

ECONOMIC MODELS AND AGRICULTURAL PRODUCTION SYSTEMS

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Summary

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

I. INTRODUCTION

Management may refer to several aspects of operating a system, but, at least with reference to commercial production in agriculture, it usually connotes manipulation of a system for economic objectives. Economic analysis for management in business and research has usually been approached through the use or development of a model of the system. A classification of such models is attempted in Section II and their applicability is reviewed in Section III. In Section IV some practical problems of modelling are reviewed with particular emphasis on simulation models.

II. CLASSIFICATION OF MODELS

Three main taxa are used in this classification: (i) whether or not a model is explicitly time-dependent, (ii) whether or not a model explicitly incorporates probabilistic elements and (iii) whether or not a model intrinsically involves an optimization process. Categories are not mutually exclusive because some classes represent limiting cases of others, and because some models may serve as sub-models of models in other classes. In referencing the classification, material is indicative rather than comprehensive, and the selection of references is biased towards the recent, the Australasian and the notable.

(a) *Static deterministic models*

Much of micro-economics is concerned with static models for which complete certainty is assumed (i.e. they are deterministic). For this (unreal) timeless and certain world, optimizing techniques are highly developed and have been applied to analysis of agricultural production with considerable fruitfulness. The fundamental model arising from the neo-classical theory of the firm is the notion of the response or production function (Heady 1952; Heady and Dillon 196 1). Such functions have usually been estimated by least squares regression analysis and manipulated in marginal analyses to indicate optimal resource use — perhaps subject to certain constraints. The static deterministic model most used by economists in studying multi-product situations has been linear programming (Heady and Candler 1958), in which a linear objective function is optimized subject to a set

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of linear constraints. Livestock “feedmix” problems are now solved routinely using linear programming (Dent and Casey 1967) and the linear programming model has become a standard planning tool in farm management (Rickards, Anderson and Kerrigan 1967).

A variety of simple non-optimizing models related to parametric budgeting models (Byrne 1964) can be used in economic analysis of agricultural production (Rickards and McConnell 1967), but these barely qualify as mathematical models. Monte Carlo programming models are not explicitly optimizing but strongly resemble linear programming formulations. They have been employed for both *feedmix* (Dent and Thompson 1968) and farm planning problems (Donaldson and Webster 1968). -

(b) *Dynamic deterministic models*

Less attention has been given to explicitly time-dependent models than to static deterministic models. Several time-dependent neoclassical models are reviewed by Dillon (1968), who illustrates the diverse ways in which time can enter production models. Mundlak and Razin (1971) have operationally extended neoclassical production models to the multi-stage multi-product case.

Other optimizing models designed to model time-dependent economic systems have been of two broad types: (i) dynamic programming (Burt and Allison 1963) employing Bellman’s (1957) Principle of Optimality and (ii) multi-period linear programming models in which several production periods are modelled simultaneously within the one matrix. Any optimizing procedure can be used in dynamic programming such as a series of linear programmes, or, as in Flinn and Musgrave’s (1967) analysis of crop response to irrigation, a series of optimized response functions. For problems involving many periods (i.e. having distant planning horizons), the size of a programming matrix may become very large and temporarily exceed the capability of available computers. Pertinent examples of deterministic multi-period programming models are provided by Loftsgard and Heady (1959) and Boehlje and White (1969). Since production is seldom deterministic and conditions change over time, most of the information generated in such multi-period models for periods other than the first is not very useful.

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 (Ball 1970). Less frequently these models have been deterministic simulation models of systems (Greig 1971). Some attempt has also been made to apply Monte Carlo programming techniques to multi-period problems (Dent and Byrne 1969).

(c) *Static stochastic models*

In recent years there has been increasing recognition of the importance of risk in production, and this has been reflected in the inclusion of stochastic elements in nearly all types of models mentioned. Stochastic versions of static neoclassical response functions have been developed by Fuller (1965), Zellner, Kmenta and Dreze (1966) and most comprehensively by Magnusson (1969). However, relatively more attention has been given to incorporating stochastic effects in mathematical programming models, dating from the pioneering risk programming model of Freund (1956) to the recent stochastic programming models of Cocks (1968), Hazel (1971) and Rae (1971). A further class of models handling stochastic

decision problems is that based on modern decision theory which formalizes the risky choice of acts given a listing of events, probabilities and outcomes (Dillon 1971; Halter and Dean 1971).

Non-optimizing static stochastic models have received only minimal attention and are represented mainly by some brief flirtation with game theory algorithms for games against nature (Dillon 1962)).

(d) *Dynamic stochastic models*

Since all agricultural production processes are intrinsically dynamic and most are intrinsically stochastic, models which adequately account for both these features are desirable, but likewise they involve the greatest modelling difficulties.

Apart from some simple models presented by Magnusson (1969), dynamic stochastic versions of neoclassical response functions do not appear to have been developed. Most operational attention to optimizing models has been placed on mathematical programming (e.g. Cocks 1968; Rae 1971). Multi-period 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 (Dudley, Howell and Musgrave 1971). Methodologically, the analysis of multi-stage risky decision trees (Hespos and Strassmann 1965; Hardaker 1969; Raiffa 1968) is closely related to the backward induction procedure of dynamic programming.

Many other operations research models such as inventory models (Dillon and Lloyd 1962), replacement models and queueing models have been developed to optimize dynamic stochastic problems, but these have seldom been applied in agriculture. Several pertinent examples of stochastic simulation models are described in Dent and Anderson (1971) and an example pertaining to a pasture-feedlot model is reported by Halter and Dean (1965).

III. APPLICABILITY OF THE CLASSIFIED MODELS

In this brief appraisal, models are considered relative to three criteria — realism, workability and communicability. An appreciation of a model cannot be divorced from the purpose for which it is intended. If an analyst is content with a rather aggregative (i.e. few variables) description of a process, then response function models may suffice. However, such models become unwieldy for analyses involving many variables and interdependencies, and for such problems (which abound in agriculture) their use is virtually ruled out on grounds of unrealism and unworkability despite the ease with which such models can be communicated to others. Another difficulty with stochastic versions of these models lies in estimation of parameters to describe the probabilistic effects in response processes.

For optimizing work the mathematical programming models generally offer the best prospects for success. Although they necessarily involve the linearization of many relationships, analysts find that this feature usually does not restrict the realism of these models too much. The logic of sophisticated programming models, however, is not so readily communicated as with other models — unless all people concerned are skilled in the methodology or programming. The question of workability is more serious. A realistic multi-period stochastic linear programming model may be conceived and formulated, but is quite likely to be either insoluble

or solvable only at very large cost on available computers. Fortunately, comparable simulation models do not encounter such workability problems; they can be as realistic as knowledge of a system will permit, and are fairly easily communicated to people other than the modellers. They may, however, also involve substantial computing costs and, in contrast to mathematical programming, standard computer programmes are not available.

Choice of a particular model depends on objectives and the nature of the problem. For example, in choosing between, say, a mathematical programming and a simulation approach, one implicit question will be whether an optimal solution to a more or less inadequately specified programming model is better than a reasonably good indication from an appropriately specified simulation model. Such general consideration of optimality raises the question examined by Day (1964, 1971) of the nature of an 'optimum' and how this reconciles with the alternatives perceived by decision makers. My guess as to the usual operational choice of models within categories of Section II is: (a) static deterministic — choose response functions for single-product and linear programming for multi-product cases, (b) dynamic deterministic — choose multi-period linear programming, (c) static stochastic — choose stochastic linear programming and (d) dynamic stochastic — choose simulation. Categories (a) and (d) will probably continue to engage most attention of agricultural economists.

IV. SOME PRACTICAL PROBLEMS IN MODELLING

Problems faced by systems modellers are multifarious and only a selection is mentioned here. The selected problems have been crystallized by the advent of systems simulation, although to some extent they apply to any modelling activity.

(a) *Interpretation of output from models*

A probable shortcoming of all the optimizing models discussed is that they optimize a single-dimensioned objective function such as total gross margin, expected profit or expected utility. Operationally this is clearly advantageous, but a real difficulty is that decision makers' goals usually have several dimensions — e.g. survival, various financial measures, non-monetary objectives etc. Formal recognition of multiple objectives is clearly important if not unavoidable in dealing with most simulation and Monte Carlo programming models where, typically, analysts are interested in tracing several variables describing the system. Informal appraisal of output usually demands at least an implicit trade-off or ranking in importance of the several variables of interest. The decision-theoretic approach would have such trade-offs made explicit either through lexicographic ordering or some weighting scheme (Dillon 1971), sometimes involving the opinions and weights of several assessors (Turban and Metersky 1971).

(b) *Experimentation on models*

Simulation modellers have concentrated on experimentation much more than modellers using optimizing models such as linear programming, who have often been too optimistic about optimization. A more appropriate approach is to view all modelling work as a framework for testing hypotheses about the modelled system (Allee 1959) and this will usually imply some more or less formal experimentation on the modelled system.

Textbook treatments of experimentation on models (e.g. Naylor 1971) concentrate rather too heavily on traditional methods of experimental design directed to multiple comparisons of means. Experimental designs merely provide an efficient way of learning about a system, so, in models characterised by many controllable variables and many output variables of interest, designs that allow efficient estimation of multi-factor response surfaces will be of greatest utility. Candler and Cartwright (1969) provide an example of using a composite design to handle several variables but do not specify any trade-off between their performance measures. In stochastic simulation experiments there is much unexploited scope for reducing error variances by developing blocking schemes based on repeatable pseudo-random number sequences for different sets of stochastic variables (Chudleigh 1971).

(c) *Sensitivity analysis*

Sensitivity analysis is the testing of a model for robustness in the performance variables Y_j , with respect to parameters (including assumptions and decision rules) X_i incorporated in the model. 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 invariably sensitive) that is of most interest. Modern linear programming routines facilitate sensitivity analysis of the optimal solution.

There are no golden rules for sensitivity analysis. Various techniques have been employed, particularly by econometricians, involving systematic perturbation of the parameters not known with certainty. That is, models are run or solved while adjustments, denoted here by ΔX_i , are made to parameters. The magnitude of ΔX_i is often taken as some multiple of the standard error of X_i where this is known or can be guessed. Assessment of relative sensitivities has then been appraised by the magnitudes of slopes, such as $\Delta Y_j / \Delta X_i$. For analysts interested in linearizing their models, some measure of symmetry can be useful — e.g. does $|\Delta Y_j / + \Delta X_i| = |\Delta Y_j / - \Delta X_i|$?

An appealing alternative that does not seem to have been used is to express sensitivities analogously to elasticities $E_{ij} = (\Delta Y_j / Y_j) / (\Delta X_i / X_i)$, so that a matrix of dimensionless measures of sensitivity could be defined. In turn, the E_{ij} might be weighted by coefficients, W_j , defining the relative importance of the different performance measures, Y_j .

Whatever the method, what steps logically follow a sensitivity analysis? A ranking of sensitivities can indicate where further refinement of parameters is best concentrated. If important model output is very sensitive to many uncertain parameters, the whole modelling exercise has probably reached the limit of its achievement — namely in explicitly quantifying ignorance of the system. If it is sensitive to only one or a few (assumed discrete) parameter(s), the correct procedure would be to conduct the remaining analysis conditional on specified values of these parameters, and as a final step combine all results as an expectation based on the analyst's subjective joint (if more than one parameter) probability distribution.

(d) *Validation*

Validation is the process of determining the acceptability or reasonableness of a model for its intended purpose. Much has been and will continue to be written on this topic, as it is certain to be the focal point for most controversies

in modelling. Most of the literature (e.g. Naylor 197 1) concentrates unduly on testing the goodness of fit between the behaviour of the model and the observed real system — usually based on some historical sequence of observations. This has been conventional practice with response functions and simulation models, whereas mathematical programmers have usually given too little attention to validation.

Validation must be essentially a subjective procedure and would be better recognised as such. This is partly because of the inevitable dependence of models on largely non-quantitative subjective knowledge, and partly because history may have little bearing on the future. 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 very limited assistance in assessing ‘variable-parameter’ validity and ‘event’ validity (Herman 1967) which are usually important for analytical purposes.

V. CONCLUSION

Analytical man likes building models, and economists interested in agricultural production systems are no exception. Thus model building will probably continue to accelerate, particularly in the dynamic stochastic class of models.

The iceberg of problems in modelling has many hidden features, and only some of the more obvious dangers have been mentioned here. Modelling is no panacea but it has often proved most effective. When embarked upon with caution, skill and scepticism it will continue to be a useful endeavour.

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