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EXPERIMENTAL DESIGNS FOR SIMULATION

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ABSTRACT

Experimental design issues are an important and integral aspect of most simulation studies. The intent of this paper is to provide an overview of research on design issues that are unique to experimentation in a simulation environment. Tactical issues such as the length of simulation runs and number of replications are not discussed here. Instead, we focus our discussion on strategic issues such as the selection of design plans, statistical models, input variables, and random number stream assignments.

1 INTRODUCTION

Experimental design and analysis techniques are widely used in simulation studies. Gordon, Ausink, and Berdine (1994) recently used experimental design strategies in a spacecraft control simulation and Kuei and Madu (1994) applied these techniques in the simulation of a maintenance float system. Examples of other recently published applications utilizing experimental design techniques in a simulation context are as follows: Bailey and Clark (1992) studied the management of taxi routes; Clark, McCommon, and Hammond (1990) considered a parallel multi-server queueing system; Hood and Welch (1992) modeled the logistics of semiconductor manufacturing; López-Valcárcel and Pérez (1994) examined the set-up of an emergency department; Madu and Kuei (1992) investigated a multiechelon repair system with cold standby machines; Montgomery (1992) considered statistical process control for product improvement; Philipoom, Malhotra, and Jensen (1993) evaluated order review and release procedures in job shops; Takakuwa (1991) studied computer-aided cart systems; and Wourms and Bauer (1991) investigated airlift system productivity.

Classical experimental design techniques were pioneered by Sir Ronald A. Fisher in the early 1900s for agricultural research and experimentation. Since that time, numerous textbooks have been written (and continually updated) to include modern developments in experimental design (e.g.; Atkinson and Donev 1992; Box, Hunter, and Hunter 1978; Cochran and Cox 1957; Fisher 1966; Montgomery 1991). A recent article in *Technometrics* (Steinberg and Hunter 1984) provides a state-of-the-art review of experimental design and analysis strategies.

A scientific approach to designing experiments is necessary if the experimentation is to be performed most efficiently and a statistical approach is needed if meaningful conclusions are to be drawn from the experimental data. A statistical approach to the design and analysis of experiments generally includes the following steps:

1. State the problem requiring experimentation and state the objective of the study (e.g.; prediction, optimization, sensitivity analysis).
2. Choose the *factors* (controllable input variables).
3. Select the *response* variable (output variable).
4. Determine the *operability region* (range of values for each factor within which the system can operate).
5. Specify the *region of interest* (a subregion of the operability region within which you want to perform the current experiment).
6. Choose a statistical model (e.g.; ANOVA, regression, spatial correlation).
7. Select a criteria for choosing an experimental design (e.g.; minimize generalized variance, minimize mean squared error).
8. Choose an appropriate experimental design class (e.g; factorial, Latin square, central composite).

9. Select the levels of the factors for each *design point* (experimental run).
10. Perform the experiments and collect data.
11. Analyze and summarize the data; check for adequacy of the statistical model.
12. Draw inferences and conclusions.

These twelve steps also apply to experimentation in simulation studies. In addition, there are a number of tactical and strategic experimental design issues that are unique to experimentation within a simulation environment:

Tactical issues

- whether to perform a terminating or steady-state simulation,
- estimating the distributions of stochastic model components,
- selecting the initial conditions or the duration of the warm-up period,
- choosing the final conditions such as run time or number of events completed, and
- deciding on an appropriate balance between run length and the number of replications (or batches).

Strategic issues

- choosing a method for the assignment of random number streams to design points, and
- deciding whether to use an appropriate variance reduction technique.

The tactical issues involved in simulation experimentation are discussed at length in many simulation textbooks whereas strategic experimental design issues often receive brief coverage. Strategic issues are discussed in the following textbooks: Banks and Carson (1984) discuss the use of a completely randomized design for an ANOVA model in a simulation context; Fishman (1974) describes experimental designs for ANOVA and polynomial regression models, incorporating both random number assignment strategies and variance reduction techniques; Fishman (1978) discusses variance stabilizing transformations and ranking procedures in the context of an ANOVA model and factorial design plan; Kleijnen (1974) briefly discusses factor screening and response surface designs; Kleijnen (1986) provides a thorough treatment of one factor at a time designs, factorial and fractional factorial designs, central composite designs, simplex designs, and screening designs; Kleijnen and van Groenendaal (1992) provide an overview of classical experimental design, factor screening, and response surface methodology; Law and Kelton (1991) discuss and provide examples of full and fractional factorial designs, screening designs, and response surface designs.

The scope of this paper is limited to the strategic issues involved in the design of simulation experiments as well as the classical issues that are an integral part of experimental design. The remainder of the paper is organized as follows. In §2, we discuss statistical models that are applicable to simulation studies as well as the types of *metamodels* that can be used to model the response variable. In §3, we discuss simulation research that incorporates random number stream assignments and/or variance reduction techniques into the experimental design. Research that incorporates Taguchi strategies into simulation design and analysis are discussed in §4. The last section, §5, includes some miscellaneous experimental design strategies and provides suggestions for future research.

2 STATISTICAL MODELS AND METAMODELS

The choice of a statistical model depends on the ultimate purpose of the simulation study. From a statistical design standpoint, there are basically two types of objectives:

1. sensitivity analysis, which involves the comparison of experimental results under alternative operating conditions (input variable settings), and
2. prediction and/or optimization of the response variable, which involves the estimation of a functional relationship between the input factors and the response variable.

Sensitivity analysis is generally performed using an ANOVA model. In the case of two alternatives to be compared, the use of variance reduction techniques such as common random numbers, antithetic sampling, and control variates is well documented in the simulation textbooks noted earlier. For experiments involving three or more alternatives, the design and analysis techniques become more complicated and are similar to those used for the second objective noted above. The statistical model for prediction and/or optimization is a *metamodel* (a statistical model of the response from a simulation model).

Issues involving the estimation of metamodels for the prediction and/or optimization of response have received recent attention in the simulation literature. Barton (1992) provides a state-of-the-art review on the use of metamodels in simulation, and Barton (1993) updates and expands on the previous study. Barton discusses experimental design issues for the following types of metamodels:

- polynomial regression and Taguchi models,
- univariate and multivariate spline models,
- radial basis functions,
- kernel smoothing models,
- frequency domain basis functions, and
- spatial correlation models.

Experimental design and analysis techniques for polynomial regression and Taguchi models are well-documented in the literature and are discussed in sections 3 and 4 of this paper. Barton provides an overview of spline models, noting that experimental design issues have yet to be addressed in the literature. Similarly, Barton describes radial basis functions, kernel smoothing metamodels, and frequency domain basis functions, noting that applications of these models in simulation are limited. On the other hand, there has been considerable research on spatial correlation metamodels. Currin et al. (1991) discuss the design of experiments for spatial correlation models and Mitchell and Morris (1992) use Latin hypercube designs in a spatial correlation approach to response surface optimization. Spatial correlation experimental design issues are also discussed by Sacks, Schiller, and Welch (1989), Sacks et al. (1989), Salagame and Barton (1993), Stein (1987), and Tang (1993).

Kleijnen (1987) points out in the preface of his book "I have found that some techniques have great appeal to practitioners; examples of such techniques are experimental designs and regression metamodels." The following section discusses the research on simulation designs for the estimation of regression metamodels.

3 RESEARCH ON DESIGNS FOR REGRESSION METAMODELS

Regression analysis is a statistical technique that can be used to summarize the changes in the simulation output due to changes in the simulation input. A regression metamodel is often used for predicting the value of the response variable for a given set of operating conditions. Sometimes RSM (response surface methodology) is employed to predict the optimum system response and/or the optimum operating conditions for the input factors. RSM is not discussed here—the reader is referred textbooks by Box and Draper (1987) and Myers (1976) and to a state-of-the-art review by Myers, Khuri, and Carter (1989).

The earliest work on simulation designs for fitting regression metamodels can be found in a book edited by Naylor (1969) and in an article by Hunter and Naylor (1970). Both of these references discuss experimental design issues in the context of simulation modeling. Fishman (1974) was one of the first researchers to include the assignment of random number streams to design points as an integral part of the design of simulation experiments for estimation of regression metamodels. Montgomery and Evans (1975) performed an empirical study that used RSM techniques in computer simulation, and Montgomery and Bettencourt (1977) extended the earlier study by considering multiple-variable optimization.

The research of Schruben and Margolin (1978) is, perhaps, the most significant contribution to the literature on the design of simulation experiments. Their proposed "Assignment Rule" has sparked a great deal of interest in the subject area. However, due to time and space limitations, the details of their work (and the follow-up work by other researchers) will not be included in this paper. References relating to the experimental design of simulation experiments are as follows: Donohue, Houck, and Myers (1994, 1993a, 1993b, 1992), Hussey, Myers, and Houck (1987a, 1987b), Joshi and Tew (1994), Kleijnen (1988, 1981, 1977), Nozari, Arnold, and Pegden (1987), Schruben (1979), Tew (1992, 1991), Tew and Crenshaw (1990), and Tew and Wilson (1994, 1992).

In the following section, we discuss research on the use of Taguchi design and analysis strategies in the context of computer simulation. Taguchi metamodels share many properties with regression metamodels and, similarly, they can be studied effectively using standard statistical techniques.

4 RESEARCH ON TAGUCHI METHODS

During the 1980s, methodology advocated by Genichi Taguchi, often called robust parameter design, gained the attention and interest of practitioners working in quality improvement. Taguchi can be commended for looking beyond manufacturing costs and considering the costs incurred by end-users of products. One of Taguchi's notable contributions to quality improvement is a strategy for incorporating variability measures into the evaluation of a process. He found that it was often more costly to control manufacturing variability than it was to make the process insensitive to this variability. The Taguchi strategy for process design is essentially an application of decision making under uncertainty. The underlying strategy requires specification of a loss function, a noise space, and a design space. Data is collected to find the process design that minimizes the expected loss over the noise space. Taguchi's tactics (rather than his underlying strategy) have sparked controversy among quality engineers and statisticians. (See, for example, Myers, Khuri, and Vining 1992 and Nair 1992.) Such research indicates that traditional design tactics and performance measures, used in conjunction with the underlying Taguchi strategy, yields the best process designs.

For an overview of Taguchi experimental design and analysis procedures (without reference to simulation), see Kackar (1985), Pignatiello (1988), and Tsui (1992). For a discussion of Taguchi methods in the context of simulation metamodeling, see Ramberg et al. (1991), Sanchez et al. (1993), Sanchez, Sanchez, and Ramberg (1994), Schruben et al. (1992), and Wild and Pignatiello (1991).

5 ADDITIONAL RESEARCH ON DESIGN ISSUES

In reviewing the literature on the design of simulation experiments, we found a number of research studies that did not fit into our metamodel framework. These articles are briefly discussed here. Mollamustafaoglu, Gurkan, and Ozge (1993) discuss experimental design issues for simulations that use object-oriented programming for output analysis. Kleijnen and Annink (1992) investigate the use of vector computers for simulation metamodeling and find them to be potentially useful. McKay, Beckman, and Conover (1979) and McKay (1992) consider experimental design issues for simulations in which the input variables are random variables (rather than controllable factors). Morris (1991) considers randomized experimental design plans for input screening in which the number of input variables does not play a role in determining the number of experimental design points. Nelson (1992) provides some guidelines on the tactical issues of experimental design for simulation practitioners. Safizdeh (1990) presents a review of optimization techniques for simulation experimentation and briefly explains the most commonly-used techniques. Welch et al. (1992) treat the simulated response variable as a stochastic process and utilize a nonparametric modeling approach. Welch et al. (1990) combine the Taguchi strategies with a computer generated design to develop a model of a simulated response variable.

Most of the recent research in experimental designs for simulation has focused on metamodeling (see §3) and Taguchi strategies (see §4). While these are important and useful areas of research, there are other important areas that have received little attention. In reviewing recent applications of experimental design techniques in simulation studies, we found that practitioners seem to use ANOVA models as often as regression models, yet recent simulation design research has focused on regression models. Therefore, research on new design and analysis techniques might also be applied to ANOVA models. Designing experiments for simulations on parallel computers is another area with potential for future application and, with the increased speed of computers, nontraditional (large) experimental designs such as Latin hypercubes might be more thoroughly investigated.

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