SIMULATION: METHODOLOGY AND APPLICATION IN AGRICULTURAL ECONOMICS

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The diverse modelling activity coming under a defined concept of Simulation is reviewed first through a general outline of suggested methodology and secondly through a survey of applications in agricultural economics and kindred disciplines. The review concludes with a consideration of present problems with and future prospects for this increasingly important tool.

1 INTRODUCTION

Simulation is a human endeavour that has emerged recently, is developing rapidly and has a large and growing literature which has from time to time been reviewed [64, 72, 184, 225, 237, 276, 338, 329, 348] compiled into bibliographies [65, 167, 200, 207, 256, 258, 265, 284, 286, 333] and condensed in expository textbooks [31, 135, 137, 165, 192, 221, 229, 236, 251, 261, 265, 268, 274, 286, 288, 326, 339, 352]. In spite of this, a wide spectrum of opinion pervades even recent writings on the definition, essential features, practice and role of simulation. Another aspect of the literature which presumably prompted the invitation for this review is the absence of a reasonably comprehensive survey of simulation in agricultural economics.

Accordingly, this review commences in section 2 with a fairly detailed outline of methodology for simulation. The didactic stance adopted is occasioned by the variety of approaches that have been suggested and employed by practitioners in many disciplines. However, it is not professed that the state of the art is such that optimal procedures are either agreed upon or readily identified. Rather, the several steps elaborated are those that typically will be followed in a successful simulation study. All steps are not always taken by all practitioners but miscreants court grave danger of rendering their work of dubious value.

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Some of the wide flexibility and scope of simulation is illustrated in the survey of applications presented in section 3. But these applications are often suggestive of the importance of several prevailing problems which continue to circumscribe the impact and role of simulation. Such problems are highlighted in section 4. The review terminates with a balancing perspective in section 5 and comments on the literature in section 6.

2 METHODOLOGY OF SIMULATION

Simulation is a technique frequently employed by practitioners who profess to be adopting a "systems approach" or doing "systems analysis". Notwithstanding the careless use of such terminology in many references (including [97]), simulation should not be confused with the broader and more philosophical concept of the systems approach [2, 3, 69, 107, 132, 134, 243]. The systems approach is a way of thinking about and looking at systems (collections of interactive and interdependent components) which features conceptualization of a whole systematic structure and a formal modelling phase. This encompasses activity much wider than shall be identified here as simulation. Systems analysis [38, 52, 268] most properly refers to the analytical phase of systems work. The term system analysis shall be used here to describe the corresponding step in the simulation of a particular system.

2.1 MODELLING IN GENERAL

The models used by agricultural economists [114] have been of almost every conceivable type; from verbal to symbolic, simple to complex, static and dynamic, deterministic and probabilistic (stochastic), optimizing and otherwise. What with agriculture being characterized as it is by its biological and meteorological dependence and its economists being what they are, a preponderance of agricultural economists' modelling has been of the symbolic-mathematical type and the models of most generally adequate and relevant construction have been of the stochastic and dynamic variety [12]. Simulation models presently and prospectively are the most feasible, most workable and probably most potentially useful types of model in this important category [12, 254].

2.2 THE UNCERTAINTY PRINCIPLE OF MODELLING

Agricultural economics systems, perhaps more so than systems of interest to many other scientists, exhibit the feature that even if they can be modelled crudely by simple deterministic symbolic models, close study of the structure of a system reveals an intricate composition of such complexity as to defy complete deterministic description. The bounds of human understanding necessarily prevent complete specification of all the mechanisms of a system. In any modelling study, these bounds will be influenced by, apart from the general objectives, the sensory, conceptual and educational limitations of the modellers involved as well as the imposed limitations of available time, experimental resources, reference material and access to outside expertise.

Imprecision or uncertainty in understanding is, at least according to the persuasive Bayesian viewpoint [106, 317], best and most operationally encoded through probability distributions. Whenever a system is modelled imperfectly—and at some level of detail this applies to all models—the model should properly become probabilistic to capture accurately the precision of understanding. Arguing in this style, Mihram has educed an Uncertainty Principle of Modelling: "Refinement in Modelling eventuates a requirement for stochasticity" [268, p. 15], from which he draws the corollary that the more conscientiously developed model will be more likely stochastic in character.

Simulation models, which are the most flexible and least-confined of symbolic models, can accomodate stochasticity easily and directly and accordingly will often find favour over more restrictive and less-easily stochasticised models whenever refined and versatile modelling is undertaken.

2.3 DEFINITIONAL AND METHODOLOGICAL OVERVIEW

In a loose sense, every model in the long history of science "simulates" its modelled system but it is worth distinguishing between a model that mimics the behaviour of a system and a crude model that does not. Most systems of interest, especially in economics, operate dynamically so that mimicry requires dynamic modelling. As has been observed, mimicry of many systems, particularly in agricultural economics, should appropriately be stochastic. This review thus concentrates on dynamic, stochastic symbolic models. Informal models of the class can be called simulation models. To be precise, we define *simulation* as numerical manipulation of a symbolic model of a system over time. A system so modelled will be referred to here as the *simuland* and the person performing the simulation as the *simulator*. Aspects of the simulation model, as opposed to those of the simuland will be qualified as *simular* (e.g. simular time). Conceptually, computers are in no way essential in simulation. Practically, however, an electronic digital computer is required to make possible the implementation of non-trivial simulation models. Our definition of simulation embraces recursive programming [93] although the accent on dynamically constrained linear programming modules in recursive programming makes it something of an atypical example—especially since practitioners (e.g. [94]) seemingly ignore the uncertainty principle of modelling and take initial conditions and environment as deterministic (an exception being [233]).

Problems tackled by a simulation approach are typically loosely structured. Perhaps not surprisingly, simulation work also often seems to follow loosely inter-connected procedures. However, several distinct stages can usually be identified and are best followed in a systematic and logical manner.

Presently these stages are quickly overviewed preparatory to subsequent and more complete elaboration of each stage as it applies in digital simulation modelling.

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(a) Stage 0: Simulation Goals and Plans. Easier said than done, at the outset an intending simulator should clearly formulate his problem and the purpose to which his planned model will be addressed. With due regard to the high cost of simulation, he should justify the *ex ante* appropriateness of a simulation approach. Such prior planning demands explicit consideration of methods of and criteria for model validation, experimentation and interpretation. Clear formulation of goals of modelling is demanding but its difficulty should be faced squarely if the simulator's time and his sponsor's money are not to be chanced away needlessly.

(b) Stage 1: System Analysis. This initial analytical stage consists of studying the system under view to determine its salient features and components and to discover their interrelationships and modes of behaviour. Definition of the system and its environment will depend crucially on the goals expressed. Analytical procedures will blend analysis of data, review of literature and the experience and other subjective inputs of the simulator.

(c) Stage 2: Synthesis. Either concurrently or when system analysis is complete, the diverse results attained therein are synthesized into a coherent and logical structure. Particular attention will be given to organizing events temporally according to a conceived simular calendar and clock. Structure will be encoded in detailed charts and relationships and decision rules specified algebraically.

(d) Stage 2.1: Stochastic Specification. Explicit consideration of probabilistic features of the system is required in both system analysis and synthesis stages. The techniques useful in both stages and those required for generation of stochastic variables in model implementation are closely allied and tend to be handled together in practice, and so for convenience are here treated as a separate stage.

(e) Stage 2.2: Model Implementation. The final step in synthesis is usually to implement the synthesized model on an electronic digital computer. This involves selection of a computer and a programming language, decisions on the progression of simular time and input/output options. Specialist programmers can render considerable assistance at this stage but are often most effective when the simulator has acquired some experience with computers.

(f) Stage 3: Checking the Model. Testing involves two distinct activities, namely verification and validation.

(g) Stage 3.1: Verification. In verification, the simulator inquires as to the adequacy with which the synthesized and implemented model measures up to intentions. Verification ensures that simular behaviour accords with knowledge gleaned in system analysis, synthesis and with common sense.

(h) Stage 3.2: Validation. Once verification has ensured the realization of the simulator's initial modelling intentions, the simulator must decide if his verified model is a sufficiently valid mimicry of the real-world simuland to justify his proceeding to model analysis.

(i) Stage 4: Model Analysis. Model analysis is concerned with learning about the behaviour of the validated model and committing it to the designed purpose.

(j) Stage 4.1: Sensitivity Analysis. One possibility is to study the sensitivity of model responses (outputs of performance variables) to changes in important structural parameters—particularly those about which the simulator is relatively ignorant.

(k) Stage 4.2: Model Experimentation. Once it is ensured that the model is not hopelessly sensitive, more formal experimentation on the model can proceed. This may explore response in relation to changes in qualitative and quantitative factors (input variables or decision rules) and usually employs experimental designs, including when appropriate those efficient in seeking optima.

(l) Stage 4.3: Interpretation. Simulation models usually feature many response variables generally stochastic in character which poses potential difficulties of interpretation of results from model experimentation. Inadequate crystallization of criteria for appraisal in Step 0 is paid for in floundering in a sea of computer paper in model analysis.

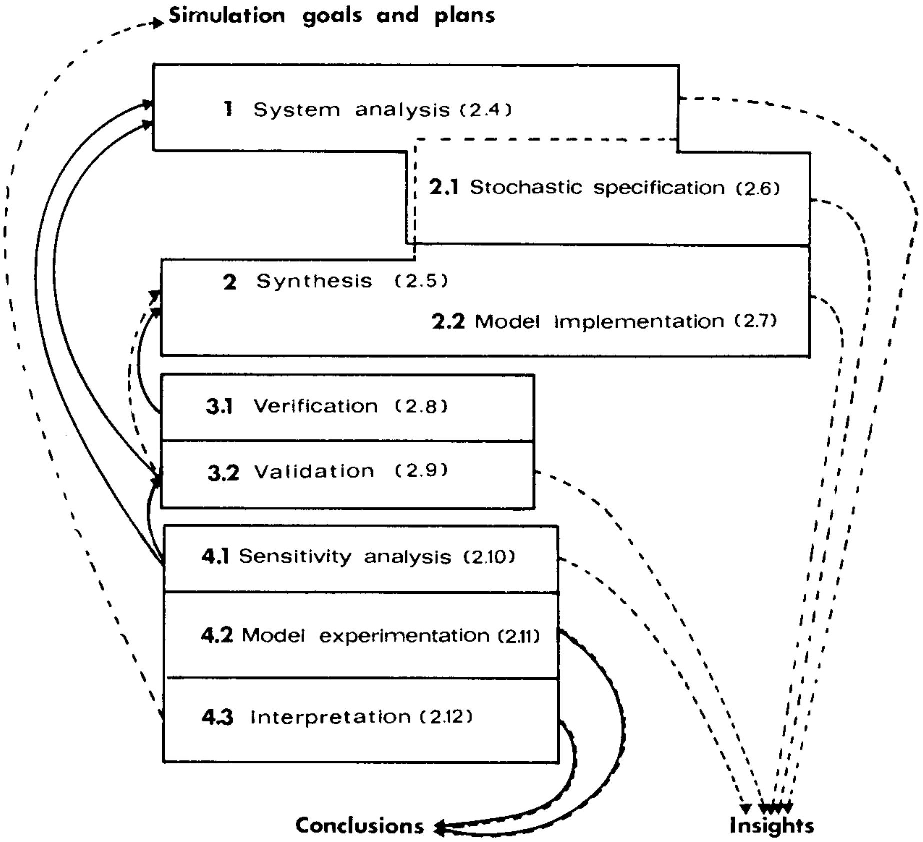

FIGURE 1: **Stages of simulation** (*and section of this review where they are elaborated*)

While these stages have been discussed as more-or-less distinct temporally and logically, simulation hardly ever proceeds smoothly from one stage to the next. As has been suggested, recycling may be initiated at several points, especially as a result of failed verification and validation. The typical process of simulation can be succinctly sketched by means of the schematic model in figure 1 which also indicates where the steps are discussed in this review. Amongst other things, figure 1 is intended to indicate that a simulation study may, through continued iteration, never reach the stage of drawing conclusions about the modelled system—a feature not, of course, unique to simulation. However, it does suggest that even in this case, it is likely that possibly valuable insights to the system will be gained. Such insights may prove to be useful in the context of research administration [17].

While some ideas have now been offered on what simulation is, the opportunity should not be missed to clarify what, under the present definition, it is not. Two techniques are sufficiently closely related to simulation to raise the possibility of a confusion that is best immediately dispelled.

The *Monte Carlo method* [179, 328] essentially involves the solution of (often deterministic) mathematical problems by means of random sampling from probability distributions—usually with the aid of an electronic computer. The method generally involves none of the dynamic considerations inherent in the simulation methodology outlined above but has sometimes been called simulation in published reports [57, 99, 113, 314, 368]. A simplistic example of the Monte Carlo method would be the evaluation of the area of a circle constructed in a unit square as the relative frequency of points falling within the circle where the co-ordinates of each point are specified as a variate uniformly distributed on the interval (0.0—1.0). Of course, the deterministic problems to which the technique has been directed in agricultural economics are much less mathematically tractible and range from applications in production function analysis [108] to sophisticated variants of linear programming problems [100, 113]. Problems involving non-linear compounding of probabilities are also readily and most conveniently amenable to a Monte Carlo approach [48, 281, 314].

Gaming models frequently possess many of the dynamic, stochastic and structural features of typical simulation models (and indeed have often been termed "simulations" [32]). However, there is one additional and distinguishing feature, namely direct human interaction in running the model. Such models, which have usually had primarily an instructional purpose, were developed initially by military instructors but in recent years have been followed-up enthusiastically by business management schools. Gaming models (e.g. [130]) have received some development also in agricultural economics and farm management but are not surveyed here (see [248]). Attention is now returned to a stepwise elaboration of the stages in simulation.

2.4 SYSTEM ANALYSIS

Probably after (but possibly before) the simulator has firmed on his goals and plans in simulation, he will embark on his detailed analysis of the system. This will involve a wide-ranging enquiry that is intended to permit the isolation of all necessary *state variables* to represent adequately the state of the simuland, and the necessary identification of the events occurring among the interrelated subsystems.

A simulation model serves to track the state of a system as it is represented by ascribed simular state variables over simular time. Each aspect of the state of a system is represented by a simular entity which may have several recorded characteristics or attributes. Entities may be variously connected directly by relationships. The attributes of an entity record the extent of changes occurring in it. Events may change (a) the number of extant simular entities, (b) attributes, and (c) relationships. Such changes may occur either instantaneously or over some duration of simular time in which case the event is begun by an initial event and ended by a terminal event. Events may be simple algebraic and logical constructions or relatively complex algorithms, such as decision analytic routines or linear programming sub-models.

Events (and their directly influenced variables) may also be classified according to their origin. Exogenous events originate from the environment and so by definition are not identifiably influenced by anything within the defined boundary. Conversely, endogenous events originate within the boundary of the system and are thus caused either directly or indirectly (through changing attributes) by earlier endogenous and/or exogenous events.

Events and relationships may be deterministic or stochastic. The simplest event is the definition of a permanent entity at the start of simular time. The simplest relationship is an identity which fixes the definition of one entity in terms of other entities. Some relationships may emerge directly from established theory but many will require empirical assessment.

Often there is a close correspondence between the conceptualized components of the simuland and the components of the model. However, this is seldom one-to-one even though the simulator probably, at least initially, aspired to model such a correspondence. His laudable aspirations, which are naturally in the spirit of the systems approach, may be foiled for various reasons but usually because the data and/or relationships available to him do not permit a one-to-one approach. Sometimes he will be forced to introduce hypothetical constructs which have no direct correspondence with components of the simuland (e.g. Bonini's [43] index of "felt pressure" on executives). Simulators of farm-plant-animal systems, for example, usually resort to some hypothetical construct to represent the growth and stock of forage in a system (e.g. [8, 11, 68, 174, 202, 219]).

The chosen approach to techniques employed for, and success achieved in system analysis are bound to be strongly influenced by the simulator's training, experience, and imagination. The end-product of analysis will depend on who does the work. "Influential" work will incorporate "publicly" acceptable assumptions and "professionally respected" work will not incorporate too many controversial and theoretically unacceptable assumptions. Recall, though, that the history of science is strewn with later-important models that were neither influential nor respected at the times of their announcements.

For most systems there exists (a) a body of relevant disciplinary literature, (b) a set of recorded (possibly published) operating data, and (c) a variety of informal states of knowledge among those people familiar with the system. Systems' diversity unfortunately precludes generalization about use of accepted and published work and of informal but informed opinions. In spite of the obvious advantage of statistical training, simulators in their system analysis should not be too shackled by conventional statistical practice. Hand-sketched curves sometimes prove more useful than elaborate least-squares equations. I think that imaginative use of prior knowledge and extraneous information will be particularly important in overcoming the problems of autocorrelation and collinearity which plague economic data, especially where delayed feedback loops are operative.

Simulations of agricultural systems (especially farms) that do not involve numerous decisions over simular time are rare. Decisions vary greatly in complexity and include such things as selecting desired inventory levels and consumption patterns, optimal farm organizations, machinery replacement times, land acquisitions or disposals, and so on. In contrast to gaming models, such decisions are built into simulation models explicitly and it must be observed that simulators have tended to be rather arbitrary in the specification, and often simply have imposed an exogenous list of fixed decisions. While one can be sympathetic to the logical and mechanical difficulties posed by incorporating, say, a few linear programming, inventory and replacement modules within an already large stochastic simulation model, the neglect of such considerations when they are appropriate deserves careful attention in interpretation. Endogenous decision rules typically are functions of performance earlier in simular time so storage of performance variables and updating in expectation models is necessary. Expectation models have ranged from simple weightings of previous yields and prices [309] to Bayesian probabilistic revisions [301]. Tactical decision rules have included deterministic budgets [309], linear programming models (embedded [94, 233] and exogenously appended [359]) and budget-based expected utility maximization models [11]. The importance of careful specification of decision rules in simulation appears to be better recognized by simulators of farm systems than by simulators of other economic systems [126].

An important part of both subjective appraisal and data analysis in system analysis concerns the description and specification of stochastic features of both the system and its environment. Discussion of these procedures is deferred to section 2.6. The preparation of detailed schematic models and flow-charts is a transitional activity between system analysis and synthesis and is taken up in section 2.5.

2.5 SYNTHESIS

As in system analysis, imagination; skill and perception predispose success in combining analysed components into a logical structure. To some extent the synthetic phase must always proceed in parallel with the analytical phase as judgments are made, for instance, about whether an event falls within or without the boundary. Diagrammatic representations often can assist such contemplation. Authorities have extolled the virtues of many different methods of charting the essential features of systems. These range from the pragmatism of "bubble charts" and "block diagrams" through to the sophistication of "event graphs" [268], but any scheme that promotes systematic thinking is useful. If it also facilitates model implementation, so much the better. Rigid adherence to any one scheme has the single possible advantage that communication of ideas to others familiar with the scheme is enhanced. It is often convenient to blend ideas from the conventional flow charts of computer programming with those from Industrial Dynamics [149, 343].

Simular time can be handled in many different ways. Real time advances continuously but only with analogue computer simulation models can simular variables be adjusted continuously. Although it is possible to program digital computers to approximate the continuous operation of analogue machines, for practical purposes all digital simulation models can be regarded as discrete-change models wherein time is advanced in unit or multiple discrete increments. The technique chosen for keeping time in discrete-change models depends on the problem at hand and the programming language employed. In general, the task of keeping simular time is assigned to an executive routine which controls the operation of the simulation model. The time variable is advanced by adding a defined time interval. Often simular time is maintained as an integer variable, so that a crucial step in synthesis is to define the minimal time step size that is common and appropriate to all simular events and entities [338].

The simplest scheme for time advance is to move time forward by single units in a so-called time-stepping simulation. Most often time-stepped simulations operate by the executive routine checking the event routines and scheduling their operation as required. However, it is also possible to store event schedule information as an attribute of each entity in which case a time-stepping simulation can proceed by checking entities. An alternative scheme that is sometimes much more efficient in terms of computer usage is event-stepping simulation in which time may be advanced in irregular increments if no events are scheduled in the intervening simular time. This scheme depends on the executive routine having access to a time-ordered sequence of events with a complete listing of operational details [288].

A discrete-change system implies that several events may occur during the same interval ("instant") of simular time although the unit of time advance is generally chosen so that the probability of more than one decision being taken in one unit of time is very small. Since digital computers are sequential processors (as opposed to parallel-processing analogue computers), it is necessary to provide a logical serial ordering of "simultaneous" events—an ordering usually easily achieved by program arrangements. The digital language DYNAMO [316], for example, permits accounting for all specified feedbacks in each unit of simular time and thus mimes analogue simulations very flexibly.

The synthesis of the mechanics of all simular activity is closely allied to logical charting and timing of the simuland's behaviour and it necessarily proceeds concurrently. In the light of goals expressed, the simulator must make judgments about setting the initial conditions of the required simular variables. For example, endogenous variables are typically stochastic and must be supplied with initial values at the start of simular time. Unless the simulator desires to treat these values as experimental factors in exploring simular performance (i.e. conditional on different initial values), it will be appropriate to sample initial values from the relevant distributions. Related consideration will guide the selection of the simuland time corresponding to initial simular time. Many authorities (e.g. [82]) regard it as good (if not essential) practice to allow a simulation to run for an initial "settling-down" period during which performance of the model is ignored so that the influence of chosen initial conditions on recorded performance is minimized. In the interest of economy it is apparent that simulators will desire to minimize the length of this unrecorded set-up period. Unfortunately there are no general guidelines on how to detect a minimal period that obscures any apparent influence of initial conditions on subsequent performance.

Attention must be given to input and output demands that will be made in subsequent stages. A desire not to be overwhelmed by a mountain of output should inspire a judicious selection of flexible options for reporting the simular state at any time. The implementation of the synthesized model on a computer (section 2.7) marks the completion of synthesis.

2.6 STOCHASTIC SPECIFICATION

The desirability of modelling stochastic features of systems has been observed at several points. Most obviously, stochastic variables and events emerge because of the limitations imposed by the conceptual boundary of a system. Simulations of agricultural simulands, for instance, often define weather as belonging to the environment and so no attempt is made to model the complex of atmospheric phenomena that, say, lead to rainfall. Consequently, relative to the simulated system, rainfall will usually be treated as a stochastic event. Exogenous events are typically stochastic. Analogous reasoning applied within the system leads to a similar conclusion, the essence of which has been encoded above in the uncertainty principle of modelling. Relationships may be depicted by mathematical expressions (perhaps produced in least-squares estimations) but careful insight inevitably reveals such expressions as being imperfect and possibly inadequate. Ignorance of this type is best described probabilistically. Stochasticity can thus arise in simulation either (a) because the process leading up to an event has not been explicitly modelled (e.g. rainfall, queue arrival times), or (b) because the relationship selected for the model is imprecise. Judgment as to the virtue of including the various stochastic features in his model is intuitive, at least until the simulator reaches the stages of validation and sensitivity analysis.

Data limitations being what they invariably are, specification of the distributions of stochastic variables is intrinsically subjective although the simulator may well wish to incorporate the degrees of belief of more knowledgeable persons including perhaps the ultimate decision makers intended to be aided or influenced by the simulation. In short, all the probability elicitation and data analysis techniques employed in decision analysis (see e.g. [317, 325]) are potentially relevant to the simulator of stochastic systems.

The residual variance about an empirical regression equation epitomizes the concept of the uncertainty principle of modelling: if this variance is ignored in a model, the "whole story" clearly has not been "told"; if it is properly captured and included, the actual state of understanding can be represented. Given that the estimation accords with the usual least-squares assumptions, the error mean square provides an unbiased estimate of the unexplained variance. If in addition (as it often can) the variation can be regarded as the sum of numerous small contributions, an appeal to the Central Limit Theorem [138] will approximate this variation as normally distributed with zero mean and variance equal to the error mean square. Such stochasticity in agricultural systems has too seldom been included by simulators (an exception being [67]).

Stochastic simulation requires the generation of variates from the specified distributions; which in turn may be simplified by describing distributions in terms of the parameters of theoretical distributions, where appropriate distributions can be found and fitted [162]. The families of distributions considered will reflect both the simulator's statistical background and the nature of the phenomena modelled (relative to rainfall processes, see [311]). For instance, binomial, triangular, geometric, Rayleigh, Weibull, Cauchy and extreme-value distributions provide simple generation via the inverse distribution transformation [288]. Normally distributed variates can readily be generated by several methods [50, 268]. Poisson, Pascal, Erlang, Chi-squared t, F, Gamma, Beta and Stacy distributions can also be generated with little difficulty [158, 268]. In fitting theoretical curves to data, the simulator may be guided by goodness-of-fit statistics such as the Chi-square and Kolmogorov-Smirnov statistics [81] but more importantly he should convince himself that a fitted distribution selected captures the completeness of understanding of the probabilistic process. This will imply both common-sense interpretations of phenomena and mathematical interpretations of visual impressions gleaned from graphically arrayed data.

The history of generation of pseudorandom variates is long [347] and the primary literature extensive. Fortunately, methods of and programs for generating variates from all the important theoretical (including multivariate [324]) distributions are extensively reviewed in secondary sources [265, 268, 274, 286, 288]. Suffice to note here that, at the very least, computer installations now have library routines available for generating uniformly distributed pseudorandom numbers (in the range zero to one) which have passed a gamut of statistical tests for randomness. It is now just a mechanical procedure to transform uniform variates to those of a desired distribution.

Failure to capture inherent stochastic dependence may detract seriously from the validity and utility of a model. Two important cases of non-independence can be identified: (a) serial dependence in a probabilistic process (e.g. rainfall in successive periods [311]), and (b) dependence between contemporaneous probabilistic processes [79] e.g. rainfalls during the same time interval at separately disperse stations [10, 340]. Testing for non-independence can be a large task if classical procedures of significance testing are applied mechanically. As is the case with judgmental joint distributions [18], informal understanding of the functioning of system and environment can be much more useful than sophisticated test procedures. Testing for serial independence [312] and computation of simple correlations can be informative and suggestive when ample data are available and the sampled distributions are conveniently symmetric, but will be of little assistance otherwise.

A pragmatic approach to serial stochastic specification seems to be called for. Implementation is simplest when successive stochastic events can be presumed independent but this may demand a time interval longer than desirable in other parts of the model. A compromise must be reached involving the accuracy of modelling and monitoring the simular structures, the choice of simular time unit, and the achievement of stochastic independence. For instance, monthly rainfall (or some transform of rainfall) may be deemed independent but performance monitoring may demand a daily accounting, such as in a crop-soil-water budget [120]. It will then be necessary to devise an appropriate scheme for allocating the generated monthly variates to individual days [312]. Again some compromise will be sought between the competing considerations of accuracy of stochastic and process modelling, and costs of synthesis and computer implementation. This work can become messy and the alternative of attempting to estimate and incorporate directly the serial dependencies [201] is also not a very attractive alternative although sensitivity analysis can give an indication of the likely effects of misspecification of serial dependence [186]. The simulator may be forced into the more pragmatic corner of using selections of actual observations of, say, daily rainfalls. At worst, the observed sequence can simply be reused over and again [349]. At best, the selection of the data of particular years can be handled pseudorandomly [59, 268, p. 236, 374, 379] and has the obvious feature of effortlessly incorporating any real serial dependencies. However, it suffers two distinct disadvantages, namely, (a) the philosophic objection that rainfall data represent no more than a restricted sample from some stochastic process, and (b) the possibly large storage requirement for the historical data.

Analogous to the difficulties noted for autocorrelated variates, multivariate contemporaneous distributions (such as the joint distribution of rainfall and temperature rainfalls at two locations) threaten practical difficulties. In fact, the only simulators to have given due emphasis to multivariate stochastic specification appear to be econometricians [363], although others have recognized the problem [276]. Biological and managerial simulators have generally given scant credence to the possibility that disturbances in several relationships may not, in fact, be independent (an exception is [71][1]. Without explicit sensitivity analysis, it is

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[1] A similar problem (noted in [231, p. 307]) concerns the possible dependence between residual disturbances and generated variables entering other and the same equations.

impossible to judge how important this neglect might have been but this reviewer suspects (some support being provided in [128]) it is much more serious than has been realized, especially by the simulators concerned.

2.7 MODEL IMPLEMENTATION

Selection of computer is an easy task for which one's ordering of priorities might usefully be: convenience, cost, size, and finally speed of computer. Simulation on distant computers or terminals can be fraught with frustration. Selection of a programming language is more difficult. Languages in which simulation models may be drafted are of two broad types, (a) general-purpose languages (exemplified by the widely-available FORTRAN), and (b) special-purpose simulation languages. These languages have already been surveyed many times [234, 239, 348, 353] and agricultural economists are referred to a review of the reviews by Charlton [61]. Numerous examples of programs written in both types of languages are available in text books, e.g. [265, 288].

Special purpose languages have been developed with the modelling of particular systems in mind. Some, like SIMSCRIPT [235, 260] are specifically adept in modelling queuing and inventory systems whereas others, such as DYNAMO [316], and FORDYN [247] are oriented to modelling systems characterized by numerous first-order difference equations and complex feedback loops. All such languages take a particular view of the world which may not correspond with that of the simulator. The main advantage of using a special-purpose language is that, once fluent the simulator should find that implementation is expedited. These languages have been designed specifically: (a) to provide a generalized structure for simulation, (b) to permit ready implementation of a synthesized model into a working program, (c) to facilitate adjustments in the model, and (d) to provide convenient and flexible output options. Included in (b) are usually featured (i) a built-in executive routine and simular clockworks, (ii) provision for generating variates from several standard distributions, and (iii) comprehensive error-checking devices. Output options in (d) typically include the possibility of periodically computing a range of statistics, histograms, time plots, etc. Even without such desirable features, general-purpose languages such as FORTRAN may often be the best choice for agricultural economists. This suggestion is founded on (a) an appreciation of the limited availability of a special-purpose language, (b) some unhappy experience with the inherent inflexibility of some special-purpose languages, (c) a belief that many intending simulators already have a background of experience with FORTRAN, and (d) a feeling that special-purpose languages loose much of their apparent appeal when due regard is given to all the setup costs involved in deploying them. Opting for a general-purpose language poses the need for the simulator to tolerate less comprehensive error checking and the need to provide his own stochastic generators, executive routine, simular time-keeping and output reports. However, these responsibilities are not very onerous especially as FORTRAN subroutines for stochastic generation and some output options are readily available [286, 288].

2.8 VERIFICATION

At the completion of implementation, the simulator is armed with a weapon of unknown capability. Before doing serious battle with it in subsequent analytical stages, he will need to assess its inherent accuracy. Its perceived ability to perform the intended purpose may induce return to earlier developmental stages before proceeding. Appraisal of whether or not a model justifies persistent analytical attention can conveniently be categorized in two fairly distinct steps [267]: (a) *verification* or checking the correctness of the model as conceived in earlier stages, and (b) *validation*, or deciding the adequacy of the model to mime the behaviour of the simuland. In this section we examine the first of these steps—steps which are not yet universally accepted in definition or concept.

Verification logically commences at the lowest level of debugging the computer program. This can be a large task that is simplified by working where possible in small modular subprograms. If stochastic generators are programmed in individual subprograms it is usually convenient to check out each one individually to supplement overall checks on stochastic output (which take some account of dependencies among generators [276]). The simulator will have specified the generation of particularly distributed random variables and verification of this aspect of modelling is slightly more subtle than demanded for a deterministic component. The standard (published) subprograms for generating variates of common theoretical distributions can, with courage, be presumed verified, subject to checks on syntax. However, it will still often be useful for the simulator to convince himself that his generator is working in accord with the data from which the distribution was synthesized. This can be checked formally by conducting statistical tests of whether the generated variates could likely have come from the stipulated population. In frequency form the Chi-squared test is convenient, and for cumulative display, the one-sample Kolmogorov-Smirnov test is very useful [245]. The logic of such a test is the reverse of that noted in testing the goodness-of-fit in stochastic specification.

A thorough review of a model to determine if its behaviour is as anticipated during construction can be regarded simply as an essay in applied commonsense. However, the process can be variously aided and three important ways are briefly noted. First, to the extent that individual components can be checked in isolation, verification will be simplified. Secondly, the simulator will be able to anticipate fairly definite direction and magnitude of relationships between particular changing levels of inputs and model response. This might be explored deterministically by degenerating all stochastic generators to yield variates equal to their mean values or, in a restricted stochastic manner, by re-running the model for the different input levels but using the same seed(s) for the pseudorandom generators, so that the same sequence of variates is obtained. In this way comparison is sharpened and verification accordingly expedited. Finally, all such comparisons of model performance with prior conception are rather subjective and often involve graphic comparisons. Preparation of numerous charts is time-consuming and onerous. Thus, the development of on-line visual display devices has greatly convenienced verification procedures for those simulators fortunate enough to have access to such equipment (see [24]).

2.9 VALIDATION

After successful verification, the simulator is confident that this model at least does what he intended and the next important question is whether the model adequately serves his professed purpose. If the simuland does not exist or, equivalently, cannot be quantitatively observed, this question has already been answered to the best of the simulator's abilities during verification. Otherwise, when data are available on the performance of a real or existing system (or subsystem [35]), additional questions (relevant in appraising adequacy and credibility) can be asked about the closeness with which the model represents reality.

Among the several stages of simulation, validation can be regarded as the least developed in terms of agreed procedures [217], and is destined to maintain its status as the most likely chink in the simulator's thin armour. This situation reflects a wide and unfinished debate about the testing of models (including hypotheses and theories). For economists (biologists could consult [297]), this debate reached a climax in a series of heated exchanges (seemingly yet unfinished [373]) in the *American Economic Review* 1963–64–65 (involving Samuelson and others) about Friedman's [154] positive economics, wherein model validity is said to depend not on the acceptability of the incorporated assumptions but on the ability of model output to conform with observed behaviour. Needless to say, Samuelson's [323] position differs to the extent that, while recognizing that models, theories and their assumptions are always imperfect, he believes that modelling will be most successful (in the tradition of good science) when assumptions are founded essentially on observed empirical regularities.

Naylor and Finger [290] reviewed several philosophical positions on validation in developing their suggested three-step procedure for verification/validation. Briefly, these steps are: (a) a rationalist step of ensuring that assumptions accord with the theory, experience and general knowledge judged relevant, (b) an empirical step of subjecting assumptions to empirical testing where this is possible, and (c) a positive step of comparing model performance with simuland performance. In terms of the present distinction of the stages in model development, steps (a) and (b) are virtually completed by the end of verification. Other suggestions for verification/validation have also been made (including that of Hermann [190]) but these differ more in the jargon used than in essential features. Verification as presently perceived also amounts to the first three considerations in Hermann's scheme of: (a) ensuring that internal linkages are as intended (internal validity), (b) ensuring that model output is superficially reasonable (face validity), (c) checking model relationships against known counterparts (variable-parameter validity), (d) predicting observed events and patterns (event or scientific validity), and (e) attempting to distinguish simular performance from that of systems that the simulation is not intended to represent (hypothesis validity).

The present concept of validation corresponds broadly with step (c) of Naylor and Finger [290] (elaborated by [362]) and step (d) of Hermann [190], and is concerned with exploring the degree of agreement between the behaviours of simuland and of model. Assessment of the acceptability of a model must take due account of the purpose of modelling, which is tantamount to saying that validity is a subjective concept. What is an acceptable validation for one simulator will be viewed by his critics as foolhardy contempt for reality. The Sussex *vs.* M.I.T. clash [153, 263] over the validation of world models and submodels in *World Dynamics* [152] and *The Limits to Growth* [262] is destined to become a classic illustration of validation controversy although it revives conceptual issues earlier irreconcilable between Ansoff and Slevin [22] and Forrester [150]—see also [380].

Subjectivity is clearly the burden of the simulator at many stages of modelling [83, 377]. It arises essentially from the human limitations to knowledge—especially regarding the behaviour of systems including human components. Much of human understanding exists in non-quantitative form so that quantitative models moulded from such clay, face no alternative to non-quantitative and subjective appraisal of validity. Thus procedures for validation are not settled and are not routine. Validation is necessarily problem-dependent and simulator-dependent, and bound to be controversial. Most of the applications reviewed in section 3 can be soundly criticized for inadequate regard to validation.

The subjectivity of all validation procedures has been emphasized. While this poses constraints on the scope for wide acceptance of validity, it can sometimes be twisted to good use. A useful approach is to generate model output under conditions similar to those pertaining to available data on the simuland. Both (unidentified), sets of data can then be submitted to a person knowledgeable about the behaviour of the simuland. If he is unable to pronounce which set is from the real system, this "Turing"-type test [362] has been passed and the simulator is presumably more or less (depending on his respect for the expert) higher in his confidence of the validity of his model. In addition to subjective appraisals such as this and also graphical comparisons of time series, innumerable statistical tests may be performed in validation. These are of such diverse sophistication and cost that the decision about when the marginal costs of further testing exceed the marginal benefits of enhanced validity, is anything but trivial and again is necessarily subjective. Certainly a simulator will never wish to conduct all possible tests and typically he will be content to conduct only a few.

To this point, little has been said of initializing or "seeding" the various stochastic generators within a model. Without loss of generality, all the differently distributed variates can be regarded as being derived from a source of uniformly distributed pseudorandom numbers. The simplest arrangement is to define a single seed and thus, for any selected value of the seed, a single sequence of generated uniform and other variates. However, an arrangement of multiple seeds can be of distinct advantage and is especially useful in experimentation. The limit to such multiple seeding is to seed individually every stochastic component although this extreme would seldom be sought except for individual verification of each such component.

Often there will be some fairly natural groupings of stochastic generators that might be separately seeded. One such grouping would separate those components whose simuland variates can readily be observed and recorded from others not directly observable, such as implied by application of the Uncertainty Principle of Modelling to an empirical relationship. The advantage of this grouping is the possibility it provides for sharpened validation tests. Thus, in comparing the behaviour of the model with the recorded behaviour of the simuland, the corresponding recorded values of the observed "stochastic" variables including the initial conditions, can be incorporated for running the model in place of generated values. Such purposive reduction in model stochasticity can greatly increase the fidelity of validation of the rest of the model and, accordingly can increase the height of confidence in the descriptive adequacy of the model. Other reductions in stochasticity might involve degenerating some stochastic variables to their mean values while not degenerating others.

As a prelude to glancing at goodness-of-fit testing, it must be noted that observations on the behaviour of the simuland can typically be regarded as random variables. Similarly, a stochastic simulation can be regarded as producing random variables if its seeds are selected randomly and independently from the admissible set. Since the same seed (either single or multiple) gives the same sequence of generated variates (and the same model response for a given program configuration under identical operating conditions) an additional requirement for generating random variables is that repetition of seeds be forbidden.

Appraising validity in terms of the similarity of simuland and model performance under similar environmental conditions has been discussed in a general way but now we might cogently enquire as to the data with which it is desired that the model concur. There are evidently four broad possibilities: (a) historical data already employed in system analysis and synthesis, (b) historical data specifically not used earlier, (c) historical data that have evolved since earlier stages have been completed, and (d) data specifically collected for validation purposes by new system experimentation [223], field work, etc. These situations are all faced with the same statistical possibilities for a given number of data and, of course, all situations may provide measured data of questionable validity. However, it is likely that successful validation in each step from (a) to (d) would progressively enhance credibility. In fact (b) is a rare situation because of a natural desire to bring all available data to bear in system analysis. Situation (c), which could be termed "extra-sample" performance judging is also rare for farming systems excepting for cases of dissertation work that has grounded on the uncharted obstacles that unfortunately imperil simulation work. Situation (d) is very rare given that the *raison d'etre* of modelling in agricultural economics is that experimentation on real systems is impossible or inordinately costly. As an unfortunate practical matter, validation is often confined to the undesirable comparison of model output with the very data from which the model has been formulated [272].

An extensive variety of parametric and nonparametric statistical tests of goodness-of-fit has been suggested as being useful in validation (e.g. [104, 199, 267, 268, 290, 330]). Choice in particular applications will depend on the statistical experience of the simulator, *a priori* parametric reasoning and whether the responses being compared are static, dynamic sampled at intervals sufficiently long to escape problems of autocorrelation, or dynamic. Consideration of dynamic response necessitates resort to time series analysis [268] and spectral techniques [45]. Otherwise the range of appropriate tests is wide and, as well as conventional two-sample goodness-of-fit tests such as the Kolmogorov-Smirnov [335], a diversity of new tests has been proposed (and criticized [5]) by simulators, including regressions of simuland response on simular response [5, 77, 203, 275, p. 334, 378] and measures of goodness-of-fit of several series simultaneously [176, 327] that are kindred to Theil's [350] Inequality Coefficients.

2.10 SENSITIVITY ANALYSIS

Models are bound to vary widely in the sensitivity of their performance to changes in structural assumptions. Diverse sensitivity surely reflects different intrinsic features of different systems, so models are not necessarily inferior simply because they are relatively sensitive in a general way. Appraisal of sensitivity must focus much more narrowly in assessing usefully the quality of a model. Specifically, a model which is very sensitive to changes in assumptions about which there is considerable uncertainty (or even just some doubt) in the mind of the simulator will warrant being viewed suspiciously or sceptically. That a model is sensitive to changes in uncontroversial and quite certain assumptions (if they exist) is only of academic interest.

Sensitivity analysis as presently conceived is addressed to learning about the structural soundness of a verified and validated model [90]. Although presented here as an initial phase of model analysis, it overlaps activities in the verification/validation stages to the extent that results obtained in sensitivity testing may return the simulator to system analysis or at least to question further the validity of the model. Some simulators will develop (and most in the past implicitly have developed) sufficient confidence from earlier stages to skip sensitivity analysis (and sometimes also validation) and proceed directly to experimentation (section 2.11). Readers may wish to do likewise.

Model experimentation is concerned primarily with exploring the connections between variables corresponding to aspects of the simuland over which managers typically exert some control and (performance) variables purporting to represent the behavioural features of the simuland in which managers are explicitly interested. Performance variables will usually be distinctively identified during the early stages of model development. The class of decision variables may include quantitative factors, parameters of decision rules, qualitative factors, etc. which are intended as control variables in model experimentation. It is all the *other* structural components and relationships that are candidates for review in sensitivity analysis [253]. Among these, interest properly centres where doubt, uncertainty and ignorance are greatest. In short, sensitivity analysis is the testing of the robustness of a model through recognition of its imperfection. Sensitivity analysis as defined here, has seemingly been undertaken rarely by simulators in agricultural economics (exceptions include [46, 203]).

A crude characterization of the performance of a simulation model can be made symbolically as: $Y = f(X, S, M)$, where Y, X, S, and M denote (in general) vectors of performance variables, decision variables, seeds and simular parameters respectively. The functional f denotes the complex connection between performance and the other variables. Indeed, the degree of complexity is typically such as to defy *a priori* knowledge of the precise effects of changes in any of X, S, and M on Y. Such effects must generally be established by running the model. The point of sensitivity analysis is to explore the influence of changes in those elements of M about where there exists some doubt. This contrasts with the analyses of electrical engineering wherein parameters of an electrical system (or model) are pertubated to design for satisfactory dynamic stability [355].

A first step in sensitivity analysis is to discover what happens when an unsure parameter, say M_1, is altered while all else remains unchanged—a *ceteris paribus* approach to dealing with complexity. Symbolically, an observation is made on the conditional response function, $Y = f(M_1 \mid \text{other } M, X, S)$. This bald statement raises an important question of what settings of the given variables are appropriate. One suggestion is as follows: S may have any particular randomly selected admissible value; X could be set at a combination of decision variables representative of standard or conventional operating conditions; the other parameters will have either their unambiguous setting or, in case of uncertain parameters, a best-bet setting or one designated by some measure of central tendency.

The second question raised concerns the extent to which it is desirable to manipulate the parameter. A key consideration is that the degree of ignorance should impinge on the selection of a range over which M_1 is varied. Where the parameter is a random variable, a range (say $\pm DM$), determined by the dispersion (say standard deviation) of the distribution seems appropriate. In the simplest case of a single unsure parameter, M_1, the model could be first run at a best-bet setting, say EM_1 and then under identical conditions at $EM_1 +$ or $- DM_1$ yielding corresponding change DY_{jt} in Y_{jt}, the j-th performance variable measured at simular time t. The interpretation of the significance of the altered performance will depend on the particular variable and is unlikely to be straightforward. The magnitude of DY_{jt} may have a direct meaning for the simulator but if, say, it is a utility function defined only up to a linear transformation, it will be necessary to express it as a ratio such as DY_{jt}/EY_{jt}.

When there are several or many performances variables, interpretation may be aided by combining individual sensitivities into a single index which weights each performance variable according to its "importance" (W_j) in overall assessment. This is analogous to specifying a separable multi-dimensional utility function of the simplest aggregation, namely $U_t = \Sigma_j W_j E Y_{jt}$. Simulation over many accounting intervals of simular time will also lead to difficulties of comprehending many performance measures at many times and it might prove expedient to sum these (probably with discounting) over the time subscript, $U = \Sigma_t U_t$ or $Y_j = \Sigma_t Y_{jt}$. The foregoing remarks pertain to exploring conditional sensitivity to changes in one parameter. Typically, however, there will be several unsure parameters and the suggested procedure of adjusting these one at a time can be applied effectively but in conscious recognition of the limitations of ignoring possible interactions between unsure parameters. Once several parameters are changed, the advantage of "standardizing" the magnitudes of DM_i in terms of the respective degrees of ignorance becomes apparent. Clearly, the simulator will want to appreciate the extent to which his model is sensitive to relatively unsure parameters and this will be aided by tabulating measures of sensitivity against different parameter changes. The dimensionality of this tabulation can get out of hand in four ways: (a) the number of unsure parameters, (b) the number of performance variables, (c) the number of accounting intervals, (d) the number of measures of sensitivity. Some attractive measures are the two already mentioned, namely the absolute changes DY_{jt} (or DY_j or DU_t or DU) and the proportional changes DY_{jt}/EY_{jt} (or DY_j/EY_j or DU_t/U_t or DU/U), and expression of sensitivity as a "slope" DY_{jt}/DM_i (or DY_j/DM_i or DU_t/DM_i or DU/DM_i) or as a dimensionless "elasticity" [12], $(DY_{jt}/Y_{jt})/(DM_i/M_i)$ or $(DY_j/Y_j)/(DM_i/M_i)$ or $(DU_t/U_t)/(DM_i/M_i)$ or $(DU/U)/(DM_i/M_i)$.[2] Each alternative measure provides a different insight into the sensitivity of the model but a simulator will probably wish to focus his attention on just one measure in order not to become overwhelmed by a mass of data. The scheme leading to the smallest table would be choosing one sensitivity measure (say the elasticities) and aggregating over performance variables and over time—namely, $(DU/U)/(DM_i/M_i)$, $i = 1, \ldots m$, a measure rather like the goodness-of-fit measure of Halter, Hayenga, and Manetsch [176].

It must be emphasized that such a sensitivity analysis is conditional on one (multiple?) seed and having the decision variables at standard settings. A simulator may well wish to repeat the analysis once or more using different randomly selected admissible seeds but the need for this can usually be circumvented by increasing the length of run (or equivalently the number of accounting periods) for a single run.

These suggestions for assessing conditional sensitivity are designed to short-circuit formal experimental procedures appropriate to testing hypotheses according to statistical methodology. When such rigor is deemed appropriate, sensitivity is properly assessed according to the methods outlined in section 2.11 which give full recognition to the stochastic components of simulation models. A statistical approach to assessing sensitivity amounts to removing the selected unsure parameters from the set M and including them in the set of "decision variables", X. On reviewing the results of his sensitivity analysis, the simulator will declare (necessarily subjectively) that the model is "sensitive" to none, one or more parameters. By "sensitive" he means that his degree of ignorance about (part of) his model is such as to affect in a serious way the ability of the model to mime the simuland for analytical purposes. If the model is not "sensitive" (i.e. is robust) he can get on with the

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[2] In the parlance of electrical engineering [355] such "slopes" in the differential limit are known as "sensitivity coefficients".

experimental phase with some confidence. If it is sensitive to many unsure parameters he might move on to experimentation very unconfidently but would be more prudent to regard himself as being back at stage 1 in his simulation. That is, he must learn more about the structure of the simuland before cycling through the stages of model development again. His sensitivity analysis will have indicated where his energies might best be concentrated, perhaps in the conduct of formal experiments or surveys to elicit particular unsure parameters more precisely.

When the model is sensitive to only one or a few unsure parameters, the simulator may choose to begin model experimentation in an explicitly cautious manner by conducting his further simulation with several versions of his model—each version taking different settings of the unsure and "sensitive" parameters across the range of possible settings. This multiple processing obviously becomes very clumsy for either many settings of one parameter or many unsure parameters. How he proceeds after this depends on the diversity of results obtained from the different versions. Should they all be similar (say, in terms of implied policy recommendations) then the model is not as sensitive as was at first thought and its sensitivity is, at least for the moment, not a problem. Where the contrary is true the simulator would make best use of his diverse results by aggregating them by means of his probability distribution on the unsure sensitive parameters [12].

Simulation modelling, with its flexibility of approach and the characteristic complexity of simuland poses potential problems of losing sight of the implications of building upon imperfectly conceived relationships. Sensitivity analysis attempts to grapple directly with this problem from the positive economics viewpoint of tracing the implications through the variables in which the simulator is most interested. Standard procedures have not yet evolved but some simplistic suggestions have been offered here. When sophisticated graphic display facilities are available, these can fruitfully be used to simplify appraisal of sensitivity [24, 300]. These facilities enable an extension to reviewing non-linear response to multi-level parameter settings which has *not* been suggested here as a practical approach in the absence of graphic display facilities.

2.11 MODEL EXPERIMENTATION

Learning from experimentation on a *model* is predicated on the faith in the veracity and verisimilitude of the model gleaned at earlier stages [270]. On this faith hangs the wisdom of drawing inferences about the simuland from simular experiments. All the considerations for the design and analysis of conventional experiments (on real systems) are more or less applicable to simular experiments. Since it is neither possible nor desirable to review the vast literature of this field, aspects of experimental techniques particularly apposite in simulation are discussed. Even the literature on simular experimentation has grown considerably, although it is sometimes repetitive [49, 204, 283, 285, 288, 289, 292] and sometimes contradictory [82 *vs.* 268]. A thorough examination of issues involved is beyond the scope of this review (see [15]) but a few topics unique to simulation are introduced.

Most authorities are agreed on the main problems, namely that simular experiments typically involve (a) many factors [211], (b) many response variables (implying multivariate analysis [21] or some utility condensation such as discussed in section 2.10), and (c) a highly stochastic model which may imply either long simulation runs or large sample sizes [125, 140, 141, 142, 143, 160, 161, 188] in order to detect differences between treatments that are statistically "significant". Sometimes precision of comparison of means may be increased by various reductions in variability within a model but in such cases care must be taken that interest indeed is only in *mean* response (as it properly would be if expected utility is the response concerned).

In fact, most of the confusion evident in the literature seems to stem from generally careless attitudes to stating the aims of experimental work. Most of the literature on experimental design is specifically directed to measuring minimal variance contrasts between treatment means. However, simulators who have gone to the bother of implementing an elaborate stochastic model can be presumed often to have an interest in aspects of response probability distributions other than the means. A closely related question is the conditionality of responses [377]. Alternatives include comparison of responses in a single random environmental sequence, in several such sequences [82], in mean environmental conditions, or in randomly and independently selected sequences [268].

The possibility for repeated comparisons (of high relative precision) in the same environments [82, 209, 352], which is unique to simular experiments, arises from the facility of repeating sequences of pseudorandom numbers by repeating the seeding identically. It must be cautioned though that, depending on the changes made in the model under different treatments and on the conditionality of the number of simular events upon different seeds, the same seed may not generate exactly comparable simular conditions for contrasting treatments. For example, a treatment may consist of changing the distribution of some number of entities each involving in turn the generation of another variate. Once the number or ordering of generated pseudorandom numbers varies between runs, the potential advantage of sharpened contrasts is lost. Thus, in selecting parts of a juxtaposed seed for use in experimental blocking schemes or in purposeful reductions in stochasticity, the structure of the model must be closely examined (and perhaps modified by dummy generations) to ensure that the intended comparability of simular conditions will pertain (as is exampled in [219]).

Use of juxtaposed or multiple seeds provides the opportunity for partial reductions in stochasticity that may be advantageous. For instance, the first part of a double seed may initiate the exogenous event generators and the second the endogenous stochastic generators. Such an arrangement then leads naturally to the layout of an experimental design in randomized blocks where each block is defined by a new sequence of exogenous events, such as weather [67]. Statistical comparison of means can then be sharpened by removing block effects in analysis of variance (equivalently with 0–1 variables in regression analysis). At the risk of being repetitive, however, should the simulator be interested in aspects of the response distributions other than the mean, he must not forget that part of the variability of response is captured in the block effects in this analysis and may need to be resurrected. The technique of employing antithetic variates [179, 339, 352] may be useful for increasing precision of comparisons of means in industrial applications (although even this is controversial [269]) but seems of very doubtful advantage to simulators in agricultural economics [43, 202].

Whether experiments have primarily either an exploratory or an optimizing purpose and whether factors are qualitative or quantitative, the number of factors involved in most simulation work will typically be of such magnitude as to demand economizing on size of experiment to avoid inordinately large computer use and cost of computation. Briefly, this will induce recourse to experimental designs such as fractional factorials [43, 74, 204] and composite and related designs [74, 266]. Consideration of the ranges of experimental variables will assist in decisions on the choice of functional equations or of the degree of polynomial equations fitted. Due contemplation of the stochastic structure of a model should suggest if appeal to the Central Limit Theorem is reasonable in parametric assumptions inherent in conventional statistical analysis [268]. In doubtful cases, more attention should be paid to careful appraisal of regression residuals than has apparently been the case. When interest ostensibly focuses on the whole distributions of simular responses, the applicable nonparametric methods of comparison [81, 335] seem to be seriously under-utilized by simulators.

The end result of exploratory experiments is an enhanced understanding by the simulator of the relative contributions to simular response(s) made by those factors that he has incorporated in his experiments. This understanding may be the end-point of the simulation exercise (as for example in the descriptive analysis of Candler and Cartwright [56]) but there is often a further interest in finding optimal values of the factors.

A variety of optimizing techniques is available [135, ch. 9] but the one most favoured is a combination of "extensive" and "intensive" searches for optimal conditions. The general procedure is to begin with an extensive search through a series of simple exploratory experiments arranged so as to converge towards the optimum and, when this is approached to switch to intensive search methods based on (at least) second-order response functions. If the surface is characterized by irregularities and discontinuities, the success of any optimizing technique that does not use an exhaustive search will be a matter of luck. Designs most suitable for the cycles of extensive search are two-level complete factorials [74] and the "equilateral triangle" design [268]. It is possible to program the automatic location of successive experiments (according to some steepest ascent procedure [264]) and the automatic switching to the intensive search which may be accomplished by simply supplementing the last factorial or triangle design into a composite or hexagonal second-order design, respectively [265].

2.12 INTERPRETATION OF OUTPUT

The general stochastic and dynamic characteristics of a simulation model introduce a degree of relative difficulty in appraising output that is not met in interpreting the behaviour of static deterministic models. Conventional experimental techniques are directly applicable to interpreting stochastic output in a purely statistical context and are addressed to answering such questions as "does factor X_i have a statistically significant influence on the performance variable (a random variable) Y_j?" The questions addressed presently are of a more wide-ranging nature and are concerned with drawing conclusions about the influence of selected factors on the overall performance of a model. The context in which overall performance is judged will depend on the nature of the system and the purpose for which the modelling exercise was undertaken [92]. For system simulation in agricultural economics attention can conveniently be confined to the interpretation of simular output for managerial decision making.

Appraisal of output from a dynamic simulation model according to some static response measure(s) has some obvious intrinsic limitations but is nevertheless a practice often adopted by simulators. Whatever the demerits of ignoring the dynamic elements *per se*, a discussion of static response provides a convenient opportunity for introducing the appraisal of stochastic output. It will be useful to introduce the idea of a manager or decision maker charged with the responsibility of interpreting the output from a model constructed by a simulator in his employ [351]. Rarely these two roles may be performed by one person wearing two different hats. The person under the manager's hat may, in fact, be a group of people [360] or the manager may be representing a large group of people and thus be interpreting model output on their behalf.

The simplicity of having to interpret only one stochastic static response variable seldom presents itself to simulators in agricultural economics. The case of deterministic static response is unlikely to be encountered in simulation work and can be regarded as a limiting case of the stochastic and one that poses no problems of managerial interpretation and choice. The manager's task in this introductory case is really to make comparisons among probability distributions and the simulator is asking the manager if one distribution is in some sense better for him than another. Fortunately, there is a well developed framework for dealing with choices among probability distributions. This is Bernoullian decision theory which exploits the notion that managers attempt to maximize expected utility [106]. Given the manager's preferences, probability distributions to be compared are generated by a series of encounters with a simulation model and expected utility indexes computed and ranked. Of course, when the steps are taken in this sequence, it is possible to incorporate such a utility function within the model and to program calculation of expected utilities and selection of most preferred distributions and corresponding treatments. The optimization experiments might simply use expected utility as the performance variable for which optimal operating conditions are sought.

Computation of expected utility can be approached in at least three different ways in simulation. The most straightforward but also most tedious is the method just outlined wherein probability distributions are built up, stored within (or without) and used in expected utility evaluations (see [105, p. 110]). A less direct method is to approach an expected utility value stochastically but running the model several times, each time transforming performance according to the utility function and accumulating the average of these transformations. This process will converge stochastically to yield an estimate of expected utility, itself of course a random variable. Convergence can be checked by noting when the estimated expected utility stabilizes. The third method of computing expected utilities employs Taylor series expansion of the utility function and the moments of the distributions of the relevant performance variable [106]. Illustrations of the moment method of estimating expected utilities for simulation models are given by Dillon [105, p. 114].

The foregoing discussion of interpreting a single stochastic performance measured in terms of expected utility analysis presumes the availability of the manager's utility function. When the manager is clearly identified and readily accessible, there is little difficulty in eliciting this function and perhaps specifying it algebraically. When such a situation does not prevail, it is important for the simulator to know how far he can go in appraising stochastic output without explicit knowledge of the manager's preferences. In fact, he can often go quite a way by using the concepts of "stochastic dominance" [172, 370] to prune out inferior distributions from those worthy of close managerial attention. Managerial interpretation of even a single stochastic performance variable usually takes the simulator into an empirical utility analysis. Needless to say, his difficulties in this respect are compounded when the manager wishes to account for several variables simultaneously (for comprehensive review see [212]). That problems of multivariable appraisal are in no way unique to interpretation of simulation output must be emphasized. Indeed, this is the normal responsibility of most managers whether they be political, public service, business or farm managers. Managers are not usually found to be immovably perplexed by their continual need to choose among multiattributed decision alternatives. Seemingly then to deal with appraisal of several simular performance measures, all that is required is to observe carefully how management balances one measure against another. The multiple variables can be divided conveniently into two broad groups: (a) those for which no tradeoff with others can be specified but merely some priority of satisfaction attached, and (b) those for which management is prepared to trade-off levels of one against levels of another. For the former a lexicographic ordering of the priorities may be established. Often such an ordering highlights the survival of an economic entity such as government, firm, or consumer. An ordering that has found occasional use in farm management studies is first that the firm must survive with some acceptably high probability and thereafter may choose to maximize expected profits [127]. In short, strategies that might lead to failure are first scrapped and then a lower priority objective is sought. Although mention is made here of such survival goals while discussing the interpretation of static simular response, estimation of "performance" measures like the probability of ruin and bankruptcy can only be adequately accomplished by closely tracking a simulation model in its dynamic operation.

Performance variables that are amalgable into a single index by accounting for the marginal rates of substitution between pairs of variables are conceptually simpler than lexicographic preference but may pose estimational difficulties. If rates of substitution conveniently happen to be constant, the multidimensional utility function is described as separable and the overall utility index is simply formed by weighting each of the individual amalgable performances with an appropriate constant, as discussed in section 2.10. Otherwise, the complete multidimensional preference structure needs be elicited and specified [18, 106]. The benefit of such additional work is in drastically simplifying the burden of interpretation of performance and providing the opportunity for substantial reductions in the volume of output recorded from the model. It must be noted that simulators have not always been too concerned with the reality of managers' preferences among several performance variables when making assumptions about multidimensional utility functions. The simplest assumption of additivity has sometimes been made implicitly with little account of its consequences. At other times, simulators have arbitrarily assumed a range of arbitrary alternative algebraic specifications of multidimensional utility functions and examined the diversity of their implications in a type of post-experimental sensitivity analysis [156]. Interpretation of dynamic response has followed many different avenues reflecting the purpose and background of the simulator. For instance, practitioners of Systems Dynamics [e.g. 149, 151, 152] seem content to appraise dynamic response of simulation models by intuitive means largely aided by graphic displays of time series output using the plotting facilities of the DYNAMO language. More recently, simulators have increasingly turned their attention to spectral analysis of the time series generated in digital simulations [144, 286, 293].

However, neither of these broad approaches seem to be very appropriate for the types of simulation model commonly found in agricultural economics. Simulations that are purely engineering or biological, for example, need not concern themselves with the questions of intertemporal preference that are implicit in simulating any economic system. Preference over time is complicated relative to static preference by such additional concepts of impatience, time perspective and persistence and, unfortunately, the state of the art of dealing with these concepts has not yet stabilized and is not entirely satisfactory. The approach most frequently adopted involves some form of discounting, presumably to give some accommodation to the impatience of managers. The better studies also meld into the discounting procedure some considerations of non-linear preference for risky outcomes and of the multidimensional nature of future preferences. If this was completely specifiable, the implicit dated discount factors would simultaneously be revealed. A pragmatic compromise is to assume that discounted utilities are additive over time [156]. There are at least two thorny difficulties with such an approach. First there is the problem of eliciting preferences for consequences in the future. This problem has led to the common practice among management scientists of aggregating discounted future financial outcomes to a present value and then applying an appropriate (present) preference function to the present value. Unfortunately this ignores the possibly important multidimensional aspects of preference in future periods. Secondly, simply summing discounted utility values does not take any account of inter-period variation which, as Dillon

[106, p. 56] and Fromm [155, p. 363] note from somewhat different viewpoints, may be very important.

The practical difficulties of such elicitation of preferences have often been observed [285] and the usual alternative adopted is merely to present output directly to the "manager" and allow him to reach his own conclusions and decisions about the merits of compared policies, decision rules and so on. Even in such cases, it should be possible for the simulator to condense his results in a manner that is informative and easily comprehended by decision makers. It is in this sense that the application of multifactor response analysis to simplify and to highlight interpretation 56, 33 1, 332] can be very useful in practice.

3 APPLICATIONS

As noted in the Introduction, simulation (sometimes under such guises as systems analysis, simulantics, simulatics, simulmantics), has spread widely across many disciplines since its pioneering days in engineering and military science. For instance, in some of the disciplines more or less related to economics and agriculture, it now finds increasing use in business management [168, 170, 183, 191], in forecasting [369], operations research [122, 198, 273, 364], and computer science [139, 208], social science [171], social planning [210] and politics [84], forestry [166, 233, 238], ecology [310, 366, 367], geology [180], and hydrology [201].

Applications of simulation more closely related to agricultural economics are to be found at all levels of aggregation of economic phenomena. For the purpose of this cursory review, four broad levels will be identified, namely the macro-, mixed, micro-, and process levels. Other related applications are noted in section 3.5.

3.1 MACRO-LEVEL APPLICATIONS

The most aggregative simulations are those few [152, 262] which attempt to model future world variables such as population, incomes, natural resource stocks, food production, etc. Not surprisingly, such futuristic simulations have encountered trenchant criticism on grounds of methodology, assumptions and data [153, 240, 380]. However, the importance of long-term appraisal is such that it can be asserted confidently that agricultural economists will ultimately become very involved in at least the improved specification of rates of technological change in food and fibre production, off-farm migration rates, income elasticities for farm products, and so on.

The bulk of activity in macro-level simulation has been in dynamic manipulation of large-scale econometric (e.g. [95, 118, 156, 199, 285, 292]) and trade [30, 300] models and is of relatively peripheral interest to agricultural economists excepting perhaps when questions of trade in agricultural commodities [136, 196] are emphasized.

A good deal of effort has been expended on simulating developing agricultural economies, notably Venezuela [196, 272], India [197], Pakistan [241], Nigeria [1, 51, 176, 187, 214, 258], Uganda [157], the

Dominican Republic [37], Paraguay [336], and Peru [294]. While there appears to be some justified scepticism both within and without these countries concerning the value of such exercises (not to mention methodological difficulties [298]), the financing of research in agricultural economics appears to be structured to support continued efforts in this direction (witness scheduled assaults on Colombia and Korea [321]) and thereby to sustain a test bed for improved methodology in data gathering, modelling and simulation.

The agricultural sector of the U.S.A. has received what is probably its fair share of simulation [244, 318, 331, 332, 361] and is destined to receive much more. The models so far developed incorporate many simplifying (if not simplistic) assumptions (such as Cobb-Douglas aggregate production functions) that are not balanced by appropriate recourse to the Uncertainty Principle of Modelling (section 2.2). This situation generally characterizes most work at the macro-level including simulation of national agricultural commodity markets [4, 34, 36, 85, 86, 255], state investment [110, 111] and off-farm migrations induced by income differentials [124, 252]. Nowhere better than in a simulation model can we appreciate the imperfection of our understanding of economic phenomena and the arbitrary and unrealistic way we are often forced to model them. Better appreciation for the Uncertainty Principle of Modelling is evident in Prior's [315] study of the size distribution of income and Reutlinger's [320] study of national buffer stocks of grains.

Of other simulation studies that fall (marginally) into the macro-level category, in that they deal with aggregates larger than individual firms and consumers, a majority deals with river basin planning [177, 178, 250, 271, 306] and reservoir management [115, 116, 117]. These topics seem good candidates for simulation since they involve significant public investment decisions, potentially describable systems, often a good supply of pertinent data, and a stochastic environment that makes alternative analytical approaches difficult to apply.

3.2 MIXED LEVEL APPLICATIONS

Mixed level simulations here encompass those that model aggregate supply or demand through the aggregation of behaviour of individual firms or consumers, respectively. The most adventurous studies of this type [303, 304, 305] have aimed to model an entire economic system and have encountered predictable difficulties in both data and computational requirements. However, such work is of importance as providing the only workable and realistic method of modelling the conceptual apparatus of economic theory and developing the linkages between individuals and groups [70].

Most mixed level simulations have tended to focus on either the supply or the demand side [28, 195]. On the demand side, attention has been concentrated on imperfectly competitive situations [7] and advertising models [236, 237]. The state of knowledge of the demand for agricultural products at the micro-level seems likely to make comparable studies in agriculture very challenging.

Typical of the situation that prevails in agricultural economics, relatively more attention has been given the supply side. Sometimes conventional economic models (e.g. of the Californian dairy industry [102]) are simulated. Some studies of meat products [33, 119] have followed the tradition surrounding behavioural simulation of the firm [76, 77, 90] whereby a study of industrial structure leads to identification of representative firms, their modelling and ultimately to simulation of their markets. This is, of course, also close to the style of Day's [93] recursive programming wherein representative farms are programmed and tracked over simular time to yield aggregate projections of supply of farm products and demand for farm goods (e.g. [94, 173]). For better or worse, considerable resources are presently being devoted to national agricultural programming models of this genus at Newcastle-upon-Tyne, Ames, Armidale and other centres of learning.

The diffusion of new techniques among farmers in traditional agricultures has also been the topic of interesting mixed level simulations. Carroll [58] has approached this from a viewpoint of rural sociology and O'Mara [301] has adopted a micro-economic approach that simulates farmer's changing beliefs (and technique switching) through Bayesian revision of probabilities as experience accumulates, and then aggregates individual switching rates to community adoption rates.

3.3 MICRO-LEVEL APPLICATIONS

Simulations in agricultural economics that are specifically micro-level have, to this reviewer's knowledge, been confined to the firm (i.e. generally farm). Activity has been fairly recent but is accelerating and now covers a wide range of types of farming including crop [120, 121, 131, 148, 226, 379], mixed [206, 233, 309], beef [8, 29, 46, 169, 174, 175, 227, 228, 356, 358], sheep [11, 56, 67, 68, 202, 219, 295, 374, 377], pig [96], dairy [23, 205], and turkey [127] farming. Studies of other types of farming are in progress.

The analytical purpose in such studies has varied extensively, e.g. investigating time of sale of product [127] or intermediate product [67, 68], feeding management rules [8, 96, 374], economics of soil conservation [120, 121], economics of amalgamation [219] and spatial diversification [11, 356], or general farm planning in stochastic environments [40, 54, 175, 193, 205, 206, 359, 379]. In most of these studies, recourse was made to simulation as the only approach feasible in coming to grips adequately with the inherent dynamic and stochastic nature of the problems posed.

This same rationale is highlighted in the growing number of studies of firm growth that have adopted a simulative approach [6, 62, 91, 127, 131, 146, 174, 185, 194, 202, 233, 246, 309, 365]. Such studies reflect a tendency (that goes beyond agriculture [43, 75, 89, 291]) for analysts to recognize a behavioural theory of decision making, and dynamics rather than statics in studying the firm.

3.4 PROCESS LEVEL APPLICATIONS

The distinction between micro-level and process level applications is not as clear as it might seem, since some studies of single-enterprise firms that feature a relatively crude modelling of the firm as an economic entity, seem best categorized as process-level simulations. At any rate, the classification employed here has no virtues other than to simplify an overview of the literature.

Of all the processes that operate on farms, just a few have monopolized the attention of simulators and these few are, as is to be anticipated, intrinsically stochastic through the operation of exogenous weather variables. A basic process that is of crucial importance because it underlies much subsequent simulation in farm management is the operation of soil-plant-water systems [53, 145, 296, 307]. Simulation submodels of this process have been incorporated in models of grazing [66, 88, 164, 203, 223, 279, 374], dryland cropping [41, 120, 121] and irrigated cropping systems where they have often been married to some rainfall model [186, 311]. Simulation has found particular favour among analysts of the economics of crop irrigation process [19, 20, 42, 59, 133, 147, 148, 223, 299]. This application seems certain to find continued importance in the future as only simulation can offer the requisite flexibility and stochastic description that this problem demands.

Apart from irrigation, two other farm processes have been subjected to several simulation studies, namely harvesting and storage. In studying harvesting economics, attention has been concentrated on efficient selection of machinery for harvesting crops [55, 112, 159, 226, 322, 341] and forage [73, 224, 346]. The question of determining efficient quantities of fodder to harvest or purchase for storage has been approached with inventory analysis, but most recently by simulation at the farm [73, 203, 278, 349] and national [354] levels.

Process simulation off the farm is represented here only by mention of one early study of control in a cheese factory [163].

3.5 OTHER APPLICATIONS

Several applications that are more or less related to agricultural economics do not fit into the above categories too well and so are tossed together here. As a pointer to where agricultural economics simulators might fruitfully cross new disciplinary boundaries we note initially a simulation of deer herd management [9] and a simulation of animal disease and its control [280].

Profit and investment appraisal has had a long history in agricultural economics but only recently has the importance of risk been explicitly recognized. One simple yet useful approach to exploring the impact of risk is to simulate project performance stochastically [27, 60, 128, 281, 314, 319]. As these simulative techniques develop they are bound to become an integral part of project appraisal. Presently, the stochastic specification in such studies tends to be exceptionally arbitrary.

Finally, there has been some discussion of the role that simulation might play in integrating agricultural research efforts [98, 277, 376] and in appraising research expenditures and priorities [2, 17, 128, 379]. While this seems to be an important potential, the problem is that it *is* still potential and the few attempts so far made in this direction [e.g. 169, 357] suggest that progress is destined to be slow and, until agricultural researchers themselves are more actively involved, its impact slight. Of course, no one would claim that simulation is always or even often necessary either to recognize gaps in knowledge or to appraise the value of filling a gap through formal experimentation (see [308]).

4 PERSISTENT PROBLEMS

Difficulties can, and usually do, arise at every stage of simulation and an attempt was made to emphasize these in the expository sections 2.3 to 2.12. The problems that arise in system analysis, synthesis validation and interpretation of output [63] are perhaps the most serious in the respect that they are more likely to be the focus of chastisement from "outsiders" or, even worse, "non-believers". However, it must be noted that these problems are encountered in all modelling and are in no way unique to simulation. Presumably one explanation for the poor reputation in this respect that simulation has in some quarters, is the transparency of the assumptions built into simulation models relative to the typical, say, programming models. A simulator who claims that he is modelling with commendible realism must have some sympathy when a critic observes that simular time is ranged over 20 years but that soil is modelled as a stable water-holding matrix of constant fertility and structure. On analysis-synthesis problems the observation of Edwards [123, p. 117] is worth reiterating—"The weakness of simulation research derives not from difficulties in the overall approach but rather in the handling of some of the details . . . . Simulation models are patched together one equation at a time. If the logic is sound and the data reliable, then the simulation is useful. But in the interests of operationalism, one can easily incorporate dubious logic and shaky data . . . .

A few other problems (i.e. beyond those discussed through section 2) do persist. One that has received little explicit attention [230] is the question of locating an efficient balance of the simulator's time and energies between the parts of a model and between the several stages of simulation. It seems good intuition that great refinement should not be built into one segment of a model while the rest of the structure is modelled in a rather cavalier way. Only explicit sensitivity analysis can hope to approach this question formally and, as noted in section 2.10, this step has rarely been taken. It seems that little guidance can be offered presently and an improvement must await an accumulation of sensitivity reported experiences with sensitivity analysis.

A closely related broad problem is that of the high cost of simulation—which may, of course, still be lower than the cost of comparable competitive formal experimentation [17, 277, 377]. Simulator's aspirations and conceptions for modelling and experimentation appear to be growing at a rate faster than effective computing costs are diminishing. In this reviewer's experience, the sums of simulator time and computer time required for simulation studies are inevitably underestimated and the result, especially when the work is for a dissertation, is that proportionally too little time is ultimately allocated to the originally intended purpose of exploiting the developed model. While it has been speculated [16, 374] that as experience accumulates, subsequent work can proceed relatively efficiently by building on earlier work (especially on particular modules), there has so far been little evidence (exceptions include [121, 295]) of this happening (this accords with an earlier observation [276]). Even a substantial revision of an operational model can involve an input of effort comparable to that of the original simulator. Needless to say, high costs of tailor-made farm simulations have narrowly circumscribed the use of the approach in commercial farm management consulting and probably shall continue to do so, despite some hope of cost reductions [39].

The problem of cost seems to have several implications for intending simulators [129]. For instance, simulation seems a relatively risky methodology for fixed-schedule dissertations. When agricultural economists are simulating systems with a large biological component, costs can probably be substantially reduced by active involvement of relevant subject-matter specialists. This suggests that a team organization [35] perhaps featuring the collaboration of biologists, economists, statisticians and computer programmers might prove desirable for effective simulation work [25]. In such a way the difficulties in modelling of (and subsequent criticism suffered for) knotty biological problems such as herbage intake [47, 169, 357] will be minimized, and the necessary "gap-filling" formal experiments may be more readily conceived and initiated.

A broader problem that pervades all modelling in systems work, and not just simulation, concerns the relationships between the modelling and the real world [103], and between the modeller and the real world decision maker. Focusing on simulation, it seems reasonable to conjecture that a considerable majority of studies have received little or no acceptance by real-world decision makers and have had little or no impact outside professional circles. Presumably the chance of a simulator's conclusions crossing the threshold of relevance to have an impact on real-world decision making depends crucially on the acceptability and accuracy with which he conceptualizes his model of the real system and the way in which he presents his model and his results [230]. Clearly this chance will be enhanced by direct elicitation of the real decision makers' view of the world but when this is infeasible the likely success of the work, or conversely the likely frustration of the worker, depends on the useful insights he can distill about all the essential aspects of the real world. In short, practitioners should temper their enthusiasm for the esoteric and the bizarre with an active appreciation for real-world realities, and should attain an orientation to ultimate applications [109]. Presumably improvement in this respect can be anticipated as simulation shifts more out of universities to research institutes and consulting firms?

5 PROSPECTS

The reviewer must confess to having suffered a diminution of optimism since an earlier attempt [16] at speculation on the prospects for simulation in agricultural economics. However, while progress may not be as fast as anticipated, simulation shall inevitably find wider use, with hopefully an improving methodology, if for no other reason than that alternative equally workable analytical apparatus does not exist and is not around the corner.

A less laudable reason for the increasing popularity of simulation is that it has probably been "oversold" in the literature. Indeed there have been many statements by practitioners that are best described as evangelical (since application is absent or minimal) (e.g. [13, 26, 44, 64, 181, 216, 232, 242, 257, 277, 345, 375]). The audience of such articles probably should have several more messages of the spirit that "simulation can be an expensive tool for solving simple problems".

A recapitulation on why people model and simulate (apart from seeking either personal enjoyment or financial reward) may be in order since the reasons seem to assure the technique of continued attention. Most important for many applications in agricultural economics is the infeasibility (in terms of time, cost, political and social factors) of manipulating the real systems (perhaps to improve estimates of parameters [87]). Thus it may be impossible or impracticable to experiment on existing systems. Alternatively, the degree of control and isolation imposed on a formal experiment may prevent ready extrapolation to the less-controlled real world. For systems that do not yet exist, there is no alternative to simulation for "experimental" work. Sometimes a real system may be so large and heterogeneous that real experiments which adequately encompass the domain of research applicability are not feasible. Simulation may in such instance make it possible to extrapolate results from a detailed general model to the diverse universe of interest [277].

Other less important reasons relate to the degree of control over variables in a simuland. A system may not permit the degree of control required for successful experimentation and an important factor operating against success of such real experimentation may be the inherent complexity of the system and the infeasibility of large multi-factor experiments. A related problem for simulation of some biological systems is that delicate systems may behave spuriously under experimental monitoring and in such cases simulation may offer the prospect of non-interference experimentation. In all these reasons for modelling, the oft-mentioned essentially dynamic and stochastic features of perceived systems, makes the choice of simulation often mandatory.

Finally, and less importantly, simulation may have purely a research orientation when the objective is simply to model in order that the extent of understanding of a system is forcefully illustrated. Relatedly, there have been suggestions that simulation might have a useful role in teaching [80, 313] but this seems to be a remote possibility.

For a variety of mainly good reasons, and in spite of the Laws and Hypotheses to be mentioned below, simulation seems destined to find continued and probably increased application by agricultural economists. But as on a previous occasion [16], it seems appropriate to conclude this review on a cautious note. Dillon [105, p. 85] has promulgated three Laws of Simulation which embrace notions well worthy of contemplation: (i) Simulation, like statistics, cannot prove anything. (ii) Simulation, like statistics, can nearly prove anything. (iii) Once started, simulation will continue until available funds are exhausted. We choose to complement these with three hypotheses: (a) Every simulation study has its trenchant critics. (b) The more aggregative the simulation, the more liable it is to criticism. (c) Study through simulation always absorbs more resources than anticipated *a priori.*

6 LITERATURE

This review concludes with a reference list that is biased in favour of the English language, Oceanic simulators and applications in agricultural management. Approximately half of the items in the list represent applications in the broad field of agricultural economics. Despite good intentions, this is by no means an exhaustive survey but it is to be hoped that few interesting applications have escaped the net cast which has yielded a catch representing something of the order of 200 man-years of simulation effort in agricultural economics. Much of the detailed literature on simulation applications is difficult to find as it tends to be contained in relatively unavailable technical bulletins, mimeographed reports and so on, because of the volume of detail.

This opportunity to nominate for some awards could not be passed up The most influential studies are possibly Fitzpatrick and Nix [145] for agronomists, Arcus [23] for animal scientists and either Zusman and Amiad [379] or Hutton [205] for agricultural economists of farm management bent. Nominations for "best" in some sense are allocated most fairly according to categories of purpose and type of publication, namely: best compendium of methodology—Mihram [268]; best expository article—Charlton and Thompson [64]; best application article—Patrick and Eisgruber [309]; best bulletin—Halter and Dean [174]; best practical advice—Conway [82]. Finally, some nominations could be made for consolation awards such as the most expensive study [258] and the most obscure article [13].

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