



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

Papers downloaded from AgEcon Search may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

1985 c

UNIVERSITY OF CALIFORNIA
DAVIS
SEP 26 1985
Agricultural Economics Library

Integrated Pest Management, Anticipated Revision
and Adaptive Control

Philip Szmedra

and

Michael E. Wetzstein*

*Respectively, Graduate Research Assistant and Associate Professor, Department of Agricultural Economics, University of Georgia, Athens, Georgia. This research was partially funded by USDA Agreement 58-319V-1-052.

Selected paper at the American Agricultural Economics Association Meetings, August 4-7, 1985, Ames, Iowa.

Integrated Pest Management, Anticipated Revision
and Adaptive Control

Abstract

Producers confronted with pest management problems must continually update information on the state of the crop, the level of pest infestation, and other factors to modify their conception of the evolving state. Determination of economic thresholds have at most been based on informational feedback systems that do not take into account possibilities for revision based on the expected states of the crop system in future periods. This paper develops a framework for applying an adaptive control methodology to pest management decisions to fully consider both present and expected future information states. By incorporating anticipated revision of producers' decisions in an adaptive control scheme, it is expected that better production system performance can be realized.

Key Words: Integrated Pest Management, Anticipated Revision, Adaptive Control.

Integrated Pest Management, Anticipated Revision

and Adaptive Control

Natural communities are quite stable due to their complexity while agro-ecosystems tend toward instability due to their simplicity (Shoemaker). The fundamental problem in controlling any agro-ecosystem is providing a determinate behavior for a system in the presence of random disturbances acting on it. A crop production system consists of the underlying models of pest, plant, and predator growth and interaction dynamics not necessarily known to producers, along with producers' control system. Estimation of such a system has traditionally been based on static microeconomic theory (Heady and Dillon). This static assumption is inconsistent with most agricultural production systems. Agricultural systems are a multi-period process and thus require a dynamic optimization methodology since all input levels are not determined simultaneously. This is particularly true with pest management in agriculture. The incompleteness of available information on future pest population states in one period leads to a myopic approach to production decisions. A more realistic approach is to recognize the incompleteness of available information in one period on future states of a multi-period production process. In this approach producer's control policies are based on sequential decisions, where information that becomes available in earlier periods may be utilized in subsequent decisions.

Antle states that sequential solutions to decision problems may be distinguished from a myopic approach by the type of information utilized in a system. Integrated pest management (IPM) is a method of acquiring information on a system in earlier periods to reduce uncertainty in

subsequent producer decisions. Thus the aim of this paper is to relate recent work in IPM to sequential production information literature. Evaluating the current state of IPM literature in terms of sequential production will clearly reveal a research gap between current production theory and IPM research. An objective of this paper is to suggest a model that bridges this gap.

IPM and Sequential Decision Making

Various types of control strategies associated with pest management can be differentiated by the information utilized in the strategies to solve a multi-period system. Antle has categorized production processes according to the level of information utilized. First, the static or one-period production process is based on the assumption that production inputs are chosen as part of a one-period decision problem.

This static process corresponds to an application of pesticides on a predetermined schedule. For example, spraying insecticides on cotton once per week. The decision to spray is determined without considering possible additional information in subsequent periods. However, as the detrimental impacts of pesticide applications developed, research was directed towards finding substitutes for pesticides. IPM has been suggested as a new technology which substitutes information for pesticides (Hall). Initial research in this direction was by Headley who only considered a single application of pesticides at one particular point in time. No dynamic effects through time were considered and only information available in the current period is employed in decision making. Headley's model assumed that damage in one period depends on the current pest population conditional on previous population levels.

Utilization of IPM in this manner is directly related to Antle's classification scheme. Specifically Antle's second classification is sequential dependence of decisions. A decision in one period depends on how it affects the production system in subsequent periods. In terms of Headley's model, a decision to apply pesticides is based on the level of pest density. If decisions are based on pest densities, then a decision to apply pesticides in one period is dependent on its affect on pest densities in subsequent periods. Generally economic thresholds currently employed by producers and suggested by the Cooperative Extension Service utilize this level of information.

Information feedback, Antle's third classification, occurs when a decision is based on information available in previous periods. In this case a pesticide application decision is dependent on the actual state of the production system. A decision is made with information based on the actual production system, rather than initial estimates. Recent research in IPM determining optimal timing and rate of pesticide applications considers information feedback (Feder and Regev; Hall and Norgaard; Hueth and Regev; Marsolan and Rudd; and Talpaz and Frisbie). Information feedback results in economic thresholds varying from one production season to another depending on the actual state of the crop system in a given season.

Anticipated revision, Antle's last information classification, has not been addressed in the IPM literature. If decisions made earlier may be revised later as new information becomes available, producer's decisions in one period will be conditional on anticipated information in subsequent periods. Knowledge that additional information on pest

densities will be forthcoming in subsequent periods may influence producer's current pest management decisions.

Since information on current and future levels of pest densities is not generally known with certainty, pest management should also be considered in a stochastic control framework. The stochastic environmental process generating the sequence of events that are experienced by the production system can be described by a probability function, the sense of which is also not directly known. However, the decision maker working within an adaptive control framework, does know the history of occurrences of significant events affecting the states of the production system, and in this sense possesses limited information concerning the parameters of the system. Subjective probabilities of future states can be applied to limit the extent of uncertainty in decision making.

Model

Consider a system whose state evolves according to the following difference equations:

$$(1a) \quad y_{1t} = a_{11} y_{1t-1} + a_{12} y_{2t-1} + b_{1t} + e_{1t}$$

$$(1b) \quad y_{2t} = a_{21} y_{1t-1} + a_{22} y_{2t-1} + a_{23} y_{3t-1} + c_{2t} M_t + b_{2t} + e_{2t}$$

$$(1c) \quad y_{3t} = a_{31} y_{1t-1} + a_{33} y_{3t-1} + c_{3t} M_t + b_{3t} + e_{3t}$$

Where without loss of generality let y_{1t} , y_{2t} , y_{3t} , and M_t be scalars measuring the state of the crop, pest population, predator population and control decision, respectively. Also, b_{1t} , b_{2t} , b_{3t} are scalars measuring the state of the system not subject to control.

In matrix notation (1) is written as:

$$y_t^* = A_{t-1}^* y_{t-1}^* + C_t M_t + b_t + e_t$$

Where $y_t^* = (y_{1t}, y_{2t}, y_{3t})'$, $C_t = (0 \ C_2 \ C_3)'$,

$$b_t = (b_{1t}, b_{2t}, b_{3t}), \quad e_t = (e_{1t}, e_{2t}, e_{3t})$$

$$A_t^* = \begin{matrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & a_{23} \\ a_{31} & 0 & a_{33} \end{matrix}, \quad y_{t-1}^* = \begin{matrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{matrix}$$

Following Chow's convention, (1) is rewritten to incorporate M_t as an element of y_t

$$(2) y_t = A_t y_{t-1} + C_t M_t + b_t + e_t$$

Where $y_t^* = (y_t^*, y_{t-1}^*, M_t^*)'$,

$$A_t^* = \begin{matrix} A_t \\ I \\ 0 \end{matrix},$$

initial state; b_1, \dots, b_T , a vector of exogenous state variables, and the random disturbances affecting the system.

The objective functional is represented by the maximization of the expected net revenue,

$$(3) V = E[R(T, y^T)],$$

where the expectation is taken over all the underlying random variables.

R is a real valued function and $y^k, k = 0, \dots, T$ is defined as $y^k = (y_i^k)_{i=0}^k$.

The maximization of expected net revenue is performed with respect to the sequence of decisions $M^T = (M_i^T)_{i=1}^T$ applied during the T stage control process; i.e., the multi-period decision problem is to choose for $k=1, \dots, T$, control variable M_k as functions of all observations of the state of the system through y_{k-1} so as to maximize (3) subject to (2),

given y_0 , the initial state of the crop, b_t , the vector of exogenous variables, and e_t , the random disturbances affecting the system.

Dynamic programming may be employed to solve this problem by working backward through time. The optimal level of M_t is first found as a function of y_{t-1} followed by determining the optimal value of M_{t-1} conditional on y_{t-2} . This process is continued until in the last stage the optimal value of M_1 is determined as a function of given information y_0 available at the beginning of period 1. Thus, the following optimal feedback control equation is determined for each time period

$$M_t^* = f[F^T, y_{t-1}], t = 1, \dots, T,$$

where $F^T = [(A_i)_{i=t}^T, (C_i)_{i=t}^T, (b_i)_{i=t}^T]$.

Specific methods for solving this type of dynamic programming model are not developed here since solutions are provided in Chow (1975, 1981) and Rausser and Hochman (1979). Of interest is how this dynamic formulation relates to Antle's classification scheme and IPM research efforts. Table 1 presents the formulations of y_{t-1} and F^T given the four decision making models outlined by Antle. The first model is the static or one-period decision problem which involves no anticipation of future changes in decisions. In this case y_t is not a function of y_{t-1} and all decisions are based on partial knowledge at the beginning of the planning horizon. Considering sequential dependence of decisions made earlier may affect those made later, y_{t-1} is then composed of elements y_{2t-1} and y_{3t-1} , pest population level and predator population levels, respectively. The optimal input choice in period t depends on how it affects optimal inputs in subsequent periods, however, no learning is taking place through time. F^T is solely a function of

Table 1 Formulation of Decision Models

| Model Type | Control Decision Criteria |
|--------------------------|---|
| 1. Static | $M_t = M_t(y_0)$ |
| 2. Sequential dependence | $M_t = M_t(F^T(y_0), y_{2t-1}, y_{3t-1})$ |
| 3. Information feedback | $M_t = M_t(F^T(y_0), y_{1t-1}, y_{2t-1}, y_{3t-1})$ |
| 4. Anticipated revision | $M_t = M_t(F^T(y^T), y_{1t-1}, y_{2t-1}, y_{3t-1})$ |

y_o and thus F^T is not updated with current information in the system. Information feedback also does not incorporate the ability to learn. It can be distinguished from sequential dependence by the condition that y_{t-1} is composed of y_{1t-1} , crop density as well as y_{2t-1} and y_{3t-1} . Optimal input choice is then based on crop density as well as pest and predator population levels.

Finally, anticipated revision incorporates all the characteristics of information feedback plus allows for learning throughout the production season. Specifically F^T in anticipated revision is a function of y^T and thus varies according to the particular states of the system.

Since previous IPM research has generally not incorporated learning into the decision model the possible implications of considering learning is unknown. If the variance of F^T is already relatively small then learning by considering the influence of y^T on F^T may not significantly improve the optimal results. However as noted by Chow (1975) how much difference learning will make can be determined only by empirical investigation.

Unfortunately empirical investigation of an anticipated revision model which considers learning is constrained by both the complexity of the modeling effort and data limitations. Even when a general quadratic objective function is specified the dynamic programming methods of optimization in each period is associated with nonlinear functions requiring quadratic approximations, which greatly complicates the estimation process. Of even more significance is the data requirements of such a model. For the various possible states of the system at each point in time, a distribution of A^T , C^T and b^T is required. The question stated by Chow (1981) as to how far one

should push the assumption of optimal behavior is appropriate here. The scientific method is one of attempting to abstract from reality. At some point the costs in attempting to model determinants of decision making will outweigh the benefits. In terms of IPM research the question of whether it will be worthwhile to incorporate learning into the decision process remains to be answered.

Summary and Implications

Economic thresholds have generally at most been based on only the information feedback level of production decisions. However, producers confronted with pest management problems must continually update information on the state of their crop, the level of pest infestation, and various other factors in order to modify their conception of the evolving state of the system. Based on these changing preceptions, a control for optimal pesticide applications should consider anticipated revision in a stochastic framework. Adaptive informational decision making based on the probable state of the crop and pest populations through time, allows the utilization of forthcoming sample information to learn about uncertain elements. As the information set expands, revision of preliminary input decisions to incorporate the new data, as well as conditional expectations of future states of the system, give better control performance than static or open-loop methods. The adaptive control scheme allows for the incorporation of anticipated revision of producer decisions to better approximate the optimal state of the crop system through the production horizon. Given the negative externalities of widespread pesticide use, including ecological disruption and interference with natural control agents, pollution, and increasing pest resistance, implementing controls that develop from broad-based

informational systems may be more cost effective than those based on myopic criteria. In particular the explicit costs of control under an adaptive control scheme, both private and public, may be less than an open-loop control formula. Adoption of this methodology in modeling pest management decisions may give better decisional criteria for producers faced with risky control alternatives.

Footnotes

1. $y^k = (y_i)_{i=0}^k$ states that y^k is composed of the elements in the vectors y_0, \dots, y_k .

References

Antle, John M., "Sequential Decision Making in Production Model," American Journal of Agricultural Economics, May 1983, p. 282-290.

Chow, Gregory, C., Analysis and Control of Dynamic Economic Systems. John Wiley and Sons, New York 1975.

Chow, Gregory, C., Econometric Analysis by Control Methods. John Wiley and Sons, New York, 1981.

Feder, G. and U. Regev. "Biological Interactions and Environmental Effects in the Economics of Pest Control," Journal of Environmental Economics and Management. 2.1975, p. 75-91.

Hall D. C., "The Profitability of Integrated Pest Management: Case Studies for Cotton and Citrus in the San Joaquin Valley." Entomology Society of America Bulletin, Vol. 27, No. 4, 1977, p. 267-274.

Hall, D. C. and R. B. Norgaard, "On the Timing and Application of Pesticides," American Journal of Agricultural Economics, Vol. 55, May 1973, pp. 198-201.

Headley, J. C. "Defining the Economic Threshold," in Pest Control Strategies for the Future. Agricultural Board Washington, D. C. National Academy of Sciences. 1972 p. 100-108.

Heady, E. O. and J. L. Dillon, Agricultural Production Functions, Iowa State University Press, Ames, Iowa, 1961.

Hueth, D. and U. Regev, "Optimal Agricultural Pest Management with Increasing Pest Resistance." American Journal of Agricultural Economics, Vol. 56, August 1974, pp. 543-551.

Marsolun, N. F. and W. G. Rudd, "Modeling and Optimal Control of Pest Populations." Mathematical Biosciences 30, 1976, p. 231-244.

Rausser, G. C., E. Hochman, Dynamic Agricultural Systems: Economic Prediction and Control, North Holland, New York, 1979.

Shoemaker, C., "Optimization of Agricultural Pest Management I: Biological and Mathematical Background," Mathematical Biosciences, 16 (1973), p. 143-175.

Talpaz, H. and R. Frisbie, "An Advanced Method for Economic Threshold Determination: A Positive Approach," Southern Journal of Agricultural Economics 7, 1975, p. 19-25.