AN OVERVIEW OF MODELLING IN AGRICULTURAL MANAGEMENT

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A synoptic review of the diverse models that have been developed for economic analysis in agricultural management is undertaken and these models are placed in broad perspective. A few practical and general problems of modelling that have been highlighted by the development of simulation procedures are also briefly reviewed.

1 INTRODUCTION

Economic analysis in agricultural management has almost always been tackled through a modelling approach. Models used have been of diverse type and mathematical sophistication but practitioners do not appear to have taken a summary view of their endeavours.

For review purposes, a classification of models is presented in section 2 and the applicability of the classified models is discussed in section 3. In section 4 a few general problems of modelling are mentioned concerning validation, sensitivity analysis and experimentation.

2 A CLASSIFICATION OF MODELS

Three aspects of models are used in their classification here: (i) whether or not a model is explicitly time-dependent; (ii) whether or not a model incorporates probabilistic (stochastic) elements; and (iii) whether or not a model serves to optimize a specified goal function. The classification provides a convenient frame of reference rather than an example of taxonomic perfection (see section 2.5). Within the four broad categories surveyed in section 2.1 to 2.4, optimizing models are discussed before non-optimizing models.

2.1 STATIC DETERMINISTIC MODELS

Much of neoclassical economics has been concerned with static models for which complete certainty is assumed (i.e. they are deterministic). For this timeless, certain and unreal world, optimizing techniques are

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highly developed. They have been applied with some success in agricultural management in spite of the fact that agricultural processes only function over time and that biological (not to mention climatological and price) variation is usually a feature of agricultural production.[1]

The simplest model arising from the theory of the firm is the response or production function which has been discussed at length in the context of agricultural production [39, 41]. Such functions, which generally assume a fixed production period, have usually been estimated by least-squares regression analysis and manipulated in marginal analyses to indicate optimal resource use—perhaps subject to various constraints. Little attention has been given to multiproduct response functions [30, 54] and the alternative static deterministic model most used in studying multiproduct situations has been linear programming [40] in which a linear goal (objective) function is optimized subject to linear constraints. The "feedmix" problems in ration compounding are now solved routinely using linear programming [20] and the linear programming model has become a standard planning tool in farm management, suitable for direct commercial application in farming by appropriate service bureaux and consultants [60]. It should be noted that many linear programming models in farm management here classified as static involve some dynamic elements such as determining fodder conservation and livestock activities through a year according to seasonal patterns of forage production.

A variety of simple non-optimizing models related to parametric budgeting has been used in agricultural management [9, 51] but these only just qualify as "models". Monte Carlo programming models are not explicitly optimizing but strongly resemble linear programming formulations. They have been employed for both feedmix [21] and farm planning problems [27]. Monte Carlo programming, although particularly useful when integer problems make linear programming inappropriate, does not provide the valuable shadow-price information that linear programming does and suffers a mechanical difficulty of the analyst comprehending and sifting numerous solutions.

2.2 DYNAMIC DETERMINISTIC MODELS

Less attention has been given to explicitly time-dependent than to static deterministic models. Several time-dependent neoclassical models have been reviewed [23], taking examples from multiharvest crops, feeding period and rations for broilers and pigs, and grazing systems to illustrate some diverse ways in which time enters production models. Neoclassical production models have now been extended to the multistage multiproduct case in potentially operational style [55].

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[1] This reference to risk and uncertainty alludes to that inherent within the modelled system rather than the analyst's uncertainty about the system or his model of it—uncertainty which could usefully be distinguished as "ignorance".

Other optimizing models designed to model time-dependent economic systems have been of three broad types: (i) dynamic programming [8] employing Bellman's [6] "Principle of Optimality"[2]; (ii) recursive linear programming [14, 42] in which a linear programming model is solved for one period, the solution used to revise the resource restraints for the next period and the process repeated for several periods; and (iii) multiperiod linear programming [7, 50, 53] in which several production periods are modelled and solved simultaneously. For problems involving many periods (i.e., having distant planning horizons), the size of multiperiod models may become large and exceed the capability of presently available computers. Since production is seldom deterministic and conditions inevitably change over time, most of the information generated in such multiperiod models for periods other than the first is not very useful except in solving the first-period decision.

Non-optimizing models developed for dynamic deterministic problems have been mostly variants of parametric budgeting often highlighting long-run aspects of development plans such as animal breeding performance [5]. Deterministic simulation models have been used infrequently [34].[3] Some attempts have also been made to apply Monte Carlo programming techniques to multiperiod problems [19] but the indications are that this is not a very fruitful line of enquiry.

2.3 STATIC STOCHASTIC MODELS

Modern decision theory [25] can be regarded as encompassing all stochastic optimizing models used in management. Recent years have seen increasing recognition of the importance of risk in production and this has been reflected in the development of decision theory and the inclusion of stochastic elements in nearly all types of models so far mentioned. Consideration of uncertainty necessarily implies some dynamic aspects. This category of "static" stochastic models therefore refers to cases where the time dimension is relatively unimportant.

Stochastic versions of static neoclassical response functions have been developed [2, 4, 33, 51], however, much more attention has been given to incorporating stochastic effects in mathematical programming models. This has followed two broad directions, the first "risk programming" being to add a second dimension to the objective function to assess risk, for example, via a quadratic programming formulation in which variance of income is minimized for given levels of expected income [32, 40, 48]. The computational difficulties of quadratic programming

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[2] Any optimizing procedure can be used in dynamic programming such as linear programming or response analysis [31]. Note that the "Principle of Optimality" can be used in the solution of mathematical problems that are not dynamic in the temporal sense used here.

[3] Some simulation modellers (e.g. [64]) have classified their models as deterministic even though an input for running them is an historical rainfall trace. Since this trace is simply a sample from a probabilistic process, such models are more properly classified as dynamic stochastic.

have recently been circumnavigated by minimizing total absolute deviations of income as the measure of risk in linear programming models [37, 38]. The next logical extension in this direction is to add a third dimension to the objective function to handle the skewness of activity incomes. However, at least this reviewer's attempts at formulation and solution of "cubic programming" models have so far been fruitless.

The other important approach (of several) to programming for stochastic variables had been to employ discrete probability distributions in "stochastic linear programming" models [13, 57, 58]. The structure of such models is essentially simple [66] and for small problems solution is straightforward and of low cost. Non-optimizing static stochastic models have received only minimal attention and are represented mainly by some flirtation with game theory algorithms for games against nature [22].

2.4 DYNAMIC STOCHASTIC MODELS

Since all agricultural production processes are dynamic and to some extent stochastic, models which adequately account for both these features have obvious merit but also involve the greatest modelling difficulties.

Apart from some simple models [51], dynamic stochastic versions of neoclassical response functions do not appear to have been developed. Most operational attention to optimizing models has been placed on stochastic linear programming [13, 57] and to a lesser extent on stochastic recursive programming [49]. Multiperiod stochastic programming models that realistically represent agricultural production systems are destined to be large and perhaps temporarily beyond feasible computability. Similar problems of extensive computation are encountered in solving realistic stochastic dynamic programming models [28]. Methodologically, the analysis of multistage risky decision trees [36, 44, 59] is closely related to the backward induction procedure of dynamic programming.

Many other operations research models such as inventory models [26], replacement models and queueing models have been developed to optimize dynamic stochastic problems but these have only seldom been applied in agriculture. On the other hand, simulation models have more often been used in non-optimizing approaches to problems of this class in agricultural management [11, 18, 35, 46].

2.5 SOME IMPERFECTIONS OF THE CLASSIFICATION

The classification presented is oriented to highlighting different techniques of modelling and to an extent this reflects the situation that has often prevailed in agricultural economics wherein practitioners have adopted a technique-oriented rather than a problem-oriented approach. However, in the future, it is likely that the classification will become less adequate as models become increasingly hybridized.

With their flexible structure, simulation models more than others will confuse the taxonomy. Simulation models usually incorporate a variety of deterministic and stochastic response functions. Linear programming models have less often been incorporated within simulation models [29, 49] but, with increasing capacity of computers, this situation is bound to change. Composite models involving simulation components will also be useful in analyzing problems presently not soluble through a stochastic dynamic optimizing model alone [66].

A decision theoretic framework is at least implicitly involved in any stochastic optimizing model. However, decision theoretic submodels have only rarely been included in non-optimizing models [3]. Again, decision analysis of some sort is required (at least implicitly) to interpret output from non-optimizing stochastic models [24] and (when necessary) to select among alternative models [63].

3 APPLICABILITY OF THE CLASSIFIED MODELS

Models are appraised here in very general terms with respect to three criteria—realism, workability and communicability [52]. Since appreciation of a model cannot be divorced from the purpose for which the model is intended, worthwhile generalizations are difficult. Purposes of modelling are almost as diverse as models themselves with some extreme points of the spectrum represented by (a) prediction, (b) learning for the sake of understanding, and (c) control or management that is optimal in some sense.

Response functions may be judged as sufficiently realistic and workable for prediction and control when a rather crude description in terms of only a few variables is appropriate. However, such models become unwieldy for analyses involving many variables and interdependencies, and for these problems which abound in agriculture, their use for such purposes is virtually ruled out on grounds of unrealism and unworkability despite the comparative ease with which such models can be communicated. A difficulty with stochastic versions of response function models lies in estimation of parameters to describe the probabilistic structures but this seems amenable to solution [4, 17].

Mathematical programming models generally offer the best prospects for success in optimizing work. Although they necessarily involve the linearization of many relationships, practitioners find that this feature usually does not restrict the realism of these models too much. The logic of programming models, however, is only readily communicated to others with some (easily acquired) knowledge of the principles of programming. The question of workability is potentially more serious. A realistic multiperiod stochastic linear programming model may be readily conceived and formulated but is quite likely to be either insoluble or soluble only at large cost on available computers. This "curse of dimensionality" is largely a function of the complex optimizing problem itself rather than of the type of model employed.

In contrast, simulation models that are comparable to such complex programming models in the sense that the same process is modelled with comparable realism, may be quite workable if and because they are used for a different purpose, e.g., formalized understanding rather than optimal control. The logic of simulation models can be communicated, even to inexperienced people, fairly readily by flow charts and block diagrams (but not by listings of computer coding!). Even when they are not explicitly optimizing, simulation models may be used to identify "reasonably efficient" decisions on resource use and control. The reasonableness will again depend on the analyst's purpose and on his philosophic perception of optimality [15, 16].

4 SOME PRACTICAL PROBLEMS IN MODELLING

Perhaps it is because the distinct steps in simulation studies tend to be recognized more explicitly than in other modelling studies that the advent of systems simulation has crystallized the recognition of some problems that are to an extent common to all modelling activities. Three such topics are briefly noted. These are the closely connected problems of validation, sensitivity analysis and experimentation.

4.1 VALIDATION

Validation is the process of determining the acceptability of a model for its intended purpose. Much will be written on this topic as it is certain to be the focal point of controversies in modelling. Most of the presently scanty literature (e.g., [56, 62]) concentrates on testing the goodness of fit between the behaviour of the model and observed data. This has been conventional practice with response function and simulation models whereas mathematical programmers have usually given little formal attention to validation.

Validation must be essentially a subjective procedure and would be better recognized as such. Of course, subjective appraisal may well be extended to involve several people knowledgeable about the modelled processes. This is partly because of the considerable dependence of models upon non-quantitative subjective knowledge and partly because history may have little bearing on the future and observed data may be of doubtful validity. Certainly models should be internally consistent and superficially valid and comparison with historical traces may assist in judging this. But historical goodness of fit is of limited assistance in assessing "variable-parameter" validity and "event" validity [43] which are usually more important for analytical purposes. Assessment of such validity will probably mean introducing other available knowledge, special new collections of data or the conduct of new experiments on the modelled system [68]. The intrinsic subjectivity of validation does not mean that modellers should be embarrassed by it and thus conceal it or fail to explain it adequately; but it does mean that validation will persist as a potential problem inherent in virtually all modelling in agricultural management.

4.2 SENSITIVITY ANALYSIS

Sensitivity analysis is a constructive step in learning about a model and the unique information gleaned can be displayed systematically and instructively. It is the testing of a model for robustness in the performance variables, Y_j, with respect to the incorporated parameters (including assumptions and decision rules), X_i, and is thus sometimes regarded as part of the validation phase. In optimizing models it is the sensitivity of the objective function, particularly in the region of the optimum, rather than of the optimal solution (which is usually sensitive) that is of most interest. Modern parametric programming routines greatly facilitate sensitivity analysis.

Various techniques for sensitivity analysis have been developed, notably by econometricians, involving systematic perturbation of parameters not known with certainty. That is, models are run or solved while adjustments, denoted here by ΔX_i, are made to such parameters. The magnitude of ΔX_i is often taken as a multiple of the standard error of X_i where these are known or can be guessed.[4] Assessment of relative sensitivities has then been appraised by inspecting ratios of response changes to adjustments, such as $\Delta Y_j/\Delta X_i$. Another possibility would be to express sensitivities analogously to elasticities, $(\Delta Y_j/Y_j)/(\Delta X_i/X_i)$, so that a matrix of dimensionless measures of sensitivity could be defined. In turn, these measures might be weighted by coefficients specifying the relative importance of each performance measure, Y_j.

A ranking of sensitivities indicates where any further refinement of parameters is best concentrated. If important output is very sensitive to many uncertain parameters, the exercise has qualified the modeller's ignorance of his system. If it is sensitive to only a few, a possible (but perhaps expensive) procedure would be to conduct the remaining analysis conditional on specified values of these parameters finally combining the results as an expectation taken over the analyst's subjective probability distribution.[5]

4.3 EXPERIMENTATION ON MODELS

It is appropriate to view all modelling work as developing a framework for testing hypotheses about the modelled system [1, 63] and this implies the need for some form of experimentation on models of all types.

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[4] A practical difficulty emerges in perturbing jointly distributed parameters. A simple yet extreme example would be in examining sensitivity of a simulation model to variations in the parameters of an embedded quadratic response function where, for instance, there will be a high correlation between the respective first- and second-order coefficients.

[5] When it is feasible, such an approach accounts for uncertainty appropriately and directly where it arises, rather than ignoring the uncertainty by simply using expected (or some other best-guess) parameter settings. In general, the expectation of a function of random variables does not equal the function evaluated at their expectations.

Simulation workers have concentrated on experimentation rather more than modellers using optimizing models, such as response functions and linear programming models, who may sometimes have been too optimistic about optimality. It may be that linear programmers often engage in considerably more informal experimentation than is revealed in reports of their work. Such a situation would arise in part from a failure to recognize explicitly that model development is a legitimate part of analysis and therefore should be recorded and, in methodological and expository reports, explained.

Experimental designs merely provide an efficient way of learning about a system so, in models characterized by many decision variables and many output variables of interest, designs that allow concise summary and presentation of information through efficient estimation of multi-factor response functions will be of greatest value [45, 47]. Candler and Cartwright [10] have demonstrated the use of a composite design to handle several variables in this context but without specifying how a trade-off [25, 67] might be made among the various performance measures. In stochastic simulation experiments there is unexploited scope for reducing error variances through blocking based on repeatable pseudo-random number sequences for different sets of stochastic variables [12, 65].

5 CONCLUSION

Agricultural economists will probably continue to give most attention to static deterministic models for "quick and dirty" analysis and to dynamic stochastic models when deeper analysis is called for. For the former type of analysis, irrespective of purpose, choice of models will usually be between response functions for single-product processes and linear programming for multiproduct processes. For analysis using dynamic stochastic models, purpose is much more important and the choice will probably be simulation when the analytic stance is one of learning and description, and probably mathematical or dynamic programming or a composite model when the stance is normative.

Modelling is a fundamental activity in the practice of economics generally and management in agriculture in particular. Accordingly, activity in this field is certain to continue at an accelerating rate. Along with the continuing improvements in capacity and capability of electronic digital computers, modelling will doubtless become more sophisticated and esoteric. Hopefully, modelling will concurrently become more adequate to the task of solving real-world planning problems. A trend towards empirical adequacy and relevance will probably involve increasing use of composites of the types of models described above, occasioned by a problem-oriented rather than a technique-oriented approach to modelling. Compromise between elegance and relevance is inevitable but hopefully will favour relevance and workability rather than sophistication for its own sake.

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