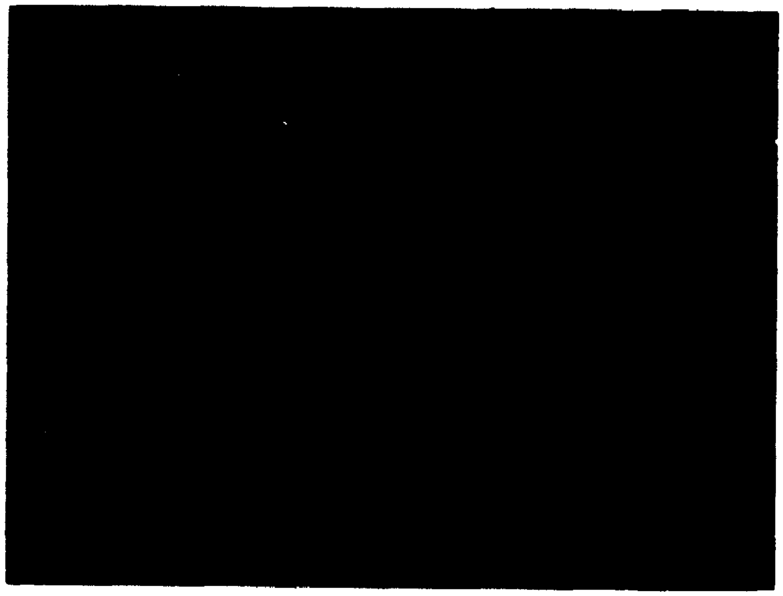
The building of DSS 3 began in late May 1991. Using the programs developed in DSS 2 as the building block, the system was built as a visual interactive simulation model showing paired-systems and paired-difference statistics. The main development task here was to program the system so that the additional graphical displays and computation of paired-difference statistics required in the system would not drag down the running speed very much. After several revisions and model tests, the system was completed in mid-June 1991.

In sum, the three decision support systems took about three months to complete. The development of DSS 1 and DSS 3 were both based on DSS 2. It was important and was considered to be essential to maintain consistency of the three decision support systems in terms of program logic, model interaction and model display. The final test of the systems took place in a pilot study of the experiment (to be discussed in Section 4.4).

Descriptions of the Systems

All three systems were coded in the GENETIK 8.50 environment and were run on a 386/25MHz IBM-PC compatible. They had similar user interfaces, both in terms of information provided (including input, output and simulation run) and ways of using various function keys for model interaction. The simulation models in all three decision support systems were programmed to run up to 150 simulated hours, and subjects could pause the simulation run at any time before this limit to look at intermediate statistical results. At the end of 150 simulated hours, the simulation would stop and subjects could look at the end results. That the simulation models were programmed to end at 150 hours was based on the observation from the pilot study that all simulation runs were terminated before 150 hours. This result occurred because either the subject believed that the simulation had already reached the steady-state or the control rule being examined had behaved so badly that it could be concluded that it was a bad control rule.

The four scheduling strategies described in the previous section were programmed into these three decision support systems (in fact, using the same lines of code). However, in order to ensure that subjects in the experiment would not be biased to analyze the four strategies in the particular order described and presented in the case, and since there were twenty-four different permutations of the four strategies, twenty-four variations of the decision support systems, each with a particular order of the four strategies, were produced. Figure 4.1 provides an example of two variations of DSS 1. Details of the three decision support systems follow.



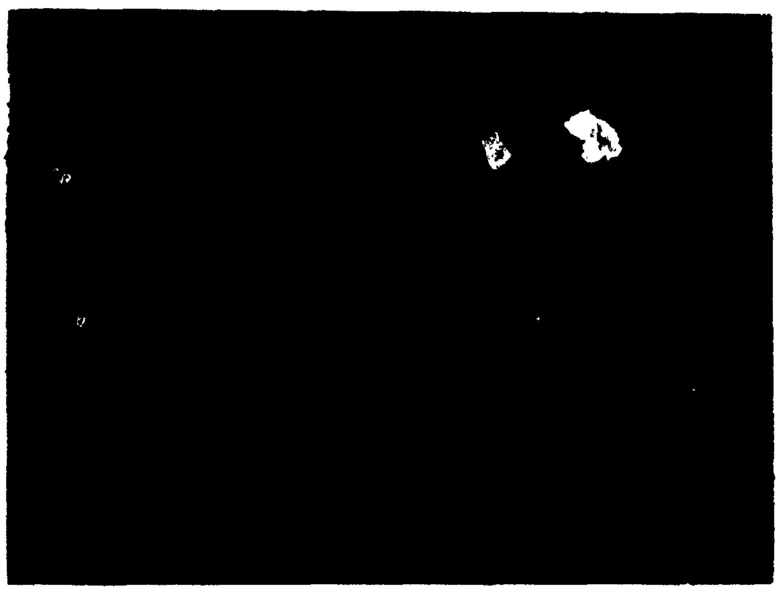


Figure 4.1 Examples of two variations of DSS 1 (The upper system has a different order of the four scheduling strategies from the lower system)

DSS 1

DSS 1 was a traditional simulation model with a user-friendly interface for model input and model interaction. Figure 4.2 shows the opening screen of the system. The four scheduling strategies were listed on the screen and the subject was asked to choose one of them by pressing the appropriate function key. Once a strategy had been chosen, the subject was asked to select the key parameters in the chosen strategy. This completed the choice of a control rule (strategy with parameters). The simulation would then be run automatically.

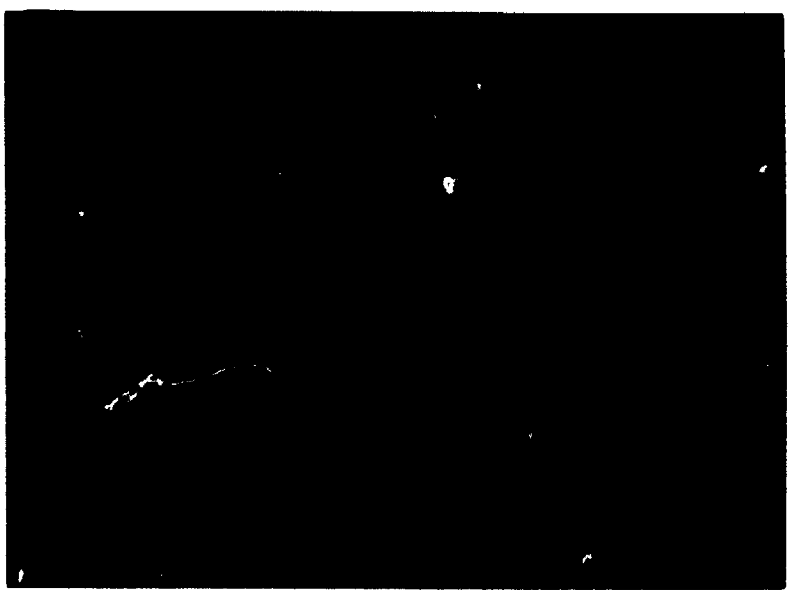


Figure 4.2 Opening screen of DSS 1

The subject could see the advancement of the simulation clock on screen and could pause the run whenever it was thought necessary (Figure 4.3). At this moment, the subject had three choices: restart for a new simulation run with a different control rule (pressing F2); see statistical results (F4); or resume the run again (F6). F2 was chosen when the subject believed that the analysis of that particular control rule was done. The subject had already obtained enough information about the behaviour of that particular run.

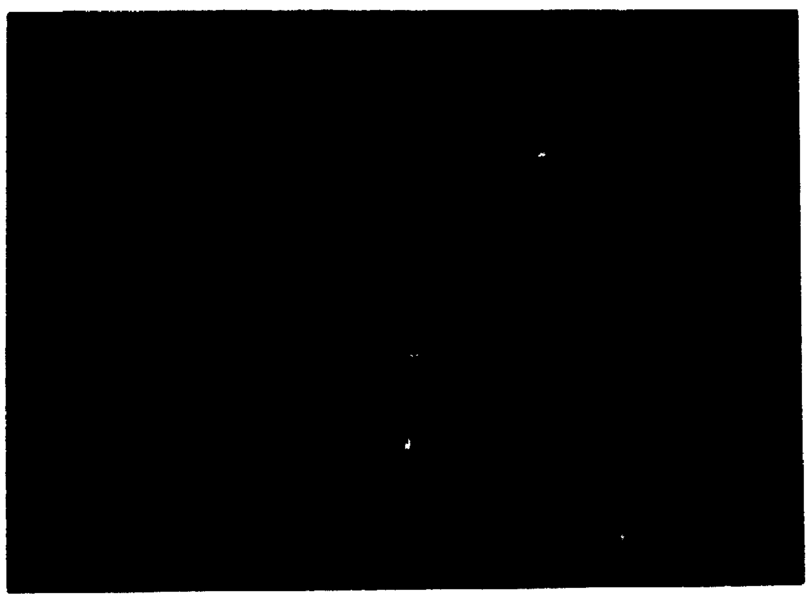


Figure 4.3 Model running screen of DSS 1

When F4 (see statistical results) was chosen, the subject would then be prompted to see one of three output screens: summary statistics; graph showing queue lengths; and graph showing average gross contribution/hour, average operating cost/hour and average net contribution/hour. Figure 4.4 showed the output screen no. 1 display of (run-to-minute) summary statistics. The display could be divided into four parts. The first part (consisting of the first four lines) presented mean arrivals/hour, mean queue length, percentage of refrigeration compartment time in use, and percentage of test failures. Numbers in the middle column were for solution type A and numbers in the last column were for solution type B. Figures in brackets were two standard deviations away from the corresponding means. For example, the mean arrivals/hour of solution type A was 2.98 batches, with 3.14 and 2.82 being the mean plus and minus two standard deviations respectively. Also, within these simulated 62 hours and 56 minutes (indicated by the simulation clock in Figure 4.3), 3.51% of the time (or 1 hour and 51 minutes) was used for the refrigeration compartment for solution type A. The second part of the display (next five lines) presented similar information to the first part, but in total units instead of average units.

The third part of the display began in the middle of the screen consisting of three lines. It presented average financial performance of the production system using the chosen control rule up to that simulation time. The interpretation of the numbers was similar to that in the first part. Finally, the last part of the display (six lines) provided total financial performance.

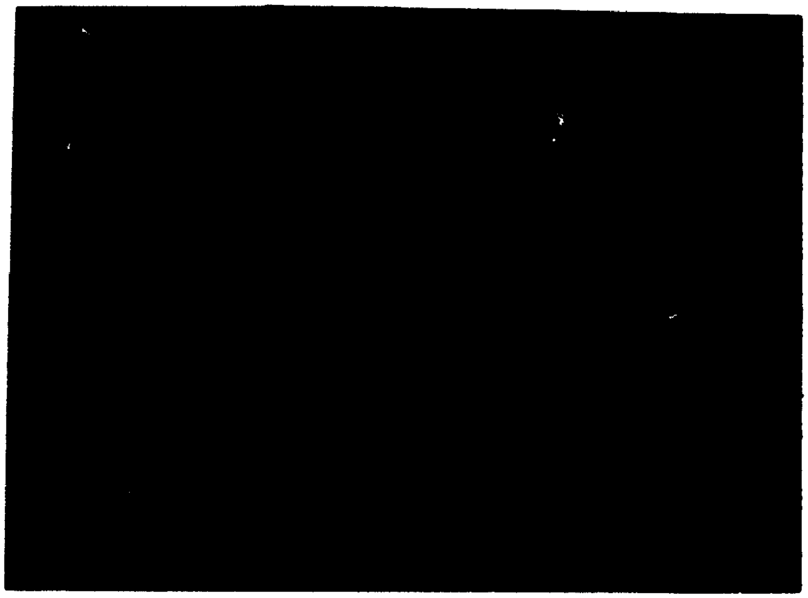


Figure 4.4 Output screen no. 1 of DSS 1

Figure 4.5 shows the second output screen: behaviour of the two waiting queues along with the simulation time. The length of each queue was recorded at the end of each simulated hour and the graph was updated accordingly. In the example shown in Figure 4.5, the queue length of type A was very stable but the queue length of type B was growing and reached its maximum (10 batches) after about 70 simulated hours. This phenomenon could be interpreted as not assigning enough time to testing type B and the control rule should be adjusted to allow more testing time for this type of solution.

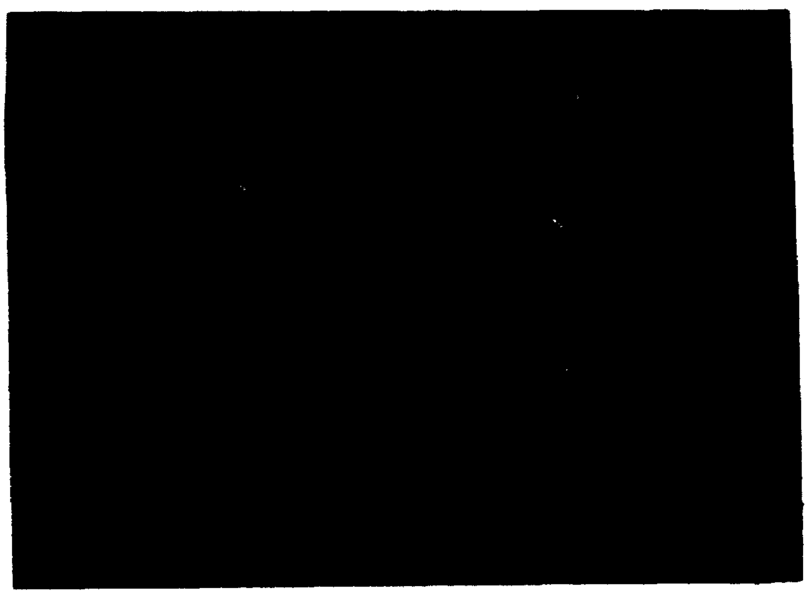


Figure 4.5 Output screen no. 2 of DSS 1

Figure 4.6 shows the third output screen: behaviour of average gross contribution/hour, average operating cost/hour, and average net contribution/hour along with the simulation time. When the simulation reached the steady-state, all three curves should have stabilized.

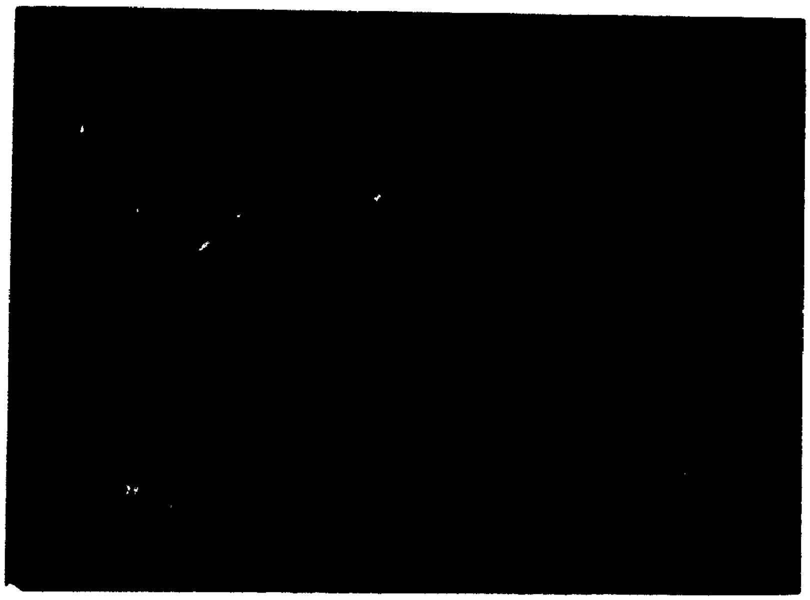


Figure 4.6 Output screen no. 3 of DSS 1

After analysis of the three output screens (Figures 4.4 and 4.6), pressing F9 (exit) could lead the subject back to the model running screen (Figure 4.3). The subject could then press F6 to resume and continue the simulation run or F2 to restart a new simulation run with a new control rule. Once F2 was pressed, the opening screen (Figure 4.2) would reappear.

The process was continued until either the subject had analyzed all the control rules that he/she intended to analyze and had come up with a final recommendation, or the time allocated for doing the experiment was reached. The subject was then asked to provide the final recommendation based on the analysis already done.

DSS 2

DSS 2 was a visual interactive simulation model which visually displayed the simulation when it was running. Various events, such as arrivals, storage/queue length conditions, current output levels, refrigeration compartment status, etc., could be observed on screen. The interface for model input was similar to the one in DSS 1 except that input information in this system was displayed in a different place on the screen. The subject could interact with the system for intermediate statistical results in exactly the same way as DSS 1. DSS 2 also provided the same statistical output information presented in the same way as DSS 1.

Figure 4.7 shows the opening screen of DSS 2. The upper part of the display presented a picture almost identical to the one in Exhibit 2 of the case (Appendix 1). The simulation clock was at the top right-hand corner while the four scheduling strategies were displayed at the bottom of the screen.

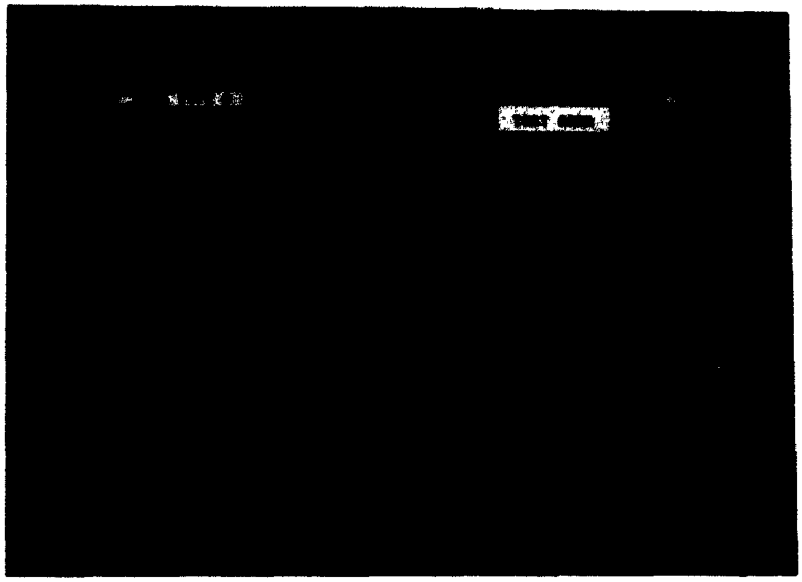


Figure 4.7 Opening screen of DSS 2

This decision support system was used in exactly the same way as DSS 1. Subjects first chose a strategy and the required parameters for specifying the control rule being examined. This control rule would be displayed right below the picture. When the simulation was running, the numbers and icons in the picture would be dynamically updated and displayed. Near the bottom of the screen were presented up-to-the-minute figures of total gross contribution, costs of using refrigeration compartments A and B, switching cost and net contribution, all of which were also updated dynamically.

Figure 4.8 was a snapshot when DSS 2 was running. In this example, the subject was examining a control rule using the "Queue difference" strategy with parameters, "7 units", "7 units" and "B fi ": respectively. The simulation had run 19 hours and 44 minutes; 62 batches of type A and 79 batches of type B had arrived. There was nothing in either refrigeration compartment. The equipment was testing type A. One batch of type A was waiting, and 8 batches of type B were waiting. Within these almost 20 simulated hours, 9 switches had been done; 52 batches of type A had passed the test and 8 had failed. As for type B, 55 batches had passed and 16 had failed. Because of the "one batch each" requirement of the final product, the final output was 52 units. According to the "$ analysis" near the bottom of the screen, since 52 units of final product had been produced with $100 of gross contribution per unit, the total gross contribution was $5200. Neither of the refrigeration compartments had been used and the total switch costs were $450. Therefore, the total net contribution was $4750 ($5200 - 0 - 0 - 450).

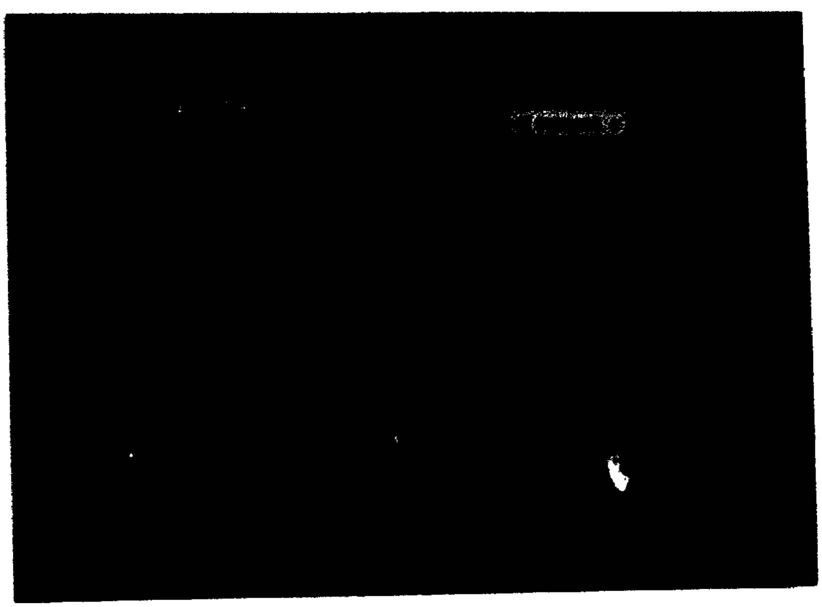


Figure 4.8 Model running screen of DSS 2

Figures 4.9 to 4.11 are the three output screens of DSS 2. Like DSS 1, they could be selected for observation once the simulation was paused and the option of "see results" was selected (F4 in Figure 4.8). Figure 4.9 presents key summary statistics. The main difference between this display and that of DSS 1 (Figure 4.4) was that here, only mean values of the variables concerned were presented while total values were omitted, because, in DSS 2, subjects could obtain all those total values in the model running screen (Figure 4.8). Figure 4.10 is exactly the same as Figure 4.5 in DSS 1 and shows the second output screen with the behaviour of the two waiting queues along with the simulation time. Figure 4.11 is the same as Figure 4.6 in DSS 1 and shows the third output screen with the behaviour of average gross contribution/hour, average operating cost/hour, and average net contribution/hour along with the simulated time. Therefore, interpretation of these figures was the same as that in DSS 1.

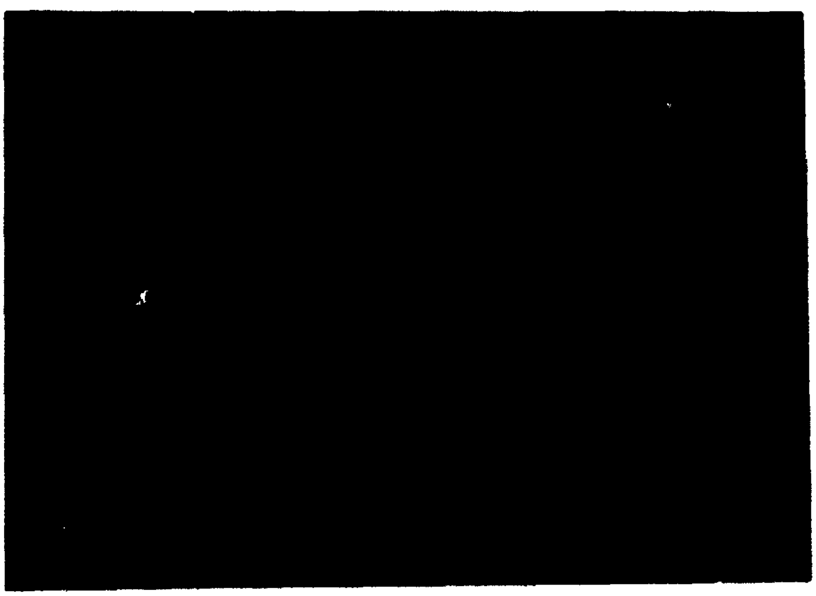


Figure 4.9 Output screen no. 1 of DSS 2

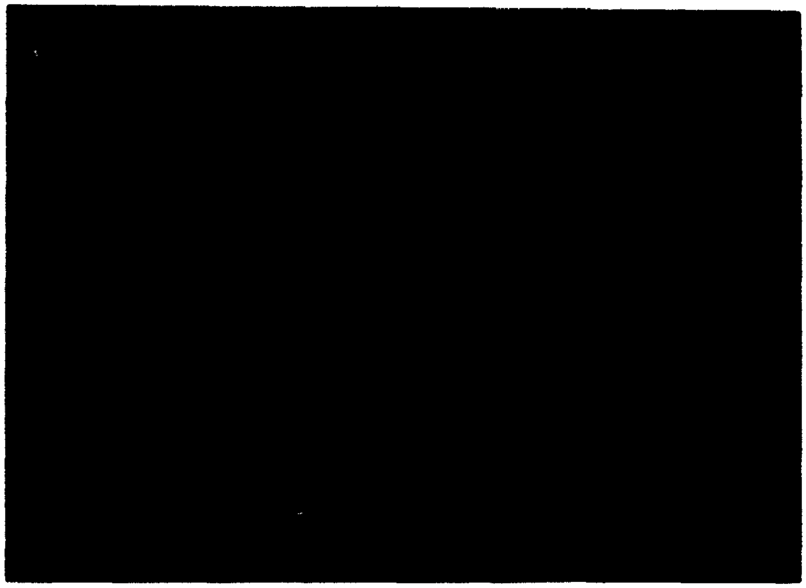


Figure 4.10 Output screen no. 2 of DSS 2

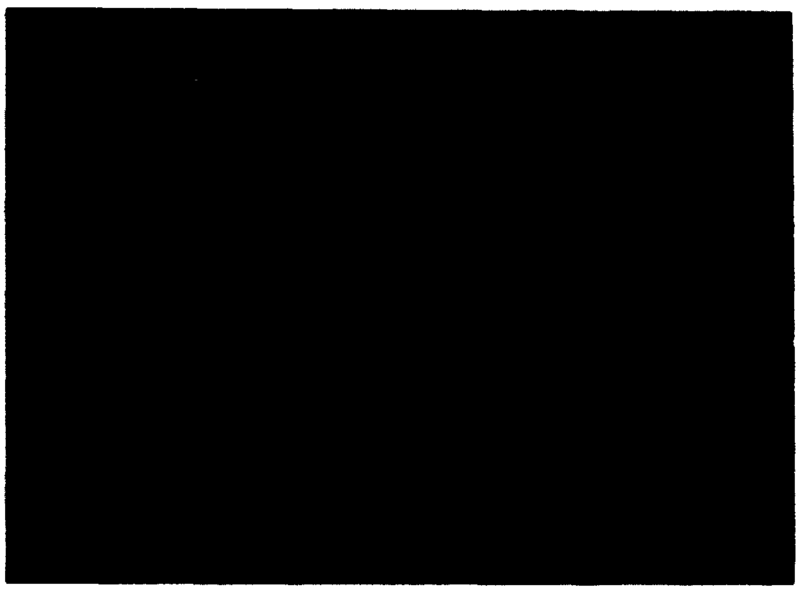


Figure 4.11 Output screen no. 3 of DSS 2

DSS 3

DSS 3 was also a visual interactive simulation moc ɜl. The main difference between DSS 3 and DSS 2 was that DSS 3 would run and display two simulated systems (with different control rules) simultaneously on the same screen, i.e., paired-systems. The input interface remained essentially the same except that the input procedures had to be done twice, once for the first system and again for the second. Methods of model interaction during the simulation run were unchanged. The statistical outputs, both intermediate and final, however, were different from previous systems. In this decision support system, instead of examining conventional "individual-sample statistics" for each of the models, paired-difference statistics were computed and displayed. This expanded the output module from one table for summary statistics and 2 related graphs (in DSS 1 and DSS 2) to one table and 4 related graphs.

Figure 4.12 shows the opening screen of DSS 3, on which, two systems (system 1 and system 2) were displayed. The four strategies remained at the bottom of the screen. The subject first picked a strategy and input parameters for system 1 and then chose another control rule for system 2. Once both control rules were determined and entered, the simulation began to run.

Figure 4.13 was a snapshot when DSS 3 was running. All numbers and icons could be interpreted like those in DSS 2 (Figure 4.8). The main difference was that in the "$ analysis" part, one additional line of information was added right below the line for "system 2". This line showed the difference between corresponding variables in system 1 and system 2.

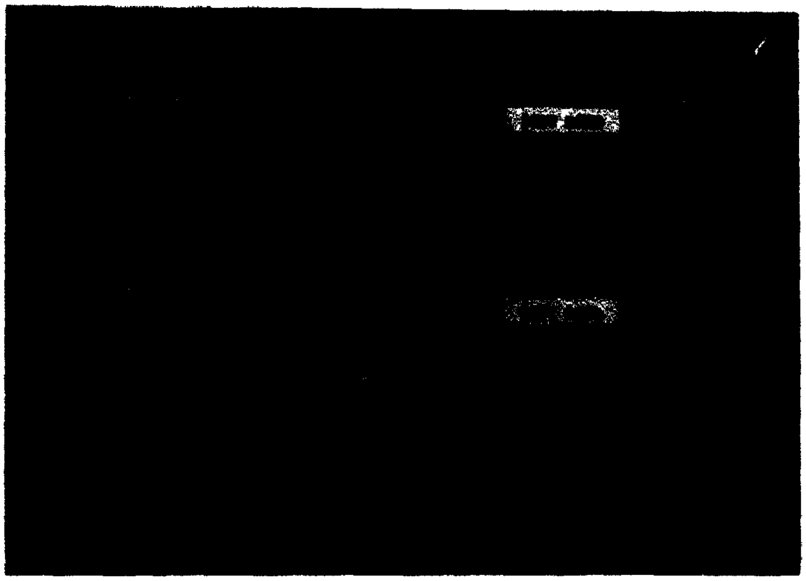


Figure 4.12 Opening screen of DSS 3

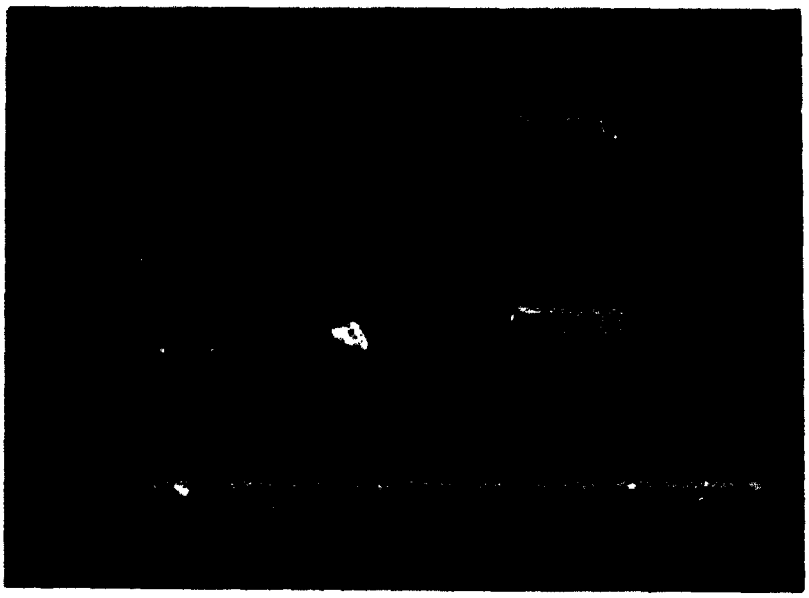


Figure 4.13 Model running screen of DSS 3

There were five output screens (instead of three in both DSS 1 and DSS 2) in DSS 3. The first output screen (Figure 4.14) was basically the same as the corresponding ones in DSS 1 and DSS 2 (Figures 4.5 and 4.10), showing the behaviour of the two waiting queues along with the simulation time. The main difference, however, was that in DSS 3, this screen displayed the difference of queue lengths between system 1 and system 2.

Figure 4.14 Output screen no. 1 of DSS 3

As stated, Figure 4.6 in DSS 1 and Figure 4.11 in DSS 2 both displayed the behaviour of average gross contribution/hour, average operating cost/hour, and average net contribution/hour along with the simulated time. In DSS 3, since the paired-difference statistics were emphasized, this display was split into three, one for each variable, in order to ensure that the subject would not be overloaded with information (Figures 4.15 to 4.17).

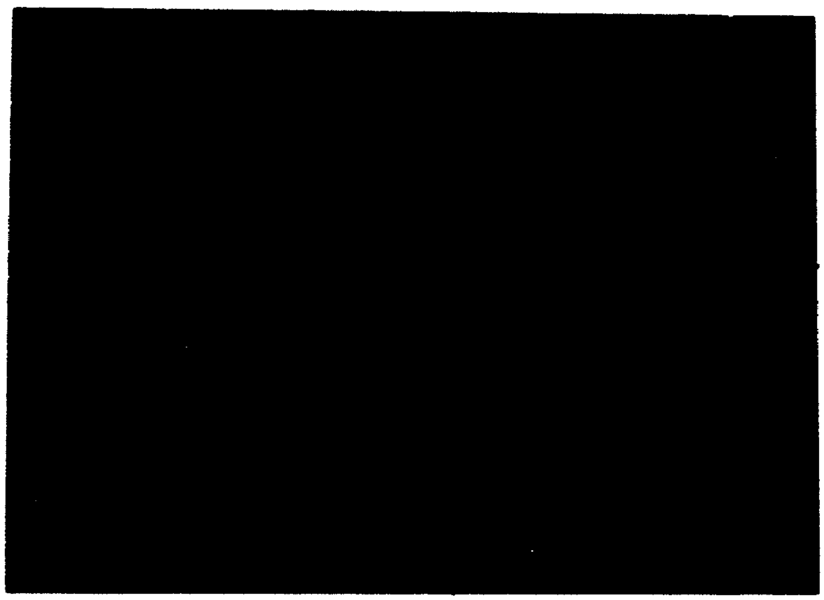


Figure 4.15 Output screen no. 2 of DSS 3

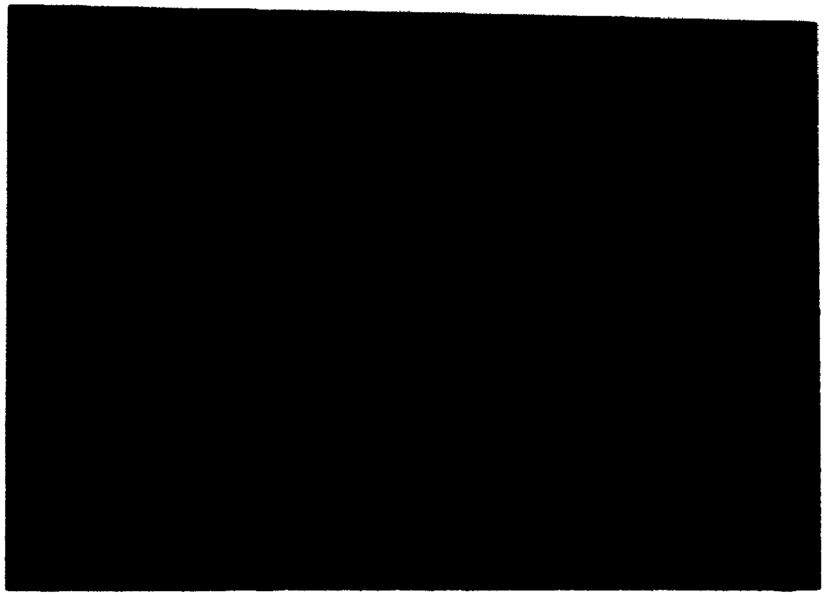


Figure 4.16 Output screen no. 3 of DSS 3

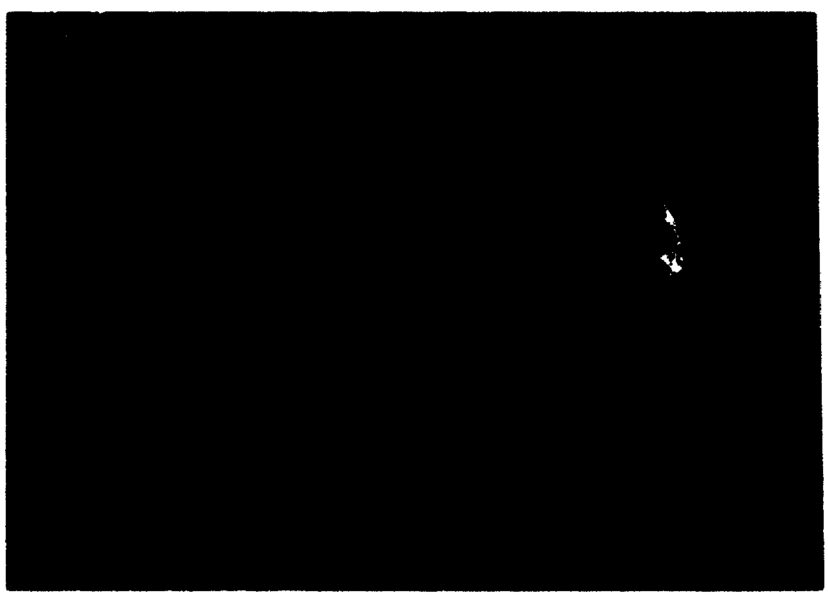


Figure 4.17 Output screen no. 4 of DSS 3

The final output screen of DSS 3 showed summary statistics (Figure 4.18). Again, it displayed information about the same variables presented in DSS 1 and DSS 2 (Figures 4.4 and 4.9). The main difference was that, here, paired-difference statistics were presented.

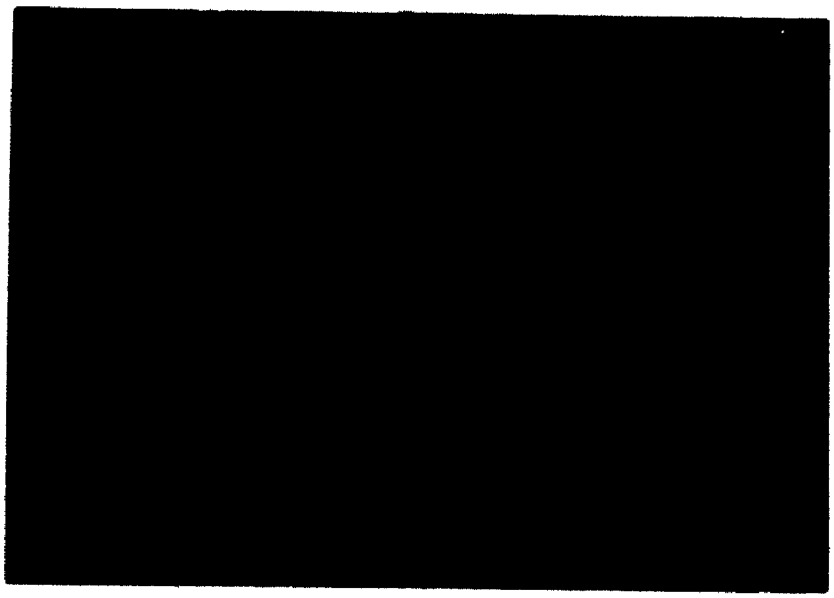


Figure 4.18 Output screen no. 5 of DSS 3

4.2.4 Experimental Design and Procedures

Experimental Design

There were three experimental groups. Subjects were randomly assigned to one of the three groups and were asked to perform the same task. Each participant was given the same case and was provided with the appropriate decision support system (of one of the twenty-four variations). The assignment was as follows:

Group 1 - DSS 1 (Traditional simulation model);

Group 2 - DSS 2 (Conventional visual interactive simulation model);

Group 3 - DSS 3 (Visual interactive simulation model with paired-systems and paired-difference statistics).

Every attempt was made to ensure that the only treatment different for the three groups was the decision support system provided. Due to the different levels of complexity of the three systems, the running speed of each was different from the others. Table 4.1 gives a comparison of the average run-time required by each of the three decision support systems for running 100 simulated hours. As shown, DSS 2 took about twice the time to run as DSS 1. Similarly, DSS 3 took about 2.5 times the time to run as DSS 2 but it evaluated two different simulated systems simultaneously. It was decided to keep these differences in running speed intact and not to adjust the systems so that they would use approximately the same run-time for the same length of simulation (in simulated hours). The reason was that various running speeds formed one of the key characteristics of the three types of simulation models being examined.

	Average time required to run 100 simulated hours (in seconds)
DSS 1	80
DSS 2	155
DSS 3	382

Table 4.1 Time required to run 100 simulated hours

Comparison of the results of Group 1 and Group 2 thus gave an answer to whether visual interactive simulation is more effective than traditional simulation in helping managerial decision making, while a comparison of the results of Group 2 and Group 3 gave an assessment of the effectiveness of the "paired-systems, paired-difference statistics" visual interactive simulation model.

Therefore, the experimental design was basically linear (Figure 4.19).

Traditional Simulation ⟵ vs ⟶ Conventional VIS ⟵ vs ⟶ VIS with paired-systems & paired-difference statistics

↑ 1st research question ↑ 2nd research question

Figure 4.19 Design of the experiment

There were three main reasons for choosing this design:

1. That visual interactive simulation was more effective than traditional simulation, and that visual interactive simulation with paired-systems and paired-difference statistics was more effective than conventional visual interactive simulation were two allegations that appeared in the literature following the development of visual interactive simulation by Hurrion [1976]. (See Hurrion [1985] for the first allegation and Bell [1989] for the second allegation.) This experiment provided a rigorous empirical test of these two allegations.

2. The linear design was chosen over a 2x2 factorial design, such as Figure 4.20.

	Traditional	VIS
Paired-systems & paired-difference statistics	**Non-visual simulation with paired-systems & paired-difference statistics**	**VIS with paired-systems & paired-difference statistics**
Single-system & individual-sample statistics	**Traditional simulation**	**Conventional VIS**

Figure 4.20 A 2x2 factorial experimental design

Compared to the chosen linear experimental design, the extra cell in the factorial design was "non-visual simulation model with paired-systems and paired-difference statistics". There were two main reasons for omitting this box:

(a) A review of the existing literature in simulation and related areas did not reveal any study discussing or proposing this type of simulation model. A comparison of two simulated systems was usually done by running the two simulated systems independently (i.e., not as a pair) many times and comparing the means of variables of interest (Law and Kelton [1982]). It was not until 1989 that Bell [1989] proposed the use of paired-systems and paired-difference statistics in (visual interactive) simulation models.

(b) In traditional simulation, comparison of two systems was mainly performed on steady-state results (or end-results in terminating simulation (Law and Kelton [1982])). It could be argued that it was not worthwhile to reprogram the simulation model to perform simulation with paired-systems and paired-difference statistics as the traditional model could achieve the same result.

3. There are also other types of simulation models such as visual interactive simulation with paired-systems but without paired-difference statistics, or visual interactive simulation models with three or four systems displayed and run simultaneously. These additional types of simulation models merit

further research, especially if visual interactive simulation models were shown to be superior to traditional simulation models in this experiment. Due to resource limitations, evaluation of these and other types of simulation models was left to future research.

Experimental procedures

The experiment was always conducted with one subject at a time. Prior to the experiment, each subject was thanked for his/her participation. A Letter of Information (Exhibit 4.1) was first provided for perusal before the Consent Form was signed (Exhibit 4.2). After signing the form, the subject received an information sheet (Exhibit 4.3) listing the purpose and duration of each of the three sections of the experiment.

Each experiment, consisting of three separate sections, lasted a total of two and one-half hours. The first section of the experiment lasted 30 minutes during which time the subject read and analyzed the case.

Exhibit 4.1 Letter of Information

The University of Western Ontario

DOCTORAL PROGRAM RESEARCH
School of Business Administration
London, Canada
N6A 3K7

Letter of Information

Dear Participant:

An Empirical Assessment of Three Simulation Modelling Approaches in Developing Decision Support Systems

The primary purpose of the research is to investigate the relative effectiveness of three simulation modelling approaches in developing decision support systems.

What you are required to do is to spend two and a half hours to solve a case with the help of a decision support system provided to you. Meanwhile, I will be available to answer any questions regarding the use of the decision support system during the experiment. You may also finish the exercise at any time you think appropriate. The location of the experiment will be the Western Business School.

To cover the cost of your time and effort spent to come to participate in this experiment, you will receive $20. Should you withdraw from the study before the time assigned, the amount will be pro-rated. Also, if you turn out to be the top performer in your experimental group, a bonus of $150 will be awarded to you.

The data collected in the experiment will be kept in strict confidence. You are under no obligation to participate and if you agree to participate you may withdraw from the study at anytime without jeopardy to your academic standing. Moreover, you will receive a summary result of the experiment around April 1992. Should you have any other questions pertaining to this research, my office is in Room 106, NCMRD and my telephone number is (519) 679-2111, extension 5133.

Yours sincerely,

Patrick CHAU
Project Director

Exhibit 4.2 Consent Form

The University of Western Ontario

DOCTORAL PROGRAM RESEARCH
School of Business Administration
London, Canada
N6A 3K7

Consent Form

An Empirical Assessment of Three Simulation Modelling Approaches in Developing Decision Support Systems

This is to confirm that I have read the letter of information, have had all questions answered satisfactorily by the Project Director, and agree to be involved in the research project described.

....

Participant's Name

....

Participant's Signature

....

Date

Exhibit 4.3 Recommended Time Allocation

The University of Western Ontario

DOCTORAL PROGRAM RESEARCH
School of Business Administration
London, Canada
N6A 3K7

Recommended Time Allocation

Duration	Time mark	Activity
	0	
30 minutes		CASE READING AND PRELIMINARY ANALYSIS
	30 minutes	
20 minutes		QUESTION PERIOD AND DSS TUTORIAL
	50 minutes	
100 minutes		CASE ANALYSIS USING THE DSS PROVIDED
	2 hour 15 minutes	
		FINAL ANALYSIS AND RECOMMENDATIONS
	2 hours 30 minutes	

The second section was a question period and DSS tutorial lasting up to 20 minutes. In these 20 minutes, the subject could ask any questions about the case in order to ensure a full understanding of the task. After all questions had been answered, the subject was shown and taught how to use the decision support system provided. The meaning of each type of screen displays was also explained in this tutorial. Two more information sheets (Exhibits 4.4 and 4.5) were handed out providing some useful hints on using the system and the ranges of model inputs. Finally, a recommendation form (Exhibit 4.6) was given asking the subject to fill in a final recommendation at the end of the experiment.

The main purpose of the first two sections was to ensure that each subject adequately understood and was familiar with the task and the use of the decision support system provided.

In the third section (about 100 minutes), the subject used the decision support system to develop the best equipment scheduling rule to maximize the average net contribution. A pencil, a calculator and paper were provided for the subject to perform any analysis and/or computations desired.

During the first and third sections, the experimenter remained in a room adjacent to the room where the experiment was being conducted and was available to answer any questions relating to input/output procedures or screen explanation. The

Exhibit 4.4 Some Useful Hints on Using the DSS

The University of Western Ontario

DOCTORAL PROGRAM RESEARCH
School of Business Administration
London, Canada
N6A 3K7

Some Useful Hints on Using the DSS

1. The DSS provided to you is BASICALLY A SIMULATION MODEL.

2. Try to ANALYZE RESULTS from previous runs before you run the next simulation.

3. Except for the first few simulation runs, try to AVOID "TRIAL AND ERROR". Mostly, you will learn very little from it and will waste your time.

4. As you have to analyze up to four different scheduling strategies, TRY TO ALLOCATE YOUR TIME WISELY.

Exhibit 4.5 Input R`nges of Respective Scheduling Strategies

Strategy	First Input	Second Input
Inventory difference (ID)	> 0	> 0
Fixed interval (FI)	1 - 240	1 - 240
Queue length (QL)	$0 \leq X \leq 10$	$0 \leq Y \leq 10$
Queue difference (QD)	$0 \leq X \leq 10$	$0 \leq Y \leq 10$

Exhibit 4.6 Recommendation Form

The University of Western Ontario

DOCTORAL PROGRAM RESEARCH
School of Business Administration
London, Canada
N6A 3K7

Recommendation

My final recommended scheduling strategy is as follows:

Strategy :

First Input :

Second Input :

A or B First :

Participant's Name

experimenter did not, however, discuss the task or interpret the meaning of outputs. Also, the subject was given four summary sheets, one for each scheduling strategy, (Exhibit 4.7 for subjects using DSS 1 or DSS 2 and Exhibit 4.8 for subjects using DSS 3) to record all the inputs/outputs of each simulation run that the subject had performed. The subject was allowed to consult these summary sheets during the whole experiment.

In experimental groups 1 and 2, before each simulation run (except the first run) the subject was asked to make a prediction on whether the simulation to be run would achieve higher or lower average net contribution than the previous simulation run. The subject was also asked to record a level of confidence about the prediction. In experimental group 3, since two alternative systems were to be compared in each run, the subject was asked to make a prediction on whether system 1 would achieve higher average net contribution than system 2 or vice versa. Again, the subject was asked to write down a level of prediction confidence. Fifteen minutes before the end of the section, the subject was reminded of the time left. However, the subject might finish the exercise and provide a final scheduling recommendation at any time before the section ended.

Upon completion of the experiment, all related materials, including any analysis and/or calculations performed during the experiment, were collected. This was to reduce the possibility of information on solutions leaking out. The subjects were then thanked for their co-operation and participation, reminded not to discuss the

Exhibit 4.7 Work-sheet for groups 1 and 2 (using DSS 1 and DSS 2 respectively)

INPUTS					
Strategy					
First Input					
Second Input					
A or B first					
Net contributions/hour (compare with the previous run, increase or decrease)					
Confidence (0-100%)					
RESULTS					
Clock					
Gross contributions ($)					
Costs in compartment A ($)					
Costs in compartment B ($)					
Switch costs ($)					
Net contributions ($)					
Net contributions/hour					

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ly)

Exhibit 4.8 Work-sheet for group 3 (using DSS 3)

INPUTS				
Strategy				
First Input				
Second Input				
A or B first				
Difference in net contributions/hour (system 1 - system 2, positive or negative)				
Confidence (0-100%)				
RESULTS				
Clock				
Difference in gross contributions ($)				
Difference in costs incurred in compartment A ($)				
Difference in costs incurred in compartment B ($)				
Difference in switch costs ($)				
Difference in net contributions ($)				
Difference in net contributions/hour ($)				

exercise with other students, and given $20 for their effort and time spent in participating in the experiment. Finally, each subject was reminded that the best performer (i.e., the one who finished with the highest long-run average net contribution) in the experimental group would be awarded a $150 bonus. The purpose of the $20 was to attract voluntary subjects, while the final bonus was to provide an incentive for the subjects to do their best and not to discuss the exercise with other participants.

4.2.5 Subjects

Subjects were recruited from the MBA program at the Western Business School. Only second-year students were invited to participate in order to ensure that all subjects had some background knowledge of production scheduling/management and that all three experimental groups were basically homogeneous. Participation in the experiment was voluntary. Subjects were solicited during a required second-year MBA course (Business Policy). The plan was to have 75 subjects, 25 in each experimental group, participating in the experiment.

4.3 Research Hypotheses and Experimental Measures

Based on the literature review (in Chapter 3) and the research questions presented at the beginning of this chapter, six sets of hypotheses were developed. The main theme of these hypotheses centred around the proposition that since visual interactive simulation models provided more information about the operating mechanism and the inter-relationship among variables of the system under study through its visual and dynamic displays, it was a more effective simulation model than the traditional simulation model in supporting decision making. A second theme was that paired-systems and paired-difference statistics in visual interactive simulation models could help the user move towards better solutions by allowing the user to compare two alternative simulated systems more effectively than individual systems showing individual-sample statistics. Therefore, the independent variable in the experiment was the decision support system provided to the subjects. The purpose was to test the effectiveness of different types of simulation models in supporting decision making.

Set #1: Hypotheses on decision performance

H 1: Users of visual interactive simulation (DSS 2) as their decision support system obtain a higher average net contribution than users of traditional simulation (DSS 1).

H 2: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system obtain a higher average net contribution than users of "conventional" visual interactive simulation system (DSS 2).

H 3: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system obtain a higher average net contribution than users of a traditional simulation system (DSS 1).

The variable used for examining this set of hypotheses was average net contribution, which was the variable that subjects were asked to maximize in the case. To avoid the start-up problem in simulation, the long-run average net contribution was not obtained from the subject's own simulation run, but was obtained afterwards by taking the average of five simulation runs (300 simulated hours each) using the final control rule recommended by the subject.

Let

$c_{i,k}$	be the long-run average net contribution obtained based on the recommendation by subject i in group k
N_k	be number of subjects in group k
where	$i \in [1,N_k]$ and $k \in [1,3]$

then define

$$\overline{C_k} = \frac{\sum_{i=1}^{N_k} c_{i,k}}{N_k}$$

which is the group average long-run average net contribution obtained based on the recommendations by subjects in group k

Table 4.2 summarizes this set of hypotheses.

Hypothesis	Decision performance
Variable measured	$\overline{C_k}$
H 1	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 2	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 3	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Table 4.2 First set of hypotheses

<u>Set #2: Hypotheses on predictive correctness</u>

H 4: Users of visual interactive simulation (DSS 2) as their decision support system have better predictions, in terms of correctness, than users of traditional simulation (DSS 1).

H 5: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system have better predictions, in terms of correctness, than users of "conventional" visual interactive simulation system (DSS 2).

H 6: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system have better predictions, in terms of correctness, than users of a traditional simulation system (DSS 1).

This set of hypotheses concerned the capability of the decision support system provided to the subject to help in predicting the resi)f the simuiation. In the experiment, each subject was asked to make predictions on the results of each simulation run before actually running the simulation. Predictions were subsequently compared with the simulation results obtained to see if they were correct. A variable, "predictive correctness", was defined as the percentage of correct times that the subject predicted that one simulation run would be better or worse than its previous one, in terms of achieving higher or lower average net contribution.

Let

$n_{i,k}$ be the number of times prediction was correct of subject i in group k

$M_{i,k}$ be the number of times prediction was made of subject i in group k

where $i \in [1,N_k]$ and $k \in [1,3]$

then define

$$P_{i,k} = \frac{n_{i,k}}{M_{i,k}}$$

$$\overline{P_k} = \frac{\sum_{i=1}^{N_k} P_{i,k}}{N_k}$$

where $P_{i,k}$ is the predictive correctness of subject i in group k

$\overline{P_k}$ is the group average predictive correctness of all subjects in group k

Due to the stochastic results obtained from the simulation run, a prediction might appear wrong (or correct) although it was in fact correct (or wrong). It was assumed that this random effect would be washed out when the number of simulation runs was big enough. (in the main experiment, on average, each subject ran about 20 simulation runs.) Therefore, it was believed that if one type of simulation model was better than another type in supporting decision making, it could help the user better understand the system and thus achieve a higher score for predictive correctness. See Table 4.3.

Hypothesis	Correctness of Prediction
Variable measured	$\bar{P}_k$
H 4	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 5	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 6	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Table 4.3 Second set of hypotheses

Set #3: Hypotheses on confidence in predictive correctness

H 7: Users of visual interactive simulation (DSS 2) as their decision support system have a higher confidence in their prediction than users of traditional simulation (DSS 1).

H 8: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system have a higher confidence in their prediction than users of "conventional" visual interactive simulation system (DSS 2).

H 9: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system have a higher confidence in their prediction than users of a traditional simulation system (DSS 1).

This set of hypotheses evaluated the (subjective) confidence that subjects had in their predictions. The experimental measure used was "confidence in predictive correctness". It was measured by asking how much confidence (0-100%) subjects had in their correctness of predictions. The confidence question was asked following the question about predictive correctness. The main idea of this measure was to examine the "subjective" side of the dependent variable, predictive correctness.

Let

$r_{m,i,k}$ be the level of confidence in the mth prediction of subject i in group k

where $m \in [1, M_{i,k}]$, $i \in [1, N_k]$ and $k \in [1,3]$

then define

$$R_{i,k} = \frac{\sum_{m=1}^{M_{i,k}} r_{m,i,k}}{M_{i,k}}$$

$$\overline{R_k} = \frac{\sum_{i=1}^{N_k} R_{i,k}}{N_k}$$

where $R_{i,k}$ is the confidence in predictive correctness of subject i in group k

$\overline{R}_k$ is the group average confidence in predictive correctness of all subjects in group k

Again, it was believed that if one type of simulation model was more helpful for a user to learn about the underlying mechanism of the simulation system than another type, the user would build up confidence in prediction faster, which would lead to a higher $R_{i,k}$ and thus, a higher $\overline{R}_k$ for that experimental group. See Table 4.4.

Hypothesis	Confidence in prediction
Variable measured	$\bar{R}_k$
H 7	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 8	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 9	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Table 4.4 Third set of hypotheses

Set #4: Hypotheses on average deviation from the long-run (steady-state) result

H10: Users of visual interactive simulation (DSS 2) as their decision support system achieve a solution which has a lower average deviation from the long-run (steady-state) result than users of traditional simulation (DSS 1).

H11: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system achieve a solution which has a lower average deviation from the long-run (steady-state) result than users of traditional simulation system (DSS 1).

H12: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system achieve a solution which has a lower average deviation from the long-run (steady-state) result than users of a conventional visual interactive simulation (DSS 2).

This set of hypotheses concerned the capability of the decision support systems provided to help subjects in determining if a particular simulation run had reached steady-state. A variable which measured the deviation between the average net contribution obtained from the subject's own simulation run with the final recommendation (which was reported in the summary sheets) and the long-run (steady-state) average net contribution (which was obtained afterwards by running the recommendation five times for 300 simulated hours each and taking the average) was created. (The choice of 300 simulated hours resulted from more than 70 simulation runs with different control rules by the experimenter during model testing.) Also, in order to eliminate the problem of "cancelling-out" positive and negative effects, the deviation was squared.

Let

$s_{i,k}$ be the average net contribution obtained by subject i in group k

where $i \in [1,N_k]$ and $k \in [1,3]$

then define

$$d_{i,k} = s_{i,k} - c_{i,k}$$

$$\overline{D_k} = \sum_{i=1}^{N_k} \frac{d_{i,k}^2}{N_k}$$

where $\overline{D_k}$ is the group average squared deviation of all subjects in group k

It was argued that a better decision support system should provide a smaller $d_{i,k}$, and thus a smaller $\overline{D_k}$. See Table 4.5.

Hypothesis	Deviation from long-run (steady state) result
Variable measured	$\bar{D}_k$
H10	Group 2 (with DSS 2) is smaller than Group 1 (with DSS 1)
H11	Group 3 (with DSS 3) is smaller than Group 2 (with DSS 2)
H12	Group 3 (with DSS 3) is smaller than Group 1 (with DSS 1)

Table 4.5 Fourth set of hypotheses

Set #5: Hypotheses on decision speed

H13: Users of visual interactive simulation (DSS 2) as their decision support system arrive at their final decisions faster, in terms of considering fewer alternative control rules, than users of traditional simulation (DSS 1).

H14: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system arrive at their final decisions faster, in terms of considering fewer alternative control rules, than users of "conventional" visual interactive simulation system (DSS 2).

H15: Users of visual interactive simulation with paired-systems and paired-difference statistics (DSS 3) as their decision support system arrive at their final decisions faster, in terms of considering fewer alternative control rules, than users of a traditional simulation system (DSS 1).

Another criterion of a good decision support system was that it could help the user arrive at the final decision quickly, i.e., efficiently. This could be measured by either counting how many alternative control rules the subject had examined before reaching the final recommendation or the actual time length that the subject used to reach a final decision. In this experiment, the first measure was used.

Let

$a_{i,k}$ be the number of alternative control rules considered by subject i in group k

where $i \in [1,N_k]$ and $k \in [1,3]$

then define

$$\overline{A_k} = \sum_{i=1}^{N_k} \frac{a_{i,k}}{N_k}$$

where $\overline{A_k}$ is the group average of number of alternative control rules considered by all subjects in group k

See Table 4.6.

Hypothesis	Decision speed
Variable measured	$\overline{A_k}$
H13	Group 2 (with DSS 2) is smaller than Group 1 (with DSS 1)
H14	Group 3 (with DSS 3) is smaller than Group 2 (with DSS 2)
H15	Group 3 (with DSS 3) is smaller than Group 1 (with DSS 1)

Table 4.6 Fifth set of hypotheses

<u>Set #6: Hypotheses on effect of number of alternative control rules considered on decision performance</u>

H16: In experimental group 1, the number of alternative control rules considered had no effect on the performance of the subject's decision making.

H17: In experimental group 2, the number of alternative control rules considered had no effect on the performance of the subject's decision making.

H18: In experimental group 3, the number of alternative control rules considered had no effect on the performance of the subject's decision making.

This set of hypotheses examined whether the "number-crunching" approach (i.e., the consideration of as many alternative control rules as possible without too much analysis) could help the user obtain a better decision-making performance. It was believed that an analysis of simulation results from previous runs, rather than just number crunching, was more useful in achieving a better solution. See Table 4.7.

Hypothesis	Effect of number of alternative control rules considered on decision-making performance
Variable measured	$\overline{C_k}$
H16	In Group 1, the number of alternative control rules considered had no effect on average net contribution
H17	In Group 2, the number of alternative control rules considered had no effect on average net contribution
H18	In Group 3, the number of alternative control rules considered had no effect on average net contribution

Table 4.7 Sixth set of hypotheses

A supplementary variable, average run length in simulated hours, measured how long (in simulated time) on average the subject ran each simulation before reaching a decision. Two opposite factors influenced the outcome of this variable. The first factor was how much information the subject could get from the simulation run itself to determine the run length required; the more information a subject believed he/she might get from the visual displays of the system during the model run, the longer he/she might run the simulation. The second factor related to the running speed of the decision support systems used in the experiment. As discussed above and shown in Table 4.1, the running speed of DSS 3 was the lowest, DSS 2 was second lowest, and DSS 1 was the highest. It was believed that the faster the system, the longer the simulation that the subject might be willing to run. Because of these two opposite factors, no hypothesis was formulated. The group average run length was computed as follows:

Let

$l_{q,i,k}$ be the run length in the qth simulation run of subject i in group k

$Q_{i,k}$ be the total number of simulation runs of subject i in group k

where $q \in [1,Q_{i,k}]$, $i \in [1,N_k]$ and $k \in [1,3]$

then define

$$L_{i,k} = \sum_{q=1}^{Q_{i,k}} \frac{l_{q,i,k}}{Q_{i,k}}$$

$$\overline{L_k} = \sum_{i=1}^{N_k} \frac{L_{i,k}}{N_k}$$

where $L_{i,k}$ is the average run length of subject i in group k

$\overline{L_k}$ is the group average run length of all subjects in group k

4.4 The Pilot Test

A pilot test using PhD students as the subjects was conducted in September 1991 in order to

1. ensure the feasibility of the design of the whole experiment, and
2. test the three decision support systems again before the main experiment.

In total nine students, three in each experimental group, participated. They were from different area groups including marketing, production and operations management, management science/information systems, business policy and organizational behaviour. Comments were focused mainly on the written case provided to the subjects. Some minor programming errors in one of the decision support systems were also discovered. Following this pilot study, the case was revised and corrections were made to the computer program.

CHAPTER 5

DATA ANALYSIS AND DISCUSSION OF RESULTS

5.1 The Main Experiment

The main experiment, which lasted 7 weeks, was conducted between December 1991 and January 1992. In total, 77 second-year MBA students were recruited and 71 of them actually participated in the experiment. Three subjects were lost because they were exchange students and had returned to their home countries before the experiment began. Another three were lost through failure to obtain a suitable time slot. Of 71 participants, 55 (77.5%) were male and 16 (22.5%) were female. They were randomly assigned to one of the experimental groups. The random assignment turned out to have a fairly even distribution between male and female subjects. See Table 5.1.

	Group 1 (with DSS 1)	Group 2 (with DSS 2)	Group 3 (with DSS 3)	Total
Male	18	19	18	55
Female	6	5	5	16
Total	24	24	23	71

Table 5.1 Distribution of participants

The experiment was conducted according to the planned framework with the exception that 71 students, instead of the planned 75, participated. A decision was made in January 1992 not to extend the subject pool to first-year MBA students for two reasons. First, the experiment was only 4 subjects short of the planned 75 subjects and results of the data analysis were not expected to be significantly different from results for a sample size of 75. Second, the introduction of first-year MBA students into the experiment might introduce a variability of subjects that was not desirable.

5.2 Best Scheduling Strategy

Based on the empirical test conducted by the experimenter, of the four scheduling strategies that subjects were asked to use to develop the best control rule, the "Queue difference approach" was, on average, the best one to choose in terms of maximizing the average net contribution. The "Fixed time interval approach" was the second, "Inventory difference approach" the third, and the "Queue length approach" was the worst. (Details of the four strategies were presented in Section 4.2.2.)

5.3 Data Analysis

Values of the experimental measures were first computed based on the formulae defined in Section 4.3 from the raw data collected from the experiment. Appendices 2, 3 and 4 contain the data generated for experimental groups 1, 2 and 3, respectively. One subject (number 14) in experimental group 1 produced a result much worse than the rest of the sample; it was believed that this subject misunderstood what he had been asked to do. Therefore, this set of data was discarded from the data analysis. The sample sizes of each of the three experimental groups were thus 23, 24, and 23, respectively. Table 5.2 provides a summary of data obtained from the experiment.

	Group 1	Group 2	Group 3
	$N_1 = 23$	$N_2 = 24$	$N_3 = 23$
Group average long-run average net contribution ($\overline{C}_k$)	229.37	237.22	243.34
Group average predictive correctness ($\overline{P}_k$)	0.61	0.64	0.74
Group average confidence in predictive correctness ($\overline{R}_k$)	0.61	0.66	0.65
Group average squared deviation ($\overline{D}_k$)	425.54	290.50	136.77
Group average number of control rules considered ($\overline{A}_k$)	24.22	21.38	18.83
Group average run length (in simulated hours) ($\overline{L}_k$)	76.46	75.35	68.03

Table 5.2 Summary of data collected from the experiment

The six sets of proposed hypotheses were then tested with the following results:

Table 5.3 shows the results of the first three hypotheses relating the decision performance of users using different decision support systems. Subjects in Group 3 (using DSS 3, visual interactive simulation with paired-systems and paired-difference statistics) achieved significantly higher average net contribution than those in Group 1 (using DSS 1, traditional simulation), with p-value = 0.007. Group 3 also performed better than Group 2 although the level of significance was not as high as that of Group 1 (p-value = 0.085). However, subjects in Group 2 did not produce significantly better results than subjects in Group 1 (p-value = 0.124). Therefore, H3 was strongly supported; H2 was supported at a 10% level of significance; and H1 was not supported.

Hypothesis	Decision performance
Variable measured	$\overline{C}_k$
H 1	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 2	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 3	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Results			
$\overline{C}_k$	Hypothesis	p-value	Significance
Group 1 : 229.37	H 1	0.124	not significant
Group 2 : 237.22	H 2	0.085	significant at 0.10
Group 3 : 243.34	H 3	0.007	significant at 0.05

Table 5.3 Results of hypotheses on decision performance

Concerning the second set of hypotheses on predictive correctness, subjects in Group 3 again achieved a significantly higher average predictive correctness than subjects in Groups 2 and 1, with both p-values = 0.000 (See Table 5.4). Subjects in Group 2, however, did not outperform subjects in Group 1 (p-value = 0.153). Therefore, H5 and H6 also were supported, but H4 was not.

Hypothesis	Correctness of Prediction
Variable measured	$\bar{P}_k$
H 4	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 5	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 6	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Results			
$\bar{P}_k$	Hypothesis	p-value	Significance
Group 1 : 0.61	H 4	0.153	not significant
Group 2 : 0.64	H 5	0.000	significant at 0.05
Group 3 : 0.74	H 6	0.000	significant at 0.05

Table 5.4 Results of hypotheses on predictive correctness

The third set of hypotheses concerned the confidence in the subject's prediction. Table 5.5 shows the results. Subjects in Group 2 had a significantly higher confidence in their predictions than subjects in Group 1, with p-value = 0.040. Subjects in Group 3 also had a higher confidence in prediction but at a lower level of significance (p-value = 0.064) than that of Group 2. The confidence in predictions of subjects in Group 2 was not found to be significantly different from the confidence of subjects in Group 3. Therefore, H7 and H9 were supported, while H8 was not.

Hypothesis	Confidence in prediction
Variable measured	$\bar{R}_k$
H 7	Group 2 (with DSS 2) is higher than Group 1 (with DSS 1)
H 8	Group 3 (with DSS 3) is higher than Group 2 (with DSS 2)
H 9	Group 3 (with DSS 3) is higher than Group 1 (with DSS 1)

Results

$\bar{R}_k$	Hypothesis	p-value	Significance
Group 1 : 0.62	H 7	0.040	significant at 0.05
Group 2 : 0.66	H 8	0.701	not significant
Group 3 : 0.65	H 9	0.064	significant at 0.10

Table 5.5 Results of hypotheses on confidence in predictive correctness

The fourth set of hypotheses evaluated the deviation of the subject's solution from the long-run steady-state result. Table 5.6 presents the results of hypothesis testing. Subjects in Group 3 performed significantly better than subjects in Group 1, with p-value = 0.039. However, they did not produce a deviation which was significantly smaller than subjects in Group 2, who, in turn, also did not perform better than subjects in Group 1. Therefore, in this set of hypotheses, only H12 was supported. Both H10 and H11 were not.

Hypothesis	Deviation from long-run (steady-state) result
Variable measured	$\overline{D_k}$
H 10	Group 2 (with DSS 2) is smaller than Group 1 (with DSS 1)
H 11	Group 3 (with DSS 3) is smaller than Group 2 (with DSS 2)
H 12	Group 3 (with DSS 3) is smaller than Group 1 (with DSS 1)

Results

$\overline{D_k}$	Hypothesis	p-value	Significance
Group 1 : 425.54	H 10	0.285	not significant
Group 2 : 290.50	H 11	0.195	not significant
Group 3 : 136.77	H 12	0.039	significant at 0.05

Table 5.6 Results of hypotheses on deviation from long-run (steady-state) result

Table 5.7 shows the results of testing hypotheses on decision speed. Subjects in Group 3 considered significantly fewer alternative control rules than subjects in Groups 2 and 1, with p-value = 0.041 and p-value = 0.004, respectively. Also, subjects in Group 2 evaluated fewer alternative control rules than subjects in Group 1 (with p-value = 0.085) although the extent was not as great as the difference between Group 3 and Group 1. Therefore, all three hypotheses in this set were supported.

Hypothesis	Decision speed
Variable measured	$\bar{A}_k$
H 13	Group 2 (with DSS 2) is smaller than Group 1 (with DSS 1)
H 14	Group 3 (with DSS 3) is smaller than Group 2 (with DSS 2)
H 15	Group 3 (with DSS 3) is smaller than Group 1 (with DSS 1)

Results

$\bar{A}_k$	Hypothesis	p-value	Significance
Group 1 : 24.22	H 13	0.085	significant at 0.10
Group 2 : 21.38	H 14	0.041	significant at 0.05
Group 3 : 18.83	H 15	0.004	significant at 0.05

Table 5.7 Results of hypotheses on decision speed

The sixth set of hypotheses examined whether the "number-crunching" approach would help to achieve a better performance in decision making. Regression analyses were done with number of alternative control rules considered as the independent variable and average net contribution as the dependent variable. Table 5.8 shows the results of the three regression analyses (one for each experimental group). The results indicated that for subjects using the traditional simulation models, the number of alternative simulated systems did have a positive effect on the average net contribution, with t-value at 2.62 (R^2 = 0.246 and β = 1.54). However, for subjects using visual interactive simulation models, more alternatives investigated did not lead to better performance. Therefore, both H17 and H18 were supported, but H16 was not.

Hypothesis	Effect of number of alternative control rules considered on decision-making performance
Variable measured	Independent: $a_{i,k}$ Dependent: $c_{i,k}$
H16	In Group 1, the number of alternative control rules considered had no effect on average net contribution
H17	In Group 2, the number of alternative control rules considered had no effect on average net contribution
H18	In Group 3, the number of alternative control rules considered had no effect on average net contribution

Results

	Hypothesis	t-value	Significance
Group 1	H 16	2.62	significant
Group 2	H 17	1.70	not significant
Group 3	H 18	-0.26	not significant

Table 5.8 Results of hypotheses on effect of number of alternative control rules considered on decision-making performance

Finally, concerning the average run lengths (in simulated hours) that subjects used to examine each simulated system, there were basically no significant differences among the three groups of subjects. As discussed in Section 4.3, there were two opposite factors affecting the subject in deciding how long each subject was willing to run a simulation. First, the faster the speed of the simulation model, the longer the user might run. Second, the more information that the user felt he/she might get from the screen, the longer the simulation might be run. The first factor favoured the traditional simulation model, while the second factor supported the visual interactive simulation model. The results of this experiment suggested that these two factors might "cancel out" each other.

5.4 Discussion of Results

The results of the experiment are summarized in Table 5.9. It was apparent from the findings of this study that of the three types of simulation models, visual interactive simulation with paired-systems and paired-difference statistics was the best type of simulation model for building simulation-based decision support systems. Conventional visual interactive simulation was the second while the traditional simulation model was relatively the worst.

	Rank			Significant between 1st & 2nd	Significant between 2nd & 3rd	Significant between 1st & 3rd
	First	Second	Third			
Group average long run average net contribution	DSS 3	DSS 2	DSS 1	Yes*	No	Yes**
Group average predictive correctness	DSS 3	DSS 2	DSS 1	Yes**	No	Yes**
Group average confidence in predictive correctness	DSS 2	DSS 3	DSS 1	No	Yes*	Yes**
Group average squared deviation	DSS 3	DSS 2	DSS 1	No	No	Yes**
Group average number of control rules considered	DSS 3	DSS 2	DSS 1	Yes**	Yes*	Yes**

* significant at p-value = 0.10
** significant at p-value = 0.05

Table 5.9 Summary of results of the experiment

5.4.1 Visual Interactive Simulation vs Traditional Simulation

In a comparison of the conventional visual interactive simulation with the traditional simulation, the results of this experiment showed that although, on average, the former type of model was better than the latter one in all five evaluation criteria, the differences were not all statistically significant. Users employing a visual interactive simulation model (i.e., DSS 2 in the experiment) did not come up with a significantly higher average net contribution than users utilizing a traditional simulation model (i.e., DSS 1), nor did they have a significantly better prediction of the simulation outcomes, or a significantly smaller deviation from the long-run steady-state result.

Nevertheless, users employing the visual interactive simulation model did have a significantly higher confidence in their decisions than users utilizing the traditional simulation model. This finding confirmed the proposition from the proponents of visual interactive simulation (for example, Hurrion [1991]) that visual interactive simulation led to model (and decision) confidence.

5.4.2 Visual Interactive Simulation with Paired-systems and Paired-difference Statistics vs Conventional Visual Interactive Simulation

The results of the experiment suggested that one type of visual interactive simulation model was significantly better than the other in helping the user to carry out analysis and make decisions. Users employing the visual interactive simulation models with paired-systems and paired-difference statistics (i.e., DSS 3 in the experiment) produced significantly higher average net contributions and significantly better predictions than users utilizing the conventional visual interactive simulation model (i.e., DSS 2). Also, the former group considered significantly fewer control rules to arrive at the final recommendation than the latter group.

Regarding the confidence in prediction and the deviation from the long-run steady-state result, there were no significant differences between the groups of users. This finding was conceivable as both confidence in prediction and deviation from the long-run steady-state result were mainly concerned with the usefulness of the visual displays in the visual interactive simulation models and the paired-difference statistics did not play any important role here. Since both DSS 2 and DSS 3 were visual interactive simulation models, finding no significant differences in these areas was explicable.

5.4.3 Visual Interactive Simulation with Paired-systems and Paired-difference Statistics vs Traditional Simulation

The results of the comparison between these two types of simulation models were most encouraging to VIS proponents. The findings indicated that compared to the traditional simulation model, the visual interactive simulation with paired-systems and paired-difference statistics model provided the user with a better decision performance, better prediction of outcomes, higher level of confidence in prediction, smaller deviation from the long-run steady-state results, and faster speed in arriving at the final recommendation. All five differences were statistically significant. Four were significant at p-value = 0.05 and one (confidence in predictive correctness) was significant at p-value = 0.10. Therefore, based on the results of this experiment, it could be concluded that the visual interactive simulation with paired-systems and paired-difference statistics model was a more effective type of simulation model than the traditional simulation in developing simulation-based decision support systems.

5.4.4 Other Findings

As pointed out in Section 4.3, the running of visual interactive simulation models was much slower than that of the traditional simulation models. Visual interactive simulation models took a much longer time to run the same length of simulation than the traditional simulation models (See Table 4.1). The results of the experiment, however, showed that users utilizing the visual interactive simulation models still performed significantly better than the group employing the traditional simulation models. This finding, therefore, indicated that it was worth using the visual interactive simulation models (in particular with paired-systems and paired difference statistics) even though they were slower. Further advancements in computer technology might make this type of simulation model even more valuable.

Subjects using visual interactive simulation with paired-systems and paired-difference statistics had much less variation in their final recommendations than subjects employing traditional simulation models. As shown in Table 5.10, 87% of the subjects of Group 3 (20 out of 23 subjects) chose the "Queue difference approach" as the recommended strategy, 75% of the subjects in Group 2 (18 out of 24 subjects) chose this strategy while only 67% of the subjects in Group 1 (16 out of 24 subjects) recommended this one. Examination of the recommendations given by subjects in Group 1 showed that all four scheduling strategies had been picked and recommended. One subject chose the "Queue length strategy" even though it would produce a negative average net contribution. This finding was encouraging considering the concern raised by O'Keefe and Pitt [1991]. (In their study, they found that performance produced by a user using a visual interactive simulation model varied considerably.) In this experiment, compared to the traditional simulation model, subjects using visual interactive simulation models had less variation in their recommendations which mainly concentrated on the best strategy.

Group	Recommended Strategy			
	Inventory difference	Fixed time interval	Queue length	Queue difference
Group 1	2	5	1	16
Group 2	2	4	0	18
Group 3	0	3	0	20

Table 5.10 Distribution of recommended strategies

Another finding of this experiment was that investigating more alternatives did not necessarily lead to better performance. Although in the case of the traditional simulation model, evaluating more alternative control rules was found to be helpful in obtaining a better decision (t-value = 2.62), this was not the case when users were using either type of visual interactive simulation model. This result confirmed the findings by O'Keefe and Pitt [1991]. Investigation of more alternatives might not lead to a better solution.

CHAPTER 6

RESEARCH CONCLUSIONS AND IMPLICATIONS

6.1 Summary and Conclusions

This research project emerged from the importance of choosing a good type of simulation model in developing simulation-based decision support systems. Simulation has always been one of the most frequently used techniques in decision support systems (Hord et al.[1987] and Eom and Lee [1990a and 1990b]). Since Hurrion developed visual interactive simulation in 1976 [Hurrion, 1976], many case studies of the use of visual interactive simulation in building successful decision support systems had been reported in the literature [Bell, 1986]. While the usefulness of computer graphics has become an important research area in the MS/OR and MIS literature, evidence to support the claims of superiority of visual interactive simulation remained largely anecdotal [Kirkpatrick and Bell, 1988]. All this work suggested the need for a more formal comparison of visual interactive simulation modelling with traditional simulation modelling. This thesis reports such a comparison.

Another research issue evaluated in this thesis was the usefulness of paired-systems and paired-difference statistics in visual interactive simulation. The power of paired-difference statistics in comparing two alternative simulated systems had been reported in the literature (Hoover and Perry [1989] and Sloan and Unwin [1990]).

Bell [1989] claimed that a visual interactive simulation model with paired-systems and paired-difference statistics might be an approach to developing effective decision support systems. A new type of simulation model which combined both visual interactive simulation and paired-difference statistics was examined in this thesis with the secondary objective of evaluating the effectiveness of this new type of model.

The thesis presented the design and conduct of a laboratory experiment. Three different simulation-based decision support systems (employing a traditional simulation model, a visual interactive simulation model, and a visual interactive simulation with paired-systems and paired-difference statistics model, respectively) were developed. Seventy-one second-year MBA students participated in the experiment and were randomly assigned to one of three experimental groups. Each group used one of the three decision support systems to solve an identical production scheduling problem. Group performances were then compared to test a number of hypotheses concerning system performance.

Most of the results turned out as hypothesized. Although the conventional visual interactive simulation model was not found to be significantly better than the traditional simulation model in terms of helping the user to obtain better decision performance and higher accuracy of outcome prediction, the second type of visual interactive simulation model (with paired-systems and paired-difference statistics) outperformed the traditional simulation model significantly on all five evaluation criteria. Users employing the decision support system built upon the visual interactive simulation with paired-systems and paired-difference statistics achieved (statistically) significantly higher average net contribution, more accurate prediction, higher confidence in prediction, and smaller deviation from the long-run steady-state results than users utilizing the traditional simulation systems. They also evaluated fewer alternatives in arriving at the final recommendation.

Moreover, visual interactive simulation with paired-systems and paired-difference statistics was found to be more effective than conventional visual interactive simulation with single system and individual-sample statistics in helping the user to carry out analysis and make decisions. Users employing the visual interactive simulation with paired-systems and paired-difference statistics achieved significantly higher average net contribution and more accurate prediction than users utilizing conventional visual interactive simulation.

The study also found that although the running of a visual interactive simulation model was much slower than that of a traditional simulation model, it was still worth using. Users utilizing visual interactive simulation models (with paired-systems and paired-difference statistics) produced much better results than users employing traditional simulation models.

The finding of this research also showed that evaluating more alternative simulated systems did not lead to a better decision performance. Doing "good" analysis, rather than using a "number-crunching" strategy, emerged as the more effective problem-solving approach.

In conclusion, this research project empirically tested three different types of simulation models and found that the visual interactive simulation, particularly with paired-systems and paired-difference statistics, was a more effective type of simulation model than the traditional simulation in developing simulation-based decision support systems.

6.2 Research Limitations

Although this research produced some very encouraging results, four limitations are apparent and should be stated.

1. Sensitivity to model The experiment assumed that all three decision support systems provided to the subjects were equally "good": a bad traditional simulation model might be worse than a good visual interactive simulation model, even though the former model might be better than the latter one when both were equally "good" or "bad". The effort to make all three decision support systems the same, in terms of program logic, model interactions and output displays, aimed to minimize the effect of this sensitivity issue.

2. Task sensitivity The task in the experiment was basically a production scheduling problem; consequently, the results might not be generalizable to supporting decision making in general. It is anticipated that the hypotheses examined in this research would be reexamined in later projects using tasks in other functional areas such as marketing and finance.

3. Subject sensitivity The subjects used in this research were MBA students. Although it might be argued that MBA students provided a good substitute for practising managers (Ashton & Kramer [1980] and Remus [1986]), their use limits the generalizability of the research results. Additional studies using practising managers as the subjects are recommended.

4. Resources limitation Because of the limitation of resources, the experiment lasted about two months. There was, therefore, a danger of information leaking from early participants to later participants about both the content of, and the solution to, the exercise. The introduction of the final bonus to the top performer in each of the three experimental groups aimed to minimize the effect of this limitation.

6.3 Research Contributions and Future Research Issues

6.3.1 Research Contributions

There were three major contributions from this research.

1. It provided MS/OR researchers with the first empirical evaluation of three different types of simulation models. The lack of empirical studies on this topic in the existing literature made this research project meaningful. The results of the study confirmed the worthiness of this project.

2. It gave a rigorous testing of two allegations given by the proponents of visual interactive simulation, that visual interactive simulation was more effective than traditional simulation, and that visual interactive simulation with paired-systems and paired-difference statistics was better than conventional visual interactive simulation.

3. The results of this research provided MS/OR practitioners with insights and evidence about which type of simulation model was better in developing decision support systems to solve managerial problems.

Since simulation is a very popular and useful technique used in building decision support systems, this research has made a significant contribution to both the academic research arena and the practical world of developing simulation-based decision support systems.

6.3.2 Future Research Issues

There are at least five major research issues suggested by this research work:

1. further empirical assessment of visual interactive simulation
2. development of a formal methodology for i. orporating paired-systems and paired-difference statistics in visual interactive simulation models
3. methods to determine how much visual display is optimal
4. empirical evaluation of other types of visual interactive simulation models
5. development of the technology employed in building visual interactive simulation models.

1. <u>Further empirical assessment</u>

The research reported in this thesis is believed to be the first report of an empirical comparison of visual interactive simulation with traditional simulation. As discussed above, several limitations of the research are known. Therefore, an important future research task is to repeat the empirical test in different settings, such as using different case exercises in areas like marketing, finance or human resource management, and using practising managers as subjects. Further positive results of the empirical test in different experimental environments will confirm the effectiveness of visual interactive simulation and will generalize the results obtained and reported in this thesis.

2. Formal methodology for incorporating paired-systems and paired-difference statistics in visual interactive simulation models

The power of paired-systems and paired-difference statistics was confirmed in this research. However, displaying paired-systems on screen and incorporating paired-difference statistics in visual interactive simulation models are new concepts and the method used in this research project was experimental. Therefore, in order to more clearly understand and fully utilize their strengths, a more formal and thorough investigation of how to use paired-systems and paired-difference statistics in a visual interactive simulation model is necessary, including when to use them, in what form (numerical or graphical, or both) and to what extent. The key questions are how to display paired-systems in case of big models and how to "optimally" combine paired-difference statistics and individual-sample statistics in terms of providing information to the user.

3. Method to determine how extensive a visual display is appropriate

As reported in this thesis, the number of alternative simulated systems considered was found to have an impact, though not significant, on the results of the decision performance. The faster the model runs, the more alternative systems can be evaluated in a specific period of time. However, the inclusion of various visual displays in a simulation model significantly slows down the model execution. Therefore, a major research issue is to develop a formal approach to determine how extensive a visual display is appropriate, including what the contents of each screen should include and whether the visual display should always be "on". If not, when should it be "on" and when should it be "off"? The main advantage of having it always "on" is that the user can watch the simulation at all times and discover unusual happenings which cannot be summarized through an average statistic. The downside of extensive graphics is that they will slow down the simulation considerably.

4. Empirical evaluation of other types of visual interactive simulation models

As discussed in the "Experimental design" section (Section 4.2.4), the design could include other types of simulation models such as visual interactive simulation with paired-systems but without paired-difference statistics, or visual interactive simulation with three or four systems displayed and run simultaneously. Because the results of the experiment reported here have shown that visual interactive simulation models are more effective than traditional simulation models in supporting decision making, the various types of visual interactive simulation models are worthy of future research.

5. Technology employed in building visual interactive simulation models

Building a visual interactive simulation model is not easy. The model is usually built using either special simulation software packages such as GENETIK or SIMAN/CINEMA or other advanced (mostly object-oriented) programming languages such as C++, and considerable time is required to develop the program. End-user model building is difficult, if not impossible. Therefore, an important future research task is to develop better technology, in terms of easier and more user-friendly programming and understanding with the objective of making the programming faster and more understandable to the end-user of the simulation model. The increasing popularity of end-user computing makes this an important research issue.

APPENDIX 1

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VP BIOCHEMICAL COMPANY

On a Saturday in March, 1991, Jim Newton, a production supervisor in VP Biochemical Company, sat down in his office to think about how to tackle the task which had been assigned to him recently. He had been asked to develop simple and practical scheduling rules for equipment used to test two different types of chemical solution. In particular, the scheduling rule would specify when solution A (B) should be tested and for how long. The scheduling rule must specify under what circumstance a switch from testing one type of solution to another was called for.

The company

VP was a medium-sized biochemical company located in London, Ontario. In 1990, its revenue was almost seven million dollars. The company had about forty employees working in three main divisions. The biggest and most important division was the Chemical Solution division which produced various kinds of chemical solutions for hospitals and medical laboratories located in the Southwestern Ontario. The Chemical Solution division accounted for more than half of the company's revenue. Most of its production facilities were automated and the division operated twenty-four hours a day and seven days a week.

SIM and its production process

The best-selling product in the Chemical Solution division was a chemical product called SIM. It was usually produced in 3.0 litre units which required 0.8 litre of chemical solution A and 2.6 litres of chemical solution B mixed together. Both types of solution were first produced separately. In order to match the requirements of SIM, each unit of solution A and solution B were 0.8 litre and 2.6 litres respectively. Therefore, each unit of SIM simply required one unit of solution A and one unit of solution B (Exhibit 1).

Before mixing the solutions A and B to produce SIM, all units had to pass a chemical test. The purpose of the test was to make sure that each unit of solution had the correct chemical properties. Production processes of solutions A and B were subjected to random failures. Based on past experience, 10% of units of solution A and 30% of solution B were defective. Any defective units had to be eliminated before SIMs could be produced. The test device was perfect. Units of solutions A and B arrived at the testing centre at random but followed a Uniform Distribution. The inter-arrival times of solution A were between 10 and 30 minutes while for solution B, the times were between 5 and 25 minutes. Once passed, the unit would be put immediately into an inventory storage area always maintained at a temperature suitable for the type of solution (-5°C for type A and 5°C for type B). The failed units would be discarded. Since the demand for SIM was always very high, it was aimed to produce as many units of SIMs as possible.

The test centre had just one single piece of equipment to test both types of solution, i.e., both tests shared the same equipment (Exhibit 2). There was separate, but limited, storage provided for arriving units (of both types of solution) which could not be tested immediately. When the storage area in the test centre was full, the arriving unit had to be temporarily stored in a refrigeration compartment located adjacent to the test centre. As soon as storage space in the test centre became available, units would be transferred to the test centre. Due to different temperature requirements, each type of solution had its own refrigeration compartment which could store up to five hundred units of solution. Because of this large capacity, all units could be stored.

The gross contribution from producing one unit of SIM was $100.00. The "variable" operating cost of using the refrigeration compartment was $60.00 per hour, regardless of how many units in the compartment. When it was empty, this cost was assumed to be zero. Switching the testing equipment from testing one kind of solution to another resulted in cost of $50, due to the necessary cleaning and re-setup. Therefore, the net contribution was gross contribution minus storage cost and equipment switching cost. (The cost of failed units was not put into the contribution calculation because whether or not a unit failed was not within the control of this portion of the production line.)

Exhibit 3 summarized the key information about the production system.

Equipment scheduling for solution testing

Jim Newton, the production supervisor responsible for the production of SIM, thought that in order to maximize the net contribution of SIM, the key issue was how to schedule the testing time for solution types A and B. Current policy adopted an "equal-split" strategy - to test type A for one hour, then type B for another hour, then type A again, and so forth. Bob Redding, Jim's boss, was not satisfied with the results based on the current policy and thought that there had to be a better way to allocate the time of the testing equipment.

At a recent meeting, Bob and Jim came up with four different easily implementable scheduling strategies.

Scheduling strategy no. 1

The first scheduling strategy was based on the inventory ratio or difference of "after test and passed" units of solution A and B in the cold storage area at that point of time (Refer to Exhibit 2). For example, a simple scheduling rule based on this "inventory difference" approach was to first test type A , then switch to type B when 3 units of type A were tested successfully. Work on type B continued until its inventory were 5 units greater than type A's. The equipment then switched back to type A. The main idea of this strategy was to maintain a good inventory ratio at any point of time. A big disadvantage of this strategy was that it might involve many switches (of equipment re-setup).

- Start with A or B.
- While working on A,

$$\text{If} \quad I_t(A) - I_t(B) \quad \begin{cases} < X \text{ units}, & \text{continue A} \\ \geq X \text{ units}, & \text{switch to B} \end{cases}$$

- While working on B,

$$\text{If} \quad I_t(B) - I_t(A) \quad \begin{cases} < Y \text{ units}, & \text{continue B} \\ \geq Y \text{ units}, & \text{switch to A} \end{cases}$$

Scheduling strategy no. 2

The second scheduling strategy concerned the throughput rate. As on average, 3 units of solution A and 4 units of solution B arrived at the test centre each hour, it might be viable to schedule the testing equipment according to the input ratio, i.e., on average 3:4. For example, 30 minutes for solution A, then 40 minutes for solution B, then 30 minutes for solution A again, and so forth. The key parameters in this strategy were the lengths of the time allocated to testing solutions A and B (for example, 30 and 40 minutes). The longer these times, the fewer switches were required, but the greater the chance of exceeding the storage areas in the test centre. This, in turn, would result in cost associated with using the refrigeration compartments.

```
 T(A) mins    T(B) mins     T(A) mins      T(B) mins
|-----------|*|-------------|*|-----------|*|------------------|*|-------------->  Time
 Working      Working       Working        Wcrking
 on A         on B          on A           on B
```

OR

```
 T(B) mins    T(A) mins     T(B) mins      T(A) mins
|-----------|*|-------------|*|-----------|*|------------------|*|-------------->  Time
 Working      Working       Working        Working
 on B         on A          on B           on A
```

* Switching time

Scheduling strategy no. 3

The third scheduling strategy was to look at the queue lengths of types A and B in the storage areas of the test centre. The testing equipment continued to work on type A (or type B) until the queue of type B (or type A) reached a certain number, say 7 units. It was then that the equipment would be switched to test the other type of solution. This strategy could lower the number of switches and minimize (if not totally eliminate) the usage of the refrigeration compartments. Therefore, the key variables in this strategy were the two numbers which triggered the switching. However, just like the second strategy, it did not guarantee a right inventory ratio.

- Start with A or B.

- While working on A,

$$\text{If} \quad Q_t(B) \quad \begin{cases} < X \text{ units}, & \text{continue A} \\ \geq X \text{ units}, & \text{switch to B} \end{cases}$$

- While working on B,

$$\text{If} \quad Q_t(A) \quad \begin{cases} < Y \text{ units}, & \text{continue B} \\ \geq Y \text{ units}, & \text{switch to A} \end{cases}$$

Scheduling strategy no. 4

Another scheduling strategy could be developed by looking at the difference of the lengths of two holding queues. This scheduling strategy issued the switch order when the difference in queue length was larger than a certain predetermined number. So, like strategy no. 3, this strategy could reduce the number of switches and the usage of the refrigeration compartments. The disadvantage of this fourth strategy, however, was that it might lead to under-utilize the storage space in the test centre, especially when the queue length difference parameters were set to be large (say, more than 5). Also, this strategy did not guarantee a right inventory ratio.

- Start with A or B.
- While working on A,

$$\text{If} \quad Q_t(B) - Q_t(A) \begin{cases} < X \text{ units}, & \text{continue A} \\ \geq X \text{ units}, & \text{switch to B} \end{cases}$$

- While working on B,

$$\text{If} \quad Q_t(A) - Q_t(B) \begin{cases} < Y \text{ units}, & \text{continue B} \\ \geq Y \text{ units}, & \text{switch to A} \end{cases}$$

The main task

Bob asked Jim to compare and analyze these four strategies. The objective of the assignment was to identify the best scheduling rule which would maximize the SIM (average) net contributions.

EXHIBIT 1

Unit Requirements of Producing One Unit of SIM

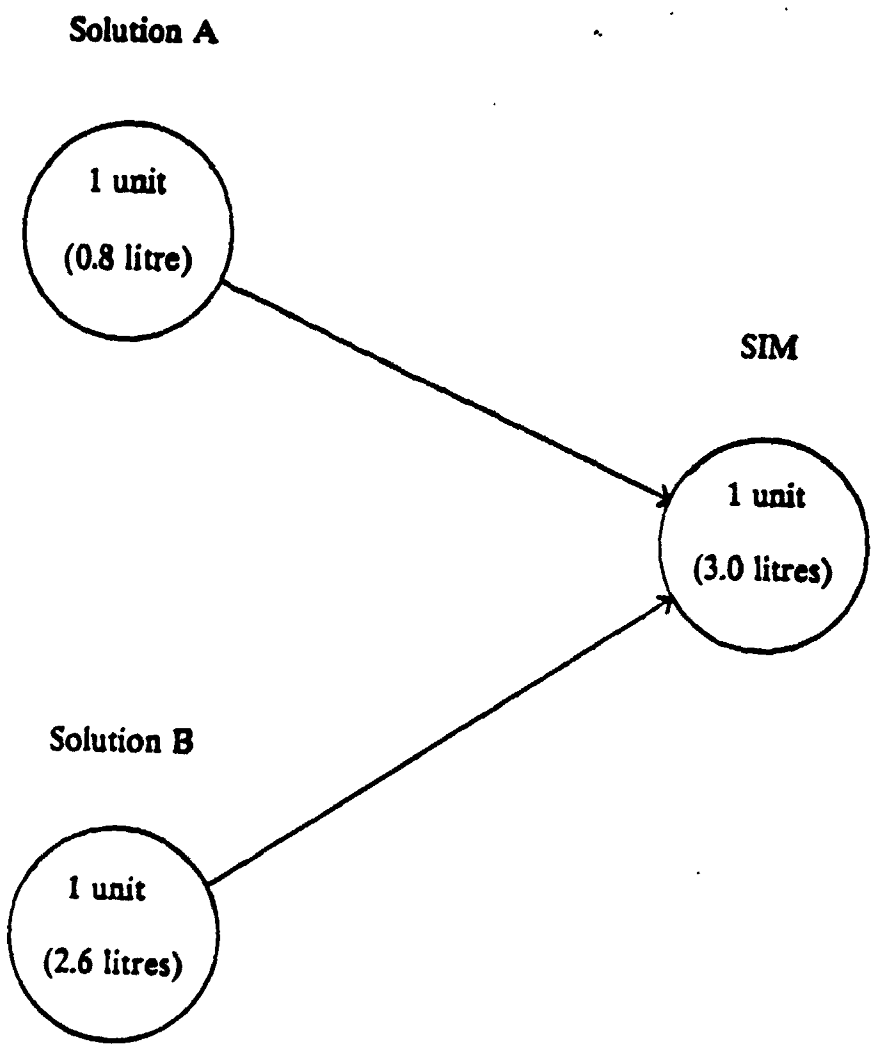

EXHIBIT 2

Flow Diagram of the Production Process of SIM

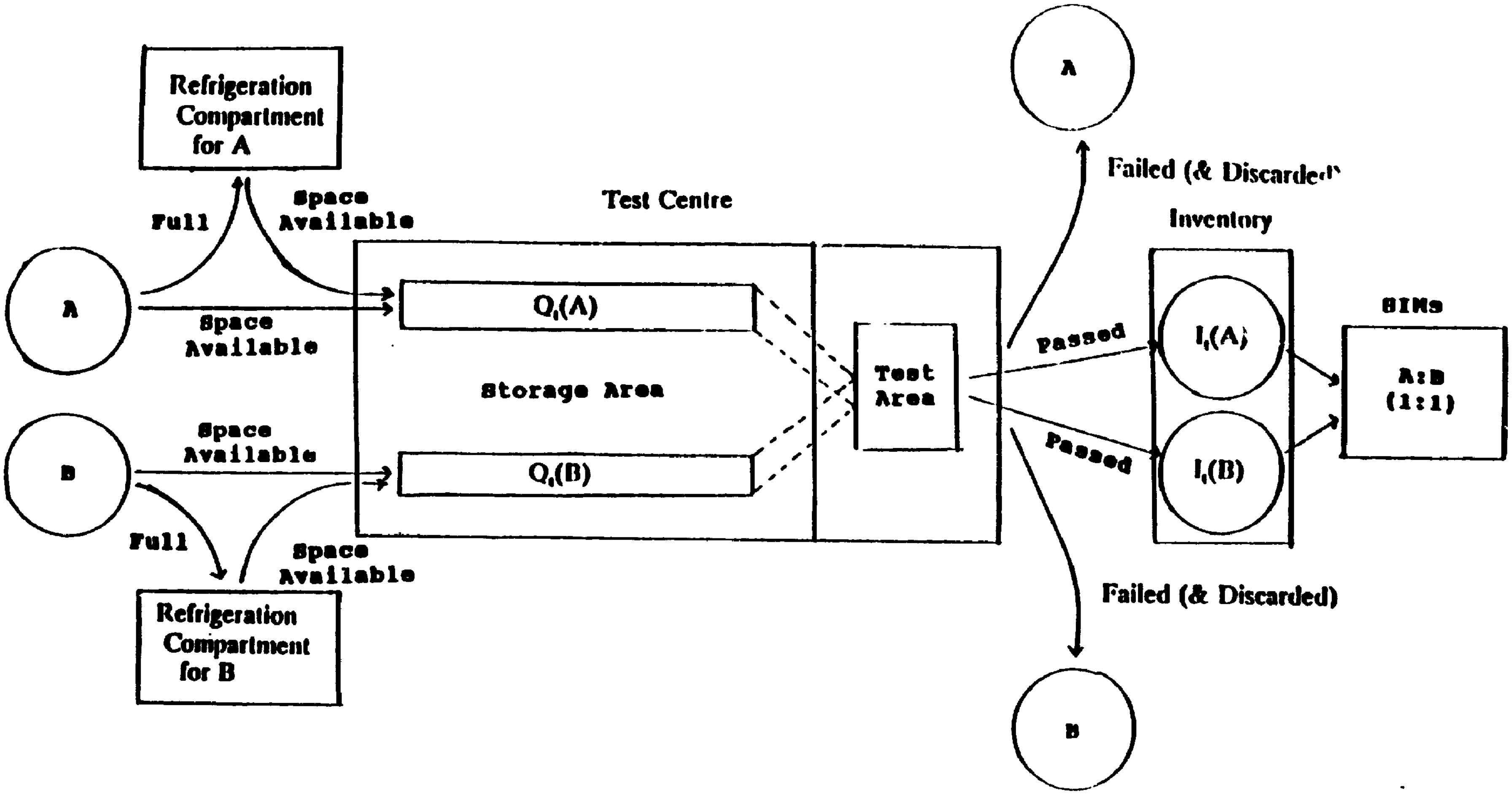

EXHIBIT 3

Key Information of the Production System

Inter-arrival time of type A solution (in minutes)	:	Uniform Distribution, between 10 and 30 minutes
Inter-arrival time of type B solution (in minutes)	:	Uniform Distribution, between 5 and 25 minutes
Storage space in the test centre for type A solution	:	10 units
Storage space in the test centre for type B solution	:	10 units
Testing time for type A solution	:	7 minutes/unit
Testing time for type B solution	:	7 minutes/unit
Time required for switching (from A to B or B to A)	:	5 minutes
Prob (type A passed the test)	:	0.90
Prob (type B passed the test)	:	0.70
Gross contribution per unit of SIM	:	$ 100.00
Cost per hour of using refrigeration compartment for type A solution	:	$ 60.00
Cost per hour of using refrigeration compartment for type B solution	:	$ 60.00
Cost per switch	:	$ 50.00

Net contribution from SIMs

= (# of SIMs produced)*$100
- (# of hours using refrigeration compartment for type A)*$60
- (# of hours using refrigeration compartment for type B)*$60
- (# of switches)*$50

Number	Recommended Strategy	$s_{i,k}$	$c_{i,k}$	$d_{i,k}$	$d^2_{i,k}$	$P_{i,k}$	$R_{i,k}$	$L_{i,k}$	$A_{i,k}$
1	QD 10 10 B	251.34	249.28	2.06	4.24	65.12	58.60	92.56	30
2	QD 7 8 A	238.79	246.03	-7.24	52.42	61.11	50.39	59.16	27
3	FI 120 170 B	240.36	206.32	34.04	1,158.72	50.00	62.00	97.13	9
4	QD 5 6 B	227.58	237.19	-9.61	92.35	60.87	58.70	66.46	23
5	FI 150 200 B	237.47	224.76	12.71	161.54	68.18	60.83	83.54	17
6	QD 10 10 A	236.93	249.23	-12.30	151.29	57.58	72.88	48.11	38
7	FI 106 149 B	222.34	192.77	29.57	874.38	63.64	63.64	67.88	30
8	FI 90 120 A	228.05	197.82	30.23	913.85	50.00	62.50	59.84	32
9	QD 10 10 B	242.69	249.28	-6.59	43.43	62.50	71.21	72.78	31
10	QD 6 8 A	241.72	243.40	-1.68	2.82	57.14	60.00	81.88	30
11	QD 7 9 A	243.29	248.16	-4.87	23.72	52.50	61.63	68.78	36
12	QD 3 9 B	230.81	242.11	-11.30	127.69	43.48	72.74	88.22	23
13	QD 3 7 A	222.00	236.69	-14.69	215.80	65.38	61.73	46.36	26
14	QL 10 7 B	145.41	-143.16	288.57	83,272.64	57.14	52.86	41.73	21
15	FI 150 200 A	229.00	228.03	0.97	0.94	56.25	55.63	103.47	17
16	QD 9 7 A	251.56	246.62	4.94	24.40	92.31	57.41	122.52	31
17	QD 7 6 B	236.36	243.01	-6.65	44.22	60.00	56.80	42.69	22
18	QD 8 8 B	239.90	248.06	-8.16	66.59	56.25	74.41	132.16	16
19	QD 8 10 A	243.17	248.31	-5.14	26.42	56.76	57.30	49.08	38
20	IO 3 5 B	213.89	155.57	58.32	3,401.22	66.67	54.00	45.46	11
21	QD 1 4 B	168.25	204.31	-36.06	1,300.32	75.00	65.25	83.19	17
22	IO 4 6 A	209.06	183.67	25.39	644.65	46.15	60.00	81.87	14
23	QD 8 7 B	243.57	245.82	-2.25	5.06	75.00	75.42	84.00	22
24	QD 10 9 A	247.37	249.13	-1.76	3.10	61.54	66.18	82.24	18

Appendix 2 Data collected from experimental group 1

Number	Recommended Strategy	$s_{i,k}$	$c_{i,k}$	$d_{i,k}$	$d^2_{i,k}$	$P_{i,k}$	$R_{i,k}$	$L_{i,k}$	$A_{i,k}$
1	OD 8 8 A	242.64	247.25	-4.61	21.25	48.39	58.71	60.90	30
2	FI 135 180 A	240.58	234.67	5.91	34.93	50.00	60.42	60.36	14
3	OD 10 4 A	233.20	244.00	-10.80	116.64	46.15	58.33	78.04	16
4	FI 120 160 A	240.78	235.36	5.42	29.38	55.56	61.82	80.79	16
5	OD 3 5 B	196.72	224.41	-27.69	766.74	76.47	82.89	80.70	21
6	OD 5 6 B	224.00	237.19	-13.19	173.98	60.00	58.13	72.32	18
7	OD 8 8 B	246.15	249.06	-2.91	8.47	55.56	74.98	60.28	21
8	OD 7 7 B	239.67	243.24	-3.57	12.74	72.22	73.57	87.32	22
9	OD 9 8 B	249.28	248.21	1.07	1.14	84.85	84.71	76.56	23
10	OD 9 9 B	242.76	248.89	-6.13	37.58	77.78	70.00	65.21	15
11	FI 125 165 B	238.48	230.14	8.34	69.56	66.67	63.33	93.47	21
12	OD 8 7 B	242.33	245.82	-3.49	12.18	58.82	62.35	76.22	18
13	FI 120 160 A	238.87	235.36	3.51	12.32	72.73	59.55	57.67	27
14	OD 10 9 A	244.88	249.13	-4.25	18.06	75.00	69.75	101.86	22
15	OD 6 6 A	244.19	240.70	3.49	12.18	63.16	58.59	43.52	27
16	OD 9 10 B	242.88	249.09	-6.21	38.56	61.54	62.31	37.75	35
17	OD 8 7 A	243.02	245.05	-2.03	4.12	60.71	67.04	57.69	26
18	OD 7 8 A	245.13	246.03	-0.90	0.81	60.00	50.50	64.93	30
19	OD 9 8 A	242.58	248.06	-5.48	30.03	58.92	81.80	79.96	21
20	OD 9 9 B	246.33	248.89	-2.56	6.55	66.67	69.58	90.00	16
21	OD 10 3 B	235.10	242.66	-7.56	57.15	64.71	67.06	80.27	22
22	10 5 5 A	215.08	176.65	38.43	1,476.86	70.00	55.36	115.36	18
23	OD 10 10 B	241.83	249.28	-7.45	55.50	61.11	71.39	78.29	19
24	10 8 2 A	238.27	175.22	63.05	3,975.30	60.00	58.33	82.13	14

Appendix 3 Data collected from experimental group 2

Number	Recommended Strategy	$s_{i,k}$	$c_{i,k}$	$d_{i,k}$	$d^2_{i,k}$	$P_{i,k}$	$R_{i,k}$	$L_{i,k}$	$A_{i,k}$
1	QD 10 10 A	232.94	249.23	-16.29	265.36	75.00	62.50	71.32	24
2	QD 8 8 A	239.15	247.25	-8.10	65.61	83.33	64.17	69.93	13
3	QD 6 7 B	226.44	242.60	-16.16	261.15	88.89	73.89	76.87	15
4	QD 7 7 B	234.18	243.24	-9.06	82.08	66.67	65.00	81.73	13
5	QD 7 7 B	236.16	243.24	-7.08	50.13	75.00	58.46	82.47	14
6	QD 8 9 B	235.51	247.64	-12.13	147.14	76.92	60.00	45.10	27
7	QD 10 8 B	243.82	249.01	-5.19	26.94	81.82	70.91	92.22	18
8	QD 10 10 B	236.25	249.28	-13.03	169.78	71.43	66.00	89.46	14
9	QD 9 9 B	237.82	248.89	-11.07	122.54	75.00	59.17	99.42	20
10	QD 10 10 B	235.89	249.28	-13.39	179.29	71.43	52.14	47.54	15
11	QD 4 5 B	223.75	230.23	-6.48	41.99	100.00	64.44	114.38	16
12	QD 10 10 B	238.84	249.28	-10.44	108.99	81.82	61.54	60.62	25
13	QD 9 9 B	228.79	248.89	-20.10	404.01	54.55	67.27	36.77	23
14	QD 7 7 A	236.05	246.16	-10.11	102.21	77.78	67.00	55.70	12
15	QD 7 8 B	237.79	246.29	-8.50	72.25	70.00	79.45	43.40	21
16	FI 120 160 B	227.40	229.41	-2.01	4.04	62.50	65.00	71.66	16
17	QD 6 8 A	238.24	243.40	-5.16	26.63	68.75	68.13	51.83	23
18	FI 135 170 B	230.61	221.22	9.39	88.17	70.00	62.73	90.09	24
19	QD 10 8 A	233.12	247.75	-14.63	214.04	81.82	68.18	108.18	15
20	QD 8 10 A	234.04	248.31	-14.27	203.63	82.50	62.35	52.56	20
21	QD 7 6 B	238.80	243.01	-4.21	17.72	64.71	75.29	43.59	21
22	QD 6 5 A	216.72	237.68	-20.96	439.32	82.35	65.29	45.00	24
23	FI 155 200 A	228.31	235.57	-7.26	52.71	66.67	64.17	43.75	20

Appendix 4 Data collected from experimental group 3

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