A SURVEY OF DECISION MODELING FORMALISM AS APPLIED TO PEST MANAGEMENT

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I.   Introduction

This is a survey of types of decision models, with respect to their use for insect and disease control in agriculture. For the purpose of this discussion, a decision model is a formal modeling structure designed to aid in decision making. This includes linear and nonlinear programming, optimal control, dynamic programming and stochastic control, as well as applied decision analysis. Although decision analysis is the most general framework, we begin (after an introductory discussion of the decision process) with the more restrictive models and work toward increasing generality.

There is no attempt in this discussion to exhaustively review the literature. I have attempted to convey some feeling for the relative potential of various approaches to pest control decision modeling, and the extent to which that potential has been exploited. Work cited has been chosen for value in illustrating these points.

II.   The Decision Process and Decision Models

Decision models are system models formulated with the purpose of systematically and efficiently examining decision alternatives, so as to select the best course of action as judged by some given criterion. In economically based agriculture, the overriding criterion is monetary return, although environmental and social factors may also be considered. Construction of successful decision models for pest control requires combined modeling of the dynamics of the pest biology and its effect on yield production, together with the effects of control technologies and economic factors.

In a general context, it is useful to think of a system as a device which takes an input and transforms that input into a system output. The transformation depends upon the structure of the system (as reflected by its internal dynamics) and usually on the past history of inputs (as summarized by an appropriate state variable).

The management of a system consists of a complex time sequence of decisions relating to the creation and the alteration of the internal structure of the system, and to the control of the inputs to the system. Decisions that alter the structure of the system usually have an affect on a broader scale with respect to space and/or time. Such broader scale decisions (e.g., varietal selection and field layout) have the effect of defining the decision parameters for lower scale decisions (e.g., chemical spray schedules). Mesarovic, Macko and Takahara (1970, Chapter 2) have a good discussion on the concept of decision hierarchies; Carlson and Main (1976) discuss hierarchies specifically related to pest management (see also Gold, et al., 1983).

The term decision is central to this discussion. Matheson and Howard (1977) suggest that a decision is "an irrevocable allocation of resources". The essential characteristic is that the allocation cannot be revoked except at some cost, i.e., allocation of additional resources. The resource committed may be time, manpower, money or other physical resource . In a broader sense (Keeney and Raiffa, 1976), it may involve simply the expression of opinion advocating such an allocation when the advocacy cannot be revoked except at some cost (for example, compromising one's credibility).

The idea of management implies a collection of decisions designed to insure that the system output satisfies some purposeful goal structure.

In this framework, any decision requires that the decision maker has the following in mind: a set of decision alternatives; a model of the system

which relates each alternative to the system output expected; and a concept of the goal structure, relative to which each of the possible system outputs may be evaluated.

A decision is made more complicated when there are conflicting goals, so that trade-offs and compromises must be made. The simplest and most studied of such trade-offs is that of minimizing cost, while maximizing benefits. Goals may be in conflict because they are at cross-purposes or simply because they compete for the same resources.

The complexity of the decision process is also increased when the decision maker is not completely certain about what output will result from any given decision. In this case, his concept (or model) of the system must include a sense of the range of possible outputs, and the degree of certainty or uncertainty associated with the output from each decision alternative.

When the decision process combines the factors of uncertainty and of conflicting goals, the element of risk enters. The decision maker is required (at least implicitly) to choose a level of risk that he is willing to incur in balancing attainment of outcomes that are more desirable but less certain, those which are not as desirable but more certain, and avoidance of undesirable outcomes. An important type of decision concerns the allocation of time and other resources for the gathering of more information. The value of information in the decision process is in reducing uncertainty, and therefore in reducing the risk factor.

Summarizing to this point, the decision process involves, at least implicitly:

a) a model of the system which relates decision inputs to the likelihoods of various possible outcomes;

b) an inventory of available decision alternatives;

c) a goal structure and concept of the relative desirability of various trade-offs and compromises;

d) an attitude toward risk tolerance on the part of the decision maker;

e) a basis upon which to estimate the value of new information in reducing uncertainty and risk, and thereby improving the decision.

These components of the decision process may be viewed as operating at an informal, implicit level for most decision making. Explicit and formal analysis is generally costly in terms of time, effort and resources. A _decision_ (i.e., commitment of time, effort and resources) to engage in such an analysis is based on the expectation that the improvement will be worth the cost. In most cases, such a commitment is forced when the complexity of the system dynamics or of the goal structure renders implicit informal methods demonstrably unsatisfactory. That this is the case for agricultural as well as forest pest control has been amply documented (Smith, et al., 1959; Rabb and Guthrie 1970; Huffacker 1980). The idea of _economic threshold_ is among the earliest attempts to formulate explicit decision criteria in this context (Stern, et al., 1959).

The use of formal decision models for pest control and management has been reviewed from different perspectives in the literature of entomology, of plant pathology, of biomathematics, of operations research, and of agricultural economics (see, for example, Getz and Gutierrez 1982; Carlson and Main 1976; Shoemaker 1973a; Feldman and Curry 1982; Webster 1977). The various models differ in the approach and degree to which the components of the decision process are made explicit and the way in which new information is incorporated into the process.

Formal decision models can be thought of as falling into one of four categories:

a) mathematical programming models (linear or non-linear programming)

b) optimal control models

c) dynamic programming and stochastic control

d) decision analytic models

The accompanying table compares these categories in terms of ability to treat system dynamics and system randomness, explicit use of new information, ease with which discontinuities in state and control variables may be accommodated, need for closed form analytic formulation, and ability to accommodate complex decision sequences. Going down the table from the top, the methods increase in their flexibility and generality, but also increase in the difficulty of application and computational complexity.

III. Mathematical Programming Models

The optimization methods of linear and non-linear programming do not account directly for the dynamics of the system; that is, for the compounding, amplification or damping of effects through time. However, such optimization methods may be brought into play after the dynamics have been accounted for by either direct calculation or through the models of optimal control theory.

In direct calculation (usually by simulation), the system dynamics may be calculated using a set of alternative control regimes. A suitably defined output function is calculated, the result being a set of output values represented as a function of the control policy. The impracticalness of exhaustive enumeration of control alternatives through direct calculation has been amply discussed by Shoemaker (1973a) and Watt (1963). Therefore the "best" control policy might be chosen by selective computer experiments or with the aid of mathematical programming methods.

A COMPARISON OF DECISION MODELING FORMALISMS

	Dynamic vs. Static	Stochastic vs. Deterministic	Ability To Treat Discrete Variables	Feedback Use of New Information	Complex Decision Sequences	Need for Analytic Formulation
Mathematical Programming (linear & non-linear)	Static	Deterministic	Yes(linear) No (non-linear)	No	No	Required
Optimal Control	Dynamic	Deterministic	With special methods	No	No	Required
Dynamic Programming, Stochastic Control	Dynamic	Either	Yes	Yes	No	Not Required
Decision Analytic	Either	Either	Yes	Yes	Yes	Not required

An example of the use of selective computer experiments is the work of Menke (1974) on damage to soybean by velvetbean caterpillar. A simulation model developed by an interdisciplinary team was used to conduct a series of computer experiments addressed to the question of finding if there is a particular instar of the insect's development in which a fixed fraction of kill will minimize percent defoliation.

An example of the use of simulation in conjunction with nonlinear programming methods deals with damage to cotton by boll weevil (Talpaz, et al. 1978; Curry, Sharpe and DeMichele 1980).

IV.   Optimal Control Models

The use of optimal control methods in pest management has been briefly reviewed by Feldman and Curry (1982). Optimal control theory is based on the Pontryagin Maximum principle and requires analytic expressions for the dynamics of the system (see Bryson and Ho 1975; Kamien and Schwartz 1981). The method deals with an objective function of the form,

$$\int_{o}^{T} f(t, \underline{x(t)}, \underline{u(t)}) \, dt \tag{1}$$

where $\underline{x} = x_1, \ldots, x_n$ is the system state vector, $\underline{u(t)} = u_1, \ldots, u_p$ is the control vector applied at time t, and f is a scalar payoff function. This expression is maximized subject to the given system dynamics expressed by

$$\frac{dx_i}{dt} = g_i(t, \underline{x(t)}, \underline{u(t)}), \, i = 1, \ldots, n \tag{2}$$

and subject to any given initial and terminal conditions on the system state. The functions $\underline{f}$ and $\underline{g}$ are assumed to be known and continuously differentiable. Note that choosing the control vector $\underline{u(t)}$ to maximize the payoff function $f(t, \underline{x}, \underline{u})$ at each time t will not, except under special conditions maximize

the total objective integral. This is completely in accord with intuition and experience, which tells us that it is often best to incur a cost in one time period to get a higher payoff in another.

The method of solution involves forming a new function, called the Hamiltonian,

$$H(t, \underline{x}, \underline{u}, \underline{\lambda(t)}) = f(t, \underline{x}, \underline{u}) + \sum_{i=1}^{n} \lambda_i(t) g_i(t, \underline{x}, \underline{u}) \qquad (3)$$

where $\underline{u}$, $\underline{x}$, and $\underline{\lambda}$ together satisfy

$$\frac{dx_i}{dt} = \frac{\partial H}{\partial \lambda_i} = g_i(t, x, u), \ i = 1, \ldots, n \qquad (4)$$

$$\frac{d\lambda_i}{dt} = -\frac{\partial H}{\partial x_i}, \ i = 1, \ldots, n \qquad (5)$$

$$\frac{\partial H}{\partial u_j} = 0, \ j = 1, \ldots, p \qquad (6)$$

Initial and terminal conditions on the λ_i depend upon whether the "conjugate variable" x_i is free or constrained at these points. Solution of this set of equations usually involves non-linear programming methods.

Although maximizing f at each point will not necessarily maximize overall payoff, the control policy that maximizes the objective integral always produces the maximum value of H at each time. This is a result of the Pontryagin Maximum principle, which is discussed in most books on optimal control theory.

The vector variable $\underline{\lambda}$ is often called the costate vector. It has an interesting interpretation. If we let

$$V(\underline{x}_0, \underline{t}_0) = \int_{t_0}^{T} f(t, \underline{x^*(t)}, \underline{u^*(t)})$$

where $\underline{u^*}$ is the optimal control vector and $\underline{x^*}$ is the resulting state trajectory,

it can be shown that

$$\lambda_i(t) = \frac{\partial V}{\partial x_i(t)} .$$

That is, λ_i is the marginal value that an increment of variable x_i has, if it is provided at time t. This interpretation provides a powerful guide for deducing the sign and qualitative behavior of the costate variables. For example, we may reason that the marginal value of an increment of pesticide in the system at harvest time is zero (neglecting health and environmental effects). It is most positive at times when the most good would be done by adding more.

In relating the optimal control framework to the components of the decision process, we find:

   a) the system model is represented by the functions g, which embody the system dynamics, and by the payoff function f. Unfortunately, these must be continuously differentiable,

   b) the set of decision alternatives is the set of time functions u(t);

   c) the goal structure is represented by the objective integral, ∫fdt;

   d) no probabilities and therefore no concept of risk is included;

   e) perfect information is already assumed, so there is no provision for value of new information.

A major disadvantage to the use of optimal control models in pest management is the requirement that the functions f and g be continuously differentiable. Costs associated with pesticide application occur in discrete increments. Moreover, since pesticide in the system enters into the dynamics, residual pesticide must usually be included as part of the state description, and its value changes in incremental jumps. Various authors have circumvented the problem in different ways. The most direct is to assume that the pesticide is actually applied continuously (Mitchiner, Kinnish and Brewer 1975). Another simplification is

to assume that the pesticide kills instantly and leaves no residue, so that it is not included as a state variable (Marsolan and Rudd 1976; Goh, Leitman and Vincent 1974; Bahrami and Kim 1975).

Another possibility, which does not yet seem to have appeared in the literature on pest control (see, however, Gold 1983) involves the use of a dummy variable, which may be interpreted as "artificial time" (Vind 1967; see also the expositions of Arrow and Kurz 1970, p. 51 and Kamien and Schwartz 1979, section 18). In this method, ordinary time becomes just another state variable of the system, with the property that (letting w be artificial time)

$$\frac{dt}{dw} = \begin{cases} 0, & \text{during pesticide application} \\ 1, & \text{otherwise .} \end{cases}$$

All time derivatives in the formulation are then taken relative to the dummy variable. The effect is that pesticide application is continuous in artificial time, but discrete in real time.

V.   Dynamic Programming and Stochastic Control

Realistic and useful models for pest management must also account for the randomness of the system dynamics and the incompleteness, as well as imprecision, of our information. Allowance must be made for efficient use of new information and observations. Stochastic control theory addresses these problems using the computational algorithm of dynamic programming. As generally applied, the dynamic programming algorithm is formulated in terms of discrete time periods. Then $\underline{x}_k$ is the value of the state vector at the kth time point, and $\underline{u}_k$ is the control decision at the kth time point. The dynamics of the system are expresed by

$$\underline{x}_{k+1} = \underline{g}_k(\underline{x}_k, \underline{u}_k) \tag{7}$$

The value of the payoff during any time period is a function of the state and of the control decision at the kth time point, $f_k(\underline{x}_k, \underline{u}_k)$. No control is applied at the very last time point N, so the last payoff is $f_N(\underline{x}_N)$. The objective function then is,

$$J = f_N(\underline{x}_N) + \sum_{k=0}^{N-1} f_k(\underline{x}_k, \underline{u}_k) \tag{8}$$

The method of solution is generally by backward iteration. It is based on the principle that in whatever state we happen to find ourselves, we can do no better than to optimize from that time on (a loose statement of Bellman's principle of optimality). So, if we look first at the last decision needed (which is $\underline{u}_{N-1}$) we choose it to get,

$$J^*_{N-1}(\underline{x}_{N-1}) = \max_{\underline{u}_{N-1}} [f_{N-1}(\underline{x}_{N-1}, \underline{u}_{N-1}) + f_N(\underline{x}_N)] \tag{9}$$

Using the dynamics, as expressed by (7), this becomes

$$J^*_{N-1}(\underline{x}_{N-1}) = \max_{\underline{u}_{N-1}} \{f_{N-1}(\underline{x}_{N-1}, \underline{u}_{N-1}) + f_N[\underline{g}_{N-1}(\underline{x}_{N-1}, \underline{u}_{N-1})]\} \tag{10}$$

This gives us the best we can do for any given state $\underline{x}_{N-1}$ at time point N-1.

Now that we know the best decision for any given $\underline{x}_{N-1}$ and that

$$\underline{x}_{N-1} = \underline{g}_{N-2}(\underline{x}_{N-2}, \underline{u}_{N-2}),$$

we can get the best sequence from any possible $\underline{x}_{N-2}$:

$$J^*_{N-2}(\underline{x}_{N-2}) = \max_{\underline{u}_{N-2}} \{f_{N-2}(\underline{x}_{N-2}, \underline{u}_{N-2}) + J^*_{N-1}[\underline{g}_{N-2}(\underline{x}_{N-2}, \underline{u}_{N-2})]\}$$

This is iterated,

$$J^*_k(\underline{x}_k) = \max_{\underline{u}_k} \{f_k(\underline{x}_k, \underline{u}_k) + J^*_{k+1}[\underline{g}_k(\underline{x}_k, \underline{u}_k)]\} \tag{11}$$

to arrive at $J^*_0(\underline{x}_0)$.

The computational algorithm lends itself to stochastic formulation, replacing (8) by

$$J = E[f_N(\underline{x}_N) + \sum_{k=0}^{N-1} f_k(\underline{x}_k, \underline{u}_k)]$$

$$= E\{f_N(\underline{x}_N) + \sum_{k=0}^{N-1} f_k[g_{k-1}(\underline{x}_{k-1}, \underline{u}_{k-1}, \underline{w}_{k-1})]\} \tag{12}$$

where E indicates expectation and $\underline{w}_k$ is a random "noise" vector. The implication is that we do the best we can expect to do. This form is also applicable to the case in which the system state is known only to within some measurement error.

The general application of the stochastic control methodology involves combining the dynamic programming algorithm of equation (11) with a process for using new observations to update the probability distribution on the state space and on the form of the system dynamics. In theory the calculation of expectations in equation (12) can allow for anticipation of new information which may result from certain of the possible control decisions.

The most widely used technique for updating the probability distributions is the Kalman filter procedure, which is fundamentally a Bayesian probability updating process (Kalman 1960; see Maybeck 1979, chapter 1 for a good exposition of the concepts underlying the Kalman filter). The Kalman filter procedure may also be used independently of the control framework, and has been suggested by Zaveleta and Dixon (1982 and 1983) as a tool in pest sampling. They emphasize the importance of combining information obtained from sampling, with information contained in a model of pest dynamics.

The most prominent application of dynamic programming to pest management is that of Shoemaker (1973 a, b, and c). The system she has treated most

extensively involves alfalfa and alfalfa weevil, together with a parasitoid that attacks the weevil. Details may be found in Shoemaker (1982) and in Shoemaker and Onstad (1983). In this treatment, each year is a single time period. The value of N in equation (8) marks the completion of the last year in the planning horizon. State variables are density of adult weevils before oviposition and density of adult parasites in spring of the year. Environmental parameters are weather pattern and parameters of the economic environment - price of alfalfa, financial discount factor and cost per insecticide treatment. Control variables are time of first harvest during the year and number of insecticide applications during the year. All variables are assumed to be observed without error before a decision is called for in the ith year. However, the weather after the current year (current with respect to the iteration being performed) is treated as a random variable with values of "cool," "medium," and "warm" each assigned a probability of 1/3. The values of the state variables (pest density and parasite density) in succeeding years, and the yield expected are computed on the basis of simulation models for the plant, parasite, weevil, and their interaction.

The principal drawback to the use of dynamic programming methods is that storage space and number of computations mount up combinatorically as the number of possible states at each time point increases. Efficient methods for parsimonious representation of the state space are therefore of paramount importance.

The stochastic control/dynamic programming model relates to the decision process in the following way:

a) The system dynamics is represented by the functions $\underline{g}_k$. Unlike the optimal control case, analyticity is not required, though it is computationally convenient. As in Shoemaker's treatment, if the functions cannot be computed analytically, they may be computed

numerically. Moreover, as discussed in conjunction with equation (12), they may be random variables so that stochastic dynamics as well as measurement error may be accommodated.

b) The set of decision alternatives is represented by the set of possible values for $\underline{u}_k$ (which need not be the same set for each time point).

c) The goal structure is represented by the objective function J and the period-by-period payoff functions f_k;

d) If the payoff functions are taken to be utilities, then the goal structure of equation (11) is characterized in terms of expected utility. The shape of the utility function represents the decision maker's attitude toward risk (see Keeney and Raiffa 1976 for a good exposition of utility theory).

e) New information is evaluated through expression (12) in terms of its ability to reduce uncertainties. For example, we are often in a position to compute the variance reduction that a certain number of additional observations will cause, and the consequent benefit in terms of a pending decision.

VI. Decision Analysis

Decision analysis formalism also makes use of the dynamic programming concept, but involves direct and explicit treatment of each of the components of the decision process. It extends the motivating concepts of stochastic control to situations which are unique, rather than repetitive, and of sufficient importance to warrant the special investigation needed (Matheson and Howard 1977).

The procedures developed, such as the use of decision trees, are especially important when the set of decision alternatives at one stage in the process depends upon previous decisions and outcomes.

The practice of decision analysis often involves the subjective evaluation of probabilities and of utilities. Indeed, it is argued that both probability and utility are by nature subjective. If this is accepted, then the greatest objectivity is achieved by attempting to accurately codify and represent the uncertainties and the value structure upon which the decisions will be based, including attitude toward risk. The process may be formulated as involving the following steps (adapted from Matheson and Howard 1977):

a) evaluation of the decision environment and decision constraints;

b) deterministic modeling of the system dynamics and of the relative value of possible outcomes;

c) on the basis of the deterministic model, establishing sensitivities to decision and to state variables;

d) encoding and modeling uncertainties, and measurement of stochastic sensitivity and of risk sensitivity;

e) estimating the value of new information in reducing uncertainties and gathering the appropriate information;

f) cycling back, updating probabilities on the basis of the new information.

Application of the decision analysis paradigm to agriculture has been advanced notably by Anderson, Dillon and Hardacker (1977) and, in a pest control context by Carlson (1970). Carlson analyzed the problem of peach brown-rot in California. He describes procedures for assessing subjective probabilities of disease and for combining this with forecasts of disease level based on regression models. He then discusses optimal pesticide use under several different utility structures and compares the result with actual practice (Carlson 1969).

The decision analytic paradigm has provided a conceptual setting for discussion of problems related to pest control. Feder (1979) specifically examines the effects of imperfect information and the perception of uncertainty by farmers on their tendency to use (or overuse) pesticides. This problem is discussed qualitatively by Norgaard (1976), who also discusses the costs associated with the decision process, especially when collective action is needed. Carlson (1980) considers the value of crop loss information to farmers, regulatory agencies and research administrators.

It seems evident from the literature cited that the decision analysis paradigm has provided a framework for study and discussion. Moreover, the idea of the decision tree to represent complex sequences of interdependent decisions has found use in the design of interactive computer programs to aid in the making of decisions. However, decision theory, involving maximization of expected utility and evaluation of potential new information in terms of the improvement it makes, does not seem to have been explicitly used in the field of pest management. It is clearly of potential value not only for short range decisions such as those involving pesticide application, but for longer range decisions such as those involving plant variety selection and determination of profitable research directions (Carlson and Main 1976).

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