Valuing Flexibility in the Control of Contagious Animal Disease (Draft)

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Abstract

Animal epidemics can bring severe damage to the livestock sector as well as the whole society. In controlling animal epidemic, the selection of suboptimal control strategies may lead to unnecessary costs which should be avoided. This paper argues that uncertainties about the state of the epidemic, irreversible actions like culling and vaccination of animals, and the possibility of learning during the epidemic requires control strategies to be flexible and the value of flexibility should be considered when evaluating control strategies. Based on Markov decision process (MDP) and dynamic programming, a decision support framework is developed to determine the optimal control strategy which accounts for uncertainties as well as flexibility in the dynamic decision making process. A numerical example illustrates our approach to quantify the value of flexibility.

Keywords: Value of flexibility; Decision-making under uncertainty; Control strategy; Contagious Animal Disease;
JEL classification: C61; D81.

1 Introduction

As evidenced by recent history, epidemics of contagious animal disease exert a major toll on the livestock industry as well as the whole society (Dijkhuizen, 1999; Yang et al., 1999; Ferguson et al., 2001; Bouma et al., 2003). Controlling highly contagious animal disease like the foot-and-mouth disease (FMD)and Classical Swine Fever (CSF) at national level has been of top concern for countries with intensive livestock production and control strategies are periodically reviewed (Ministry of Agricultural, Nature, and Fishery, 2002; DEFRA, 2002). Disease control, at the cost of current social, financial resources, maintains future benefits of livestock production (Dijkhuizen et al., 1995). Clearly, this act of incurring immediate costs in expectation of future rewards embodies the economic behavior of investment. This analogy has lead to wide application of investment appraisal techniques in developing decision support system for epidemic control, see for example, Berentsen et al. (1992); Jalvingh et al. (1998); Morris (1999); Mangen (2002); Schoenbarum and Disney (2003). In providing decision support, these applications usually focus on evaluating a fixed number of strategies rather than seeking an optimal control strategy as also observed by Toft et al. (2004),. More insights are needed into the decision making process underlying the choice of a control strategy.

Like most investment decisions, decision on control strategy shares the three characteristics as described by Dixit and Pindyck Dixit and Pindyck (1994): 1)Uncertainty: The spread of disease involves many biological and social processes that are subject to inherent randomness (Keeling et al., 2001). As a result, the effects of control measures cannot be predicted with certainty when these measures are taken. 2)Irreversibility: Decisions on culling or vaccination of animals, once carried out, can not be reversed. 3)Leeway in timing: During an epidemic, a series of actions needs to be taken and the decision-maker can decide whether and when to implement some control measures. For investment under uncertainty, the impact of irreversibility (sunk cost) has been widely recognized, e.g. Pindyck (1991). The most important message delivered from their analysis is that, in a world where uncertainty exists, any decisions taken now has an opportunity cost, in the sense that it kills off the option of waiting for further information and the possibility of making better decisions later. This message has led to robust developments of the real options approach within and beyond investment problems. In strategic management, real options analysis highlights the value of managerial flexibility when uncertainty and irreversibility exist (Trigeorgis, 1996). In the area of animal disease control, the concept of irreversible investment has been introduced by Mahul and Gohin (1999), where the possibility of waiting for new information about the dissemination of the contagious animal disease is analyzed and the “quasi-option value” for the campaign of vaccination evaluated. Their results show that if the subjective dissemination rate is not high, keeping flexibility by waiting can avoid unnecessary loss from vaccination.

From a strategic point of view, decision-making in the control of contagious animal disease has more distinctive features than general investment problems which gives rise to the concern of flexibility. For most investment decisions, a single action is considered (for example, to invest or not to invest.) and once the action is taken, the results unfold and the case is finished. For disease control, however, a variety of control actions need to be considered. Take foot-and-mouth disease as an example, besides regular "Stamping out" scheme for EU countries, movement restriction, preemptive culling, and emergency vaccination are all options in the Netherlands (Mourits et al., 2002). These actions can all lead to irreversible costs (Morris, 1999). More importantly, these actions may need to be considered recursively at a later stage of the epidemic, as long as the epidemic is not over. During the epidemic, actions taken earlier can shape the development of the epidemic and therefore limit the choices for future decisions. In other words, options to these actions interact with each other and need to be simultaneously considered. Therefore, controlling animal diseases can be better seen as a dynamic game against nature where flexibility is needed to compensate for the lack of information when decisions were made. The advantage of keeping flexibility is that adjustment can be made afterwards when the revealed state of the epidemic differs from what was expected at the onset of the epidemic or when better information becomes available in a later stage. This implies that flexibility has impact on the whole decision making process rather than just on individual strategies. Therefore, the value of flexibility should be considered on a much richer framework than simple investment appraisal techniques.

The objective of this paper is to describe a decision support framework which accounts for flexibility in the dynamic decision making process of controlling contagious animal disease. We define the decision problem as the selection of an optimal strategy for a stochastic dynamic system. For this type of sequential decision problem where actions chosen earlier have uncertain consequences at later time instances, the combination of Markov decision process and dynamic programming is a natrual choice (Howard, 1960). Markov decision process is a power tool for the analysis of stochastic dynamic system. An optimal strategy in Markov decison process satisfies the famous "Bellman equation", known as *the Principle of Optimality*(Bellman, 1957). Over the past half century it has been widely applied in agricultural research like herd replacement modeling, where the term "Markov decision programming" was coined (Kristensen, 1993). Our framework will make extensive use of Markov decision programming to find optimal strategy when uncertainties about the epidemic can be represented by probabilistic relations.

The paper proceeds as follows: Section 2 describes the decision support framework. Sections 3 discusses various aspects regarding to the application of the framework. A numerical example is developed in Section 4 to illustrate the approach. Section 5 discusses various aspects in the application of the framework and concludes.

2 The decision support framework

The elements for Markov decision process are those of *states*, *actions*, *rewards* and *transitions* (Kristensen, 1993). Once these elements are defined, the solution for an optimal strategy (dynamic programming) is often a matter of computational convenience (Kallenberg, 2001). We therefore present our framework by describing these elements.

2.1 The state variables

In Markov decision process, the properties of the system under consideration are represented by *state variable(s)* which can take certain values. A *state* is an instance of the state variable(s). When the system is in a certain state, the state represents all essential information of the system to the decision maker (Tijms, 2003). The collection of states, the state space, spans all possible status of the system,i.e., covers all future eventualities. Markov decision programming seeks a rule which assigns the optimal action to each possible state of the system. For this approach to be operational, the states must be also observable and represent all available information.

In theoretical epidemiological models, the number of infected animals is often used as a state variable (Diekmann and Heesterbeek, 2000). Unfortunately, if the number of infected animals is used as a state variable in Markove decision process, the contingency plan becomes not operational. The reason is that the lag between infection and detection makes the state of infection only partially observable at the time of decision. From observatory point of view, a natural choice is to use the number of detected case as state variables. However, this information alone does not completely describe the system because (expected) future states cannot be derived solely from this information.

More state variables are needed to describe the complete knowledge about the state of the epidemic. Our solution is to include the current estimates of disease spread parameter as state variables too. With this setup we generate all future eventuality of FMD development and based on the assumption about the underlying stochastic process, transition probabilities between the states can be deduced. This disease spread parameter can be the dissemination rate as defined in Mahul and Gohin (1999) or the reproduction ratio R_0 as defined in Keeling et al. (2001) or any other parameters that represent the belief on further spread of the epidemic and therefore link future number of detection to current number of detection.

2.2 Actions

Since the possibility of postponing and learning lies in the heart of flexibility, the action of "no action", i.e. waiting, is explicitly stated in the action set. Depending on the actions being considered, "waiting" can be defined as an option to a whole fixed strategy (like vaccination), or as one action in a flexible strategy (for example, culling).

2.3 Rewards

We propose to define rewards according to the chosen control objective and leave the choice of control objective to the decision maker himself. Correspondingly, different "optimal strategy" may emerge as a result of different control objectives. We allow for the explicit choice of control objective rather than fix some objectives. This flexible approach may provide more insights to the decision maker when tradeoffs must be made between different control objectives.

For given control objective, the quantification of immediate rewards from various actions can be assessed by the same methods as other simulation models, e.g, Bos et al. (2001); Dewi et al. (2004).

2.4 transitions

The transitions in the system are subject to control measures and random disturbances. The intervention of control action changes subjective estimates of disease parameter. We use dynamic models to represent the continuous inference process (West and Harrison, 1997). Using their terminology, we can define the observation equation as:

$$D_{t+1} = \theta_t D_t + \epsilon_1 \tag{1}$$

where θ_t is estimated based on contact structure and control actions taken (or to be taken).And the system equation:

$$\theta_t = \delta(a_{t-1})\theta_{t-1} + \epsilon_2 \tag{2}$$

where $\delta(a_{t-1})$ is a reduction factor representing the effect of action taken at time t-1 (a_{t-1}). The disturbance terms are assumed to be white noises, i.e., $\epsilon_1 \sim$ N(0, σ_1) and $\epsilon_2 \sim$ N(0, σ_2). The values of σ_1 and σ_2 have to be obtained outside the framework. Possible sources can be expert opinion or simulation.

With this setup, the real number of detected animals (the observation) is expected not to be always the same as predicted by D_{t+1} observation equation because of the disturbance term ϵ. The probability of this discrepancy however can be calculated if the parameters σ_1 and σ_2 can be assumed as described by West and Harrison (1997), which provides the transition probabilities of the states. Therefore, the information for the state space is complete in a probabilistic sense and dynamic programming as a solution techniques can be readily applied. The employment of dynamic models in optimization based on Markov decision process has been carried out by Lien and Kristensen in their search for optimal length of grassland (Lien et al., 2003). With this set up, the fact that incoming information (the observed states) changes the subjective estimates of the parameters is modeled as changing state of the system. An optimal action can be found by looking up the optimal action corresponding to this new state.

2.5 Decision

From the analysis above, if we use D_t as the detected information available at time t, θ_t as the value for the spread parameter, A(t) as the action set at time t and R_t to show the reward corresponding to the given criteria, the set $\Gamma = \{D_t, \theta_t, A_t, R_t)\}$ contains all the information for the decision problem at time t. The decision is therefore to choose the optimal A_t^* and the results would be V_t^*.

2.6 Quantify the value of flexibility

It can be naturally expected that adding the option to wait and learn in the action set would possibly lead to different optimal strategies, i.e. based on different action sets, the "optimal strategy" as a result of solving the decision problem Γ and $\Gamma^{'}$ can be different. Since the gain comes from the fact that we allow for the flexibility in carrying out the actions, we may safely define this extra value as the value of flexibility. The value of flexibility is defined as the difference from the optimal solutions over two actions sets. One with the option to wait, the other without. VF $\equiv$ max $(V^{*^{'}} - V^*, 0)$.

It can be seen that the value of flexibility we defined is an aggregated value from option values from various control actions and represents the overall value of flexibility.

3 Application of the framework

3.1 Parameter estimates and updating

To operationalize the mathematical models developed, the estimation of parameters has been the main concern of mathematical epidemiologist. Various methods have been used or proposed, among which the method of maximum likelihood (see for example, Meester et al., 2000). Lately the technique of Bayesian analysis is also used (Streftaris and Gibson, 2004). The use of these parameters is however limited in the simulation models. Relying on the first estimates..updating of parameters are often done on a retrospective basis. A significant hiatus in this line of working is how to link the uncertainty over parameter estimates to the decisions on an best available strategy? What are the implications to current decision knowing that current information is imperfect and will be improved in future?

The conceptual model we proposed takes into account the fact that parameter estimates might change over time as a result of better information and better knowledge and this change of parameter estimates necessarily changes the forecast of the development of the epidemics. With updating, initial error about the parameters will soon be corrected. This also justifies our concern about flexibility in control measure. This effect has been taken into account in the sense that the possible change of belief is accounted for in the state space. Parameters are not only uncertain, but also dynamic. This comes as a result of changing environment caused by control actions.

3.2 Data Requirement

Hard data is the ultimate means to calibrate and operationalize the model. Information is an important input of any decision making process. For the model to be operational, various inputs are needed. In general the more information is used, the better As we have been stressing, real time reports, simulation outputs. Species mix, animal numbers and the number of distinct land parcels in a farm are central to explain regional variation in transmission intensity(Ferguson et al., 2001)(Ferguson et al., 2001).The model is designed to be run with real-time data, which means the daily reporting of outbreak are critical to update information.

The requirement of data for the model can vary according to the objectives of the decision maker and the level of decision making. The optimization model, however, does not require more information than commonly used simulation models. On the one hand, more information can improve the certainty of the situation. On the other hand, it is also worthwhile to decide beforehand what information is essential or needed according to given objectives. Sensitivity analysis of the model can shed light on the the type and precision of information necessary for better decision.

3.3 Computation

We have formulated the decision making problem as a Markov decision problem and sketched the computation scheme following the spirit of dynamic programming. It is however no secret that the problem may not be solvable. Given a probabilistic system and decisions with rewards, dynamic programming is a suitable choice. But there has long been a saying that "more problems can be formulated than being solved" because the explosion of states, commonly known as "the curse of dimensionality" (Kristensen, 1988). Fortunately, as far as replacement or similar problems are concerned, it has been proved that with a hierarchical structure, a state space with more than a million states can be solved with modern computer (Kristensen, 2003).

4 Example

To illustrate our approach in selecting optimal control strategy we used a simple example. Suppose contagious animal disease X breaks out in country A where all animals are susceptible. Further assume all herds are homogeneously distributed with a herd density of 30 herds per πkm^2. For simplicity we also assume that all herds have the same number of animals

4.1 Control strategies

Mirroring reality we assume country A has to take a minimum set of measures which can reduce the spread of the disease. Additionally, country A have following options to take during the epidemic of X:

1. Wait: Wait for detected case for further action.
2. Preemptive Culling (PC): preemptive culling of all herds within 1 km radius around the detected case, although they are not detected yet.
3. Emergency Vaccination (EV): vaccinate all herds within 1 km radius around the detected case.

4.2 State Variables

The state of the epidemic at any time is defined by two variables: N, the number of detected herd; β, the subjective estimate of the spread parameter. It is assumed that the variances in the number of detection and the estimates for β are known from either simulation studies or expert opinion. Further we assume that N can take 5 integer values (0,1,2,3,4) while β takes 10 (0, 0.2,... 2.0).

4.3 Rewards

Assume the government as the decision maker wants to control disease X with minimal costs to the government. The costs to the government consists of the costs to cull or vaccinate the herds and in case of culled herds, the compensation paid to the owner of the herds.

For each state i=(N_i, β_i), the immediate reward r(i, a) can be easily calculated based on the parameters given below.

4.4 Transitions

Transition probabilities are defined based on the assumed disturbance structure of the estimated β. The model is solved by the linear programming algorithm as described by (Kallenberg, 2001).

4.5 Parameters

For demonstration, numbers are randomly chosen for the parameters needed and are shown in Table 1

Table 1: Parameters used for the example model

Parameter	**Explanation**	**Value**
cost_cull	The cost of culling per herd	1
cost_comp	Compensation paid to farmers per culled farm.	500
cost_vac	The cost of vaccination per farm.	10
σ_1	The standard deviation of β	0.6
σ_2	The standard deviation of N	3
$\delta(wait)$	The reduction ratio of waiting	0.9
$\delta(EV)$	The reduction ratio of emergency vaccination	0.7
$\delta(PC)$	The reduction ratio of preemptive culling	0.5

Table 2: Optimal action and their rewards in different states

State		Action set 1		Action set 2		Value of
Detection	β	Optimal Action	Costs	Optimal Action	Costs	Flexibility
0	0.2	Wait	9	EV	2373	2764
0	2.0	EV	13	EV	3292	3279
1	0.2	Wait	11	EV	2864	2853
1	2.0	EV	17	EV	4121	4104

4.6 Results

The example shows that adding the option to wait can greatly change the overall consequence of the epidemic even when the choices of optimal action at certain states coincide. Including waiting as an option decreases overall costs of an epidemic. The numbers from this very simplistic example should not be taken seriously but it does show the way how the value of flexibility can be quantified. Sensitivity analysis on key parameters can give more insights to the factors that influence the value of flexibility.

5 Discussions and Conclusions

Our framework makes use of optimization technique for the control of stochastic systems. Essentially it is an optimization model. An optimization model has the advantage of explicitly stating the objective and constraints. A state-space representation of the problem gives a concise way of organizing information and experience. The result gives a complete view of the solutions. It should however be emphasized that any result from optimization techniques only provides "optimal" solution to the problem characterized by the model. The optimality of the result is conditional on many aspects among which the risk-attitude and the preferences of the decision maker. As noted by many researchers, different objectives and risk attitudes can significantly alter the criteria for an optimal strategy (Dijkhuizen et al., 1995). We argue, however, for any given set of objectives, as long as there is uncertainty about the situation, irreversible actions and possibility of learning, the value of flexibility should not be ignored. The proof of this proposition needs further elaboration which deserves another article.

We propose a working definition of the value of flexibility when multiple actions are involved and when there are multiple uncertainties. This definition of flexibility can be readily extended to decision making with multiple objectives. We expect that quantification of the value of flexibility can be used to develop rules of thumb to determine the timing and scale of control actions.

Our framework differs from other decision support systems which were solely based on simulations of a limited set of predetermined strategies and ignore the real development of the epidemic. We explicitly model the uncertainties in the decision process and consider the issue of flexibility in the dynamic decision making process on strategic level. Flexibility concern is integrated into a decision support framework. With our framework, the influence of uncertainties can be investigated in a more realistic setting and the recognition of the value of flexibility would lead to a flexible strategy that minimizes the unnecessary cost of an epidemic. Our illustration has been rather general in the hope that with detailed specifications, the model can be applied to many highly contagious animal diseases that share the characteristics we described. Currently an optimization model accounting for flexibility is being developed for the optimal control of foot-and-mouth disease in the Netherlands.

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