CHAPTER 2

ROBUST INSPECTION FOR INVASIVE SPECIES WITH A LIMITED BUDGET

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Abstract. Invasive species can inflict significant costs on agriculture. Approaches to prevent introduction and/or to contain introduced species can also be very costly. Approaches to managing invasive-species problems include pre-emptive actions against potential invaders in foreign locales, border activities such as inspections to prevent introductions across international boundaries, domestic monitoring and control to prevent establishment if introductions occur, management of domestically established introductions through use of various forms of interference (e.g., vector control, enemies, pathogens, symbionts, endophytes, hosts, and/or physical factors perhaps as part of areawide management programs), and combinations of these approaches. This paper focuses on providing applicable quantitative decision support to the process of establishing efficient protocols for border protection under the severe uncertainty and resource constraints that characterize the inspection process. In this paper, a hybrid info-gap model is used in conjunction with stochastic dominance to develop a cost-effective protocol for invasive-species detection efforts. The model is illustrated by a detection problem faced at international ports. Problem characteristics advantageous to robust preparedness protocols are investigated.
Keywords: risk; stochastic dominance; severe uncertainty

INTRODUCTION

Productivity levels that have been achieved in modern economies through specialization and centralization may have been accompanied by vulnerabilities in the biosecurity realm that are only recently receiving attention from economists (Perrings et al. 2000). Modern agricultural, food, and health-care systems may present special challenges from a biosecurity perspective though other economic sectors such as transportation and education may also be based on bio-susceptible foundations (Wheelis et al.). Major resource commitments may be required to reduce both long- and short-term vulnerabilities in such systems.

Of particular concern in the United States are invasive species. An invasive species is defined as a species that does not naturally occur in a specific geographic

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area and whose introduction does or is likely to cause economic or environmental harm (Office of the President 1999). Included are species of plants, animals and other organisms such as microbes. By definition, a non-native species need not cause direct harm to be invasive. For example, the glassy-winged sharpshooter, recently introduced in California, causes relatively little harm by itself but vectors an important native plant pathogen.

As evidenced by weed pests such as purple loosestrife, which arrived via sailing ships in the 1800s, the presence of invasive species in the United States is not a new phenomenon. Moreover, as was the case with purple loosestrife, human actions have traditionally been theprimary means of invasive species introductions. What may be different in more recent times is an increase in the frequency with which such exotic pests arrive. For example, so called 'jet age' insect pests such as Comstock mealybug, Egyptian alfalfa weevil, cereal leaf beetle, Russian wheat aphid, and pink hibiscus mealybug may all have come to areas of the United States aboard commercial aircraft (eg. Ervin et al. 1983; White et al. 1995; Moffitt et al. 1993; Moffitt 1999; Ogrodowczyk and Moffitt 2001). Moreover, there does not seem to be a shortage of potential invaders. One study estimates that there are 6,000 insect pests not in the United States but known to cause harm in foreign areas having ecological equivalents to the United States (McGregor 1973). A recent study takes an economics perspective in identifying a number of potentially important invaders (Moffitt and Osteen 2004).

Preparedness for introduction of invasive species may become much more important in the years ahead than it has been in the past. The trend toward reduction in barriers to trade may increase the volume of goods traded internationally and thereby increase the opportunity for introduction of biological materials across international boundaries. In addition, the development of the internet is rapidly increasing the volume of small-scale commerce in biological commodities globally and is adding greatly to the difficulty faced by regulatory authorities in protecting domestic environments. Finally, there is a growing awareness of the potential for related terrorist activities. The latter, in particular, adds to the uncertainty associated with biosecurity preparedness in an unprecedented way.

According to some recent estimates, the cost of improved biosecurity in the United States alone will be billions of dollars (Endress 2002; O'Hanlon et al. 2002). Internationally, it can only be presumed that costs will be perhaps prohibitive in many cases. In all cases, difficult management decisions will be made about the level of security that will be provided in order that efforts be sustainable. All of these decisions will be made under the severe uncertainty that characterizes biosecurity efforts generally.

This paper focuses on a new approach to developing a cost-effective strategy for managing biosecurity risk under severe uncertainty through detection effort. A hybrid info-gap model (Ben-Haim 2001b) is used in conjunction with stochastic dominance to determine an optimal robust strategy in invasive species detection. While the foundation of the model is explicitly info-gap in its use of a performance requirement, the nature of the performance requirement utilized here extends the hybrid info-gap approach to account for risk preference. Integration of stochastic dominance conditions into the hybrid info-gap framework facilitates traditional risk management under severe uncertainty.

The next section provides background for the economic model presented in the third section. The fourth section illustrates use of the economic model to determine an optimal robust strategy in a detection problem faced at a port of entry. The fifth section investigates the characteristics of the problem that are advantageous to use of robust preparedness protocols. Some concluding remarks are given in the final section.

RISK, UNCERTAINTY AND ROBUSTNESS

In the decades since Knight (1921) made a distinction between decision making under risk and decision making under uncertainty, most related economic research has focused on decision making under risk; that is, decision making with a probability distribution assigned to uncontrolled events (Hamouda and Rowley 1996). Traditional decision criteria under risk include mean-variance analysis and expected utility maximization with many applicable criteria having roots in the latter. Despite the economic research emphasis on risky decision making, there has often been difficulty in measuring and interpreting probability distributions associated with uncontrolled events and concern about risk assessment has been evident among researchers and practitioners alike. For example, in the preface of the 1935 edition of his book, Knight himself remarked "... I (am) still puzzled at the insistence of many writers on treating the uncertainty of result in choice as if it were a gamble on a known mathematical chance ...". In view of these concerns, several non-probabilistic alternatives for measuring risk have emerged (e.g. Katzner 1998; Ben-Haim 1999) and interest in alternatives among private- and public-sector managers is apparent.

Though receiving less emphasis than decision making under risk, decision making under uncertainty has not been ignored by economists. Traditional applied decision criteria under uncertainty include the maximin, maximax, Laplace, and Hurwitz criteria (see e.g. Render et al. 2003). While none of these criteria require knowledge of probability distributions for application, the first two represent polar extremes in terms of optimism and pessimism while the latter two require information similar to probabilities in order to be applied. Similarly, quantification of other notions related to uncertainty such as ignorance and surprise have also required specification of functions confined to the unit interval (Katzner 1998; Horan et al. 2002). Additionally, Kelsey (1993) developed a distinctive decision theory requiring a ranking of event probabilities rather than a specific probability distribution. Perhaps for these reasons, none of these decision criteria under uncertainty have achieved the widespread application in economics afforded traditional risk criteria.

Some recent decision theory research has focused on the notion of robustness in decision making as a means of coping with uncertainty. An important contribution due to Broens and Klein Haneveld (1995) not only formalizes the distinction between robustness and flexibility but also utilizes a notion of robustness that mirrors the most modern contributions to to this research area. Ben-Haim (1999) has developed and utilized a single-parameter characterization of uncertainty known as information (info)-gap decision theory (Ben-Haim 1994; 1999; 2001a). Info-gap decision theory is designed for decisions made under uncertainty; that is, for cases in which probability distributions for uncontrolled events are not available. The essence of info-gap is pursuit of a performance requirement over the largest possible 'range' of uncontrolled events. This concept of robustness is identical to that considered by Broens and Klein Haneveld (1995) in their analysis of natural gas investments which they refer to as commercial scope. A special case of the info-gap theory referred to as the hybrid model (Ben-Haim 2001b), treats a family of probability distributions as uncertain and seeks robustness with respect to the distributions. There have been a number of applications of the info-gap theory to problems ranging from selection of financial portfolios to optimal search in predator-prey systems (Ben-Haim 2001b).

The basic info-gap decision model due to Ben-Haim (1999) assumes that uncertainty about uncontrolled events cannot be characterized by probability and that realization of an event resolves uncertainty. The basic info-gap decision model is distinctive in utilizing a non-probabilistic characterization of uncertainty. In this decision-making environment, reward is a definite monetary amount that follows from a decision about a controlled factor and the realization of an uncontrolled event. A performance requirement, in terms of a monetary amount, is specified to guide decision making about the controlled factor. The robust optimal decision maximizes the 'range' of uncontrolled events over which the performance requirement is achieved. This notion of robustness is based analytically on a nested family of convex sets where the degree of nesting is characterized by a single parameter. In brief, the decision maker does not know the event faced; the basic info-gap model seeks a decision that is robust with respect to possible events.

The hybrid info-gap model (Ben-Haim 2001b) assumes that uncertainty about events can be characterized by a probability distribution but that the probability distribution is unknown. Uncertainty is resolved in this context by identification of the probability distribution rather than by realization of an event. In this decision-making environment, reward is a not a definite monetary amount but rather a probability distribution over rewards. Decisions need to be robust with respect to probability distributions rather than events.

In view of the nature of reward in the hybrid model, an extension of the performance requirement in the basic info-gap model is pursued here by specifying performance in terms of expected utility. The robust optimal decision in the extended hybrid model maximizes the 'range' of probability distributions over which the performance requirement is achieved while accounting for risk preference. Unlike traditional decision criteria under uncertainty, this extension of the hybrid info-gap model integrates traditional expected utility-based risk considerations into a decision model in which event probabilities are unknown. In brief, the decision maker does not know the gamble faced; the hybrid info-gap model developed here seeks a decision that is robust with respect to possible gambles while accounting explicitly for decision maker preferences for bearing risk.

The next section presents a hybrid decision model based on the info-gap theory with expected utility as a measure of performance. While information requirements of the performance measure may appear at first prohibitive, well known results from the economic theory of stochastic efficiency suggest otherwise. Stochastic dominance can be used to facilitate application of the model as is illustrated in modelling inspections for invasive species at international ports in section four.

THE MODEL

The following model depicts allocation of scarce resources to condition the probability density function of a random variable, taken to be reward, when the probability density function of reward is itself uncertain. Because of the uncertainty about the probability density function of reward, resources are allocated in order to achieve an outcome that meets a performance requirement and is as robust as possible with respect to the specification of the probability density function.

Let ε be a random variable, x be a vector of decision variables which impact the probability density function of ε , $f_{\varepsilon|x}$ be the probability density function of ε conditional on x, g be a probability density function for ε used in specifying a performance requirement, and U(ε) be a von Neumann-Morgenstern utility function. With this notation, in the terminology of info-gap (Ben-Haim 2001b), the *system model* defines rewards and is taken to be expected utility, $\overline{U}_{(\cdot)}$, where the expectation is evaluated with respect to the subscripted probability density function. Note that in this context, the latter is not assumed to be known. The *uncertainty model* incorporates prior information in the system model and, in the case of the hybrid model, consists of a set of conditional probability density functions $\{ f_{\varepsilon|x} \}$. The *robustness function,* α (x), expresses the level of uncertainty over which the *performance requirement* (smallest acceptable reward) $\overline{U}_g$, will be achieved.

The *robust optimal decision* solves

$$\underset{(x)}{\text{Maximize}}\,\alpha(\text{x}) \tag{1}$$

$$\textit{Subject to}\ \overline{U}_{f_{\varepsilon|x}} \geq \overline{U}_g \tag{2}$$

$$\int f_{\varepsilon|x}\, d\varepsilon = 1 \tag{3}$$

$$f_{\varepsilon|x} \geq 0 \tag{4}$$

$$x \in X \tag{5}$$

where the set X reflects any constraints on x other than the performance requirement and those constraints on the conditional density $f_{\varepsilon|x}$ related to the definition of a probability density function. Assuming a solution exists, the solution to (1) - (5) provides a specific value of the vector of decision variables, x^*, and associated conditional density function $f_{\varepsilon|x^*}$. The latter is superior to the performance requirement in terms of expected utility and maximizes robustness. Given an appropriate specification of robustness, the latter condition suggests that the performance requirement will be achieved not only under $f_{\varepsilon|x^*}$ but also under perhaps a wide range of related densities.

As it stands, the model (1) - (5) poses a very difficult constrained optimization problem mainly because its information requirements seem so extensive. Two key elements needed to implement (1) - (5) include specification of the robustness objective function and the performance requirement which is shown in (2) as a constraint on expected utility. As demonstrated in the next section, it is possible to make meaningful specifications for both of these elements.

The robustness function, $\alpha(\mathrm{x})$, reflects the conditions under which the performance requirement will be achieved and can be specified in different ways (Ben-Haim 2001b). In the hybrid info-gap model, the elements in the uncertainty model are probability density functions. An intuitive interpretation of robustness, consistent with the spirit of its usage in the basic info-gap model, suggests that at the optimal solution to (1) - (5), not only does $f_{\varepsilon|x^*}$ achieve the performance requirement but other related conditional densities, one of which may turn out to be the correct one, do likewise. A specification of the robustness function suitable for all cases is perhaps not possible or even necessary. A number of criteria including Euclidian distance, variance, relative entropy, Gini's mean difference and a host of other measures can be utilized to identify, in a particular sense, the least advantageous probability density function that achieves the performance requirement in order to maximize the potential for achieving the performance requirement under a wide “range” of densities (Ben-Haim 2001b; Ebrahimi et al. 1999; Hansen and Sargent 2001; Yitzhaki 1982). In the case where the different conditional densities are characterized by a single parameter, Euclidian distance provides an intuitive measure of robustness. For the model presented in the next section, both variance and entropy will also provide equivalent measures.

If the expected utility of $f_{\varepsilon|x}$ exceeds the expected utility of g; i.e., $\bar{U}_{f_{\varepsilon|x}} = \int_{-\infty}^{\infty} \mathrm{U}(\varepsilon) f_{\varepsilon|x}\, \mathrm{d}\varepsilon > \int_{-\infty}^{\infty} \mathrm{U}(\varepsilon)\mathrm{g}\mathrm{d}\varepsilon = \bar{U}_g$, then $f_{\varepsilon|x}$ is preferred to g as required by (2). An important result in the economic theory of stochastic efficiency based on expected utility is known as second-degree stochastic dominance (SSD) (Mas-Colell et al. 1995). In brief, SSD can be stated as follows: a risk-averse individual will prefer $f_{\varepsilon|x}$ to g if and only if $\int_{-\infty}^{\varepsilon} (\mathrm{G(t)} - F_{\varepsilon|x}\mathrm{(t)})\mathrm{dt} \geq 0$ for all ε with a strict inequality for at least one ε where $F_{\varepsilon|x}$ and G denote the cumulative distribution functions associated with $f_{\varepsilon|x}$ and g, respectively. The significance of the SSD criterion is that it permits comparison of different gambles over the class of risk-averse individuals using only the cumulative distribution functions of the gambles; i.e., individual utility functions need not be known in order to implement the constrained optimization of robustness depicted in (1) - (5). Figure 1 depicts the SSD conditions diagrammatically for the case where the cumulative distribution functions cross only once. Note that in the figure, SSD requires only that the area labelled 'A' exceed the area labelled 'B'. In cases in which the cumulative distribution functions cross more than once, such as the illustration presented in the next section, similar graphical conditions can be identified.

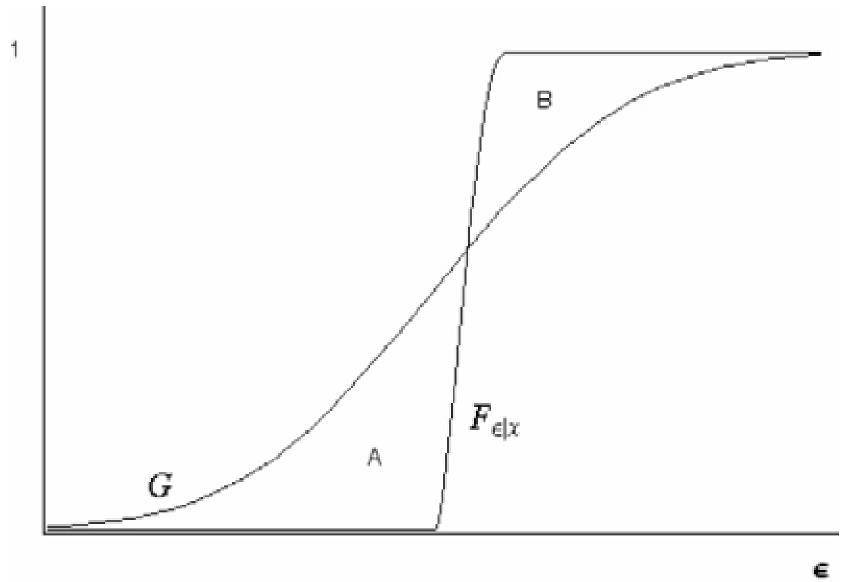

Figure 1. *$f_{\varepsilon|x}$ dominates g by SSD since area A is greater than area B*

ROBUST DETECTION AT AN INTERNATIONAL PORT OF ENTRY

This section illustrates use of the model developed in the previous section for allocating scarce resources to manage invasive-species risk under uncertainty. Risks are managed through detection effort consisting of inspection of shipments for the presence of invasive species. Hence, use here of the model developed in the previous section is intended to focus on a robust detection effort.

Let B denote the benefit due to shipping activity at a port of entry without an invasive-species threat, p denote the probability that an invasive species is present on one of N shipments that will call at the port, L denote the cost of failure to prevent passage of the species through the port, and n denote the number of shipments inspected at cost c(n) where $c' > 0$, $c'' > 0$, and c(0) = f. Hence, the cost function is assumed to be increasing at an increasing rate; that is, cost is a strictly convex function of number of shipments inspected. Fixed costs, f, are permitted but may be zero. Budgetary considerations limit expenditure on detection effort to C_0. The probability, p, is completely unknown; hence, a hybrid info-gap model is used to investigate optimal inspection.

The conditional probability density function, $f_{\varepsilon|x}$, for net benefit, ε, due to activity at the port where x = (n, p) is

$$f_{\varepsilon|x}(\varepsilon) = \begin{matrix} 1-\frac{p(N-n)}{N}; \text{if } \varepsilon = B - c(n) \\ \frac{p(N-n)}{N}; \text{if } \varepsilon = B - L - c(n) \end{matrix} \quad (6)$$

Note that a probability density function for net benefit is associated with each possible p and each possible value of detection effort, n.

Gauging the performance of stochastic systems by the probability of failure and establishing a performance requirement in terms of failure probability are common. To establish a performance requirement for detection effort in terms of the probability of biological material passing through the port undetected (failure probability), note again that this probability is given by $\frac{p(N-n)}{N}$. Let p_c denote the largest acceptable value for this probability. Note that p_c is realized as the actual probability of biological material passing through the port undetected if and only if p = 1 and n = N(1 - p_c). As it stands, p_c is a performance parameter without any economic component. However, the unique probability density function over net benefit associated with p_c makes evident its economic implications. Call the associated probability density function g where

$$g(\varepsilon) = \begin{matrix} 1-p_c; \text{if } \varepsilon = B - c(N(1-p_c)) \\ p_c; \text{if } \varepsilon = B - L - c(N(1-p_c)) \end{matrix} \quad (7)$$

According to (7), any inspection errors including failure to detect as well as fall alarms, are assumed to be negligible. With this definition of g, $\bar{U}_g$ in the model (1) - (5) is $\bar{U}_g$ = U(B - c(N(1 - p_c))) (1 - p_c) + U(B - L - c(N(1- p_c))) p_c. The performance requirement, $\bar{U}_{f_{\varepsilon|x}} \geq \bar{U}_g$ in (1) - (5) is then

$$\begin{aligned} &\mathrm{U(B - c(n))}\left(1-\frac{p(N-n)}{N}\right) + \mathrm{U(B - L - c(n))}\frac{p(N-n)}{N} \geq \\ &\mathrm{U}(\mathrm{B} - c(N(1-p_c)))(1-p_c) + \mathrm{U}(\mathrm{B - L} - c(N(1-p_c)))p_c \end{aligned} \quad (8)$$

Note that under the assumptions about U, second-degree stochastic dominance can be used to express (8) in simpler terms that do not involve an expression for the utility function. This is accomplished by comparing cumulative distribution functions according to SSD conditions as depicted in Figure 1. The cumulative distribution functions in this case are step functions corresponding to the discrete probability density functions specified for $f_{\varepsilon|x}$ and g. In particular, SSD conditions reveal that (8) holds if and only if p_c ((B - L - c(n)) - (B - L - c(N(1 - p_c)))) $\geq$ ($\frac{p(N-n)}{N}$ - p_c) ((B - c(N(1 - p_c)) - (B - L - c(n))). The preceding inequality simplifies to become p_c L - $\frac{p(N-n)}{N}$ (L + c(n) - c(N(1 - p_c))) $\geq$ 0. Given expressions (6) and (7) for $f_{\varepsilon|x}$ and g, respectively, the latter inequality corresponds to a relationship between areas under cumulative distribution functions similar to those areas depicted in Figure 1 as areas A and B.

Since the uncertainty model consists of a set of probability density functions characterized by a single parameter (p) confined to the unit interval, the robustness function can be specified meaningfully as that parameter. Maximizing robustness in this case means selecting detection effort to identify the largest value of p for which the model constraints hold. The implication of the robust optimal decision is that budgetary and performance requirements will be achieved for smaller values of p as well.

In this case, the model (1) - (5) is

$$\underset{(n,p)}{\text{Maximize}} \tag{9}$$

$$\textit{Subject to } \frac{p(N-n)}{N} (L + c(n) - c(N(1 - p_c))) - p_c L \leq 0 \tag{10}$$

$$p \leq 1 \tag{11}$$

$$c(n) \leq C_0 \tag{12}$$

$$n, p \geq 0 \tag{13}$$

Characteristics of this problem that are expected to offer advantages to risk averse decision makers for use of the model (9) - (13) are investigated in the next section.

Use of (9) - (13) is illustrated by considering detection effort at a hypothetical, moderate-sized container port. Consider a port at which 1,000 vessels call annually handling cargo with an estimated value of $25 billion. The port generates tax revenue along with jobs providing a significant sum of wages each year. A biosecurity failure that interrupts activity at the port for an extended period of time will cost approximately $100 million annually. The port commission has recently implemented heightened security measures in response to the threat of invasive species. The annual budget reveals $5 million is allocated for inspection. Cost for complete inspection of n vessels is estimated to be c(n) = 1000 + 100 n^2 - 100 n. Assuming a failure probability p_c = 0.05, complete inspection of N(1- p_c) = 950 vessels costs over $90 million per year and is not possible within the port's security budget, which permits complete inspection of only 224 vessels each year. Solving (9) - (13) reveals n^* = 68 vessels and p^* = 0.521. Annual inspection cost for 68 vessels is approximately $5 million. The cumulative distribution functions associated with robust optimal detection ($F_{\varepsilon|x^*}$) and the failure probability (G) are shown in Figure 2. For any p < 0.521, $F_{\varepsilon|x^*}$ is preferred to G by all risk-averse decision makers. Moreover, spending the entire security budget to inspect 224 vessels provides a probability distribution which is less robust (preferred by risk averse decision makers for a smaller range of values for p) than that achieved by inspecting only 68 vessels.

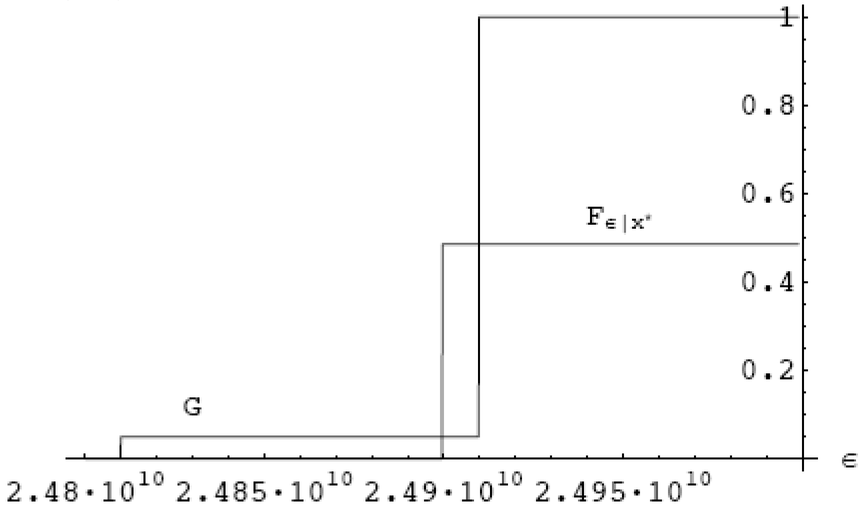

***Figure 2**. Cumulative distribution functions associated with inspection of 950 vessels (G) and 68 vessels ($F_{\varepsilon|x^*}$)*

This illustration enables some additional insight into the nature of a robust protocol based on the hybrid info-gap model with performance expressed in terms of a risk averter's expected utility. The outcome of the robust protocol (spend about half of the budget to inspect only 68 vessels rather than spend the entire budget to inspect 224 vessels) seems perhaps counterintuitive at first glance. At a purely intuitive level, perhaps many would expect to see robustness attached to risk-averse decision makers inspecting a larger rather than a smaller number of vessels. On the other hand, rationalizing the optimality of the lower detection effort as due simply to a convex cost function abstracts away from the essential fact that the detection problem involves decision making under uncertainty and decision-maker risk preferences. Some additional insight into the optimal robust inspection effort can be obtained by focusing on the relationship between maximum robustness and inspection level.

To see more clearly why inspecting only 68 vessels subject to available resources is preferred by all risk-averse decision makers for a larger range of values of p than inspecting 224 vessels, consider Figure 3. The figure displays the largest value of p at each inspection level, n, for which the resulting pdf of reward is preferred by all risk averters to the pdf associated with the failure probability. Note from the figure, that if budgetary considerations restrict inspections to less than approximately 900 vessels, then the largest value of p is found where n is 68. The inspection effort associated with this relative internal maximum in Figure 3 is the n^* associated with $F_{\varepsilon|x^*}$ in Figure 2.

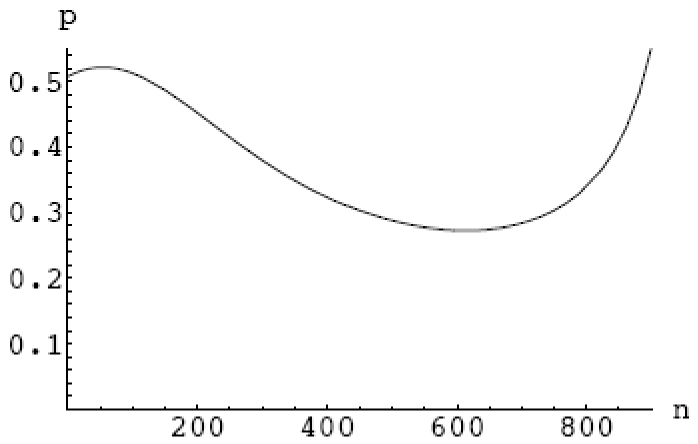

Figure 3. *Largest p given n for which a risk averter prefers the gamble based on n to the gamble based on the failure probability,* p_c

Identification of the factors that contribute to the shape of the relationship between robustness and inspection level helps to discern the source of the advantages that may be forthcoming from use of robust protocols in the presence of a resource constraint. Consider the shape of the relationship depicted in Figure 3 as inspection increases from n = 0. As n rises, both the 'downside' risk, $\frac{p(N-n)}{N}$, and reward, B - L - c(n), associated with $F_{\varepsilon|x}$ are affected. The impact on 'downside' risk initially dominates the impact on reward permitting greater robustness. This forms the initial upper sloping portion of the robustness-inspection level relationship shown in Figure 3. This relationship between risk and reward impacts persists until a relative internal maximum for robustness occurs at n = 68. Beyond this point, the convexity of the cost function yields reward impacts to further inspection that dominate, at least for a range of inspection levels, the associated risk impact. As a result, robustness declines steadily until approximately n = 625, where robustness reaches a relative internal minimum. As inspection effort grows larger still, the hyperbolic relationship between p and n in the expression for 'downside' risk assumes primacy enabling robustness to rise again despite the convexity of inspection cost and its impact on reward. Hence, without resource constraints, G will prevail; with even a modest constraint, a much different inspection level is preferred.

The relative internal maximum represented by $F_{\varepsilon|x^*}$ reflects the most robust balance between risk and reward relative to the balance embodied in G that is sufficient for any risk averter with a limited budget. In this illustration, this result follows from the nature of inspection cost and inspection's impact on downside risk. The next section investigates in more detail the characteristics of this problem that enable robust protocols to offer advantages over simpler alternatives for risk-averse decision makers.

CHARACTERISTICS AND POTENTIAL ADVANTAGE FOR ROBUST PROTOCOLS

This section considers, in more detail, characteristics of the problem considered in the previous section that make use of a robust protocol potentially advantageous for risk-averse decision makers. In brief, the objective of this section is to determine problem characteristics that enable rapid screening for potentially fruitful application of (9) - (13). Two propositions are used to assist in identification of relevant characteristics. Proposition 1 helps to define the nature of the solution to (9) - (13) that holds potential for a robust protocol to represent an improvement over standard protocols such as expenditure of a budgeted amount or pursuit of a target failure probability. Proposition 2 extends the result of Proposition 1 to more basic and readily recognizable problem characteristics.

At an intuitive level, if the constraint on robustness (11) is binding or if the budget constraint (12) is binding, resource allocation under a robust protocol may not differ much from simpler alternative protocols. In such cases, either resources permit maximum possible robustness to be achieved or else robustness is maximized by expenditure of all available resources, respectively. In neither case is there potential for more cost-effective risk management through detection efforts. The following proposition confirms this reasoning.

Proposition 1: The robust optimal decision associated with (9) - (13) offers a more desirable probability distribution for risk-averse decision makers than would be achieved through expenditure of a budgeted amount or pursuit of a target failure probability if and only if the performance requirement (10) is the sole binding constraint; i.e., $n^* < \min(c^{-1}(C_0), N(1-p_c))$ if and only if $\frac{p^*(N-n^*)}{N}$ (L + c(n^*)- c(N(1 - p_c))) - p_c L = 0, $n^* > 0$, $p^* > 0$, $p^* < 1$, and c(n^*) $< C_0$.

Proof: The Kuhn-Tucker Lagrangian, L , and conditions associated with (9) - (13) are

$$\mathrm{L}(\mathrm{n}, \mathrm{p}, \lambda_1, \lambda_2, \lambda_3) = p - \lambda_1\left(\frac{p(N-n)}{N}\left(L + c(n) - c\left(N\left(1-p_c\right)\right)\right) - p_c L\right)$$
$$- \lambda_2(p-1) - \lambda_3\left(c(n) - C_0\right) \tag{14}$$

$$\frac{\partial \mathrm{L}}{\partial n} = \frac{p\lambda_1\left(L + c(n) - c\left(N\left(1-p_c\right)\right)\right) + \left(np\lambda_1 - N\left(p\lambda_1 + \lambda_3\right)\right)c'(n)}{N} \leq 0 \tag{15}$$

$$\frac{\partial \mathrm{L}}{\partial p} = 1 - \lambda_2 - \frac{(N-n)\lambda_1\left(L + c(n) - c\left(N\left(1-p_c\right)\right)\right)}{N} \leq 0 \tag{16}$$

$$\frac{\partial \mathrm{L}}{\partial \lambda_1} = Lp_c - \frac{(N-n)p\left(L + c(n) - c\left(N\left(1-p_c\right)\right)\right)}{N} \geq 0 \tag{17}$$

$$\frac{\partial \mathrm{L}}{\partial \lambda_2} = 1 - \mathrm{p} \geq 0 \tag{18}$$

$$\frac{\partial \mathrm{L}}{\partial \lambda_3} = C_0 - \mathrm{c(n)} \geq 0 \tag{19}$$

$$n\frac{\partial \mathrm{L}}{\partial n} = p\frac{\partial \mathrm{L}}{\partial p} = \lambda_1\frac{\partial \mathrm{L}}{\partial \lambda_1} = \lambda_2\frac{\partial \mathrm{L}}{\partial \lambda_2} = \lambda_3\frac{\partial \mathrm{L}}{\partial \lambda_3} = 0 \tag{20}$$

$$n, \mathrm{p}, \lambda_1, \lambda_2, \lambda_3 \geq 0 \tag{21}$$

Under regularity conditions, (14) - (21) characterize the solution to (9) - (13). If no subset of conditions (17) - (19) hold as equalities, then (15) and (16) admit no solution. Hence, a subset of conditions (17) - (19) must hold as equalities at the solution. If (18) holds as an equality, then n^* = N(1- p_c) while if (19) holds as an equality, then n^* = $c^{-1}(C_0)$. If (18) and (19) both hold as equalities, then $n^* = c^{-1}(C_0)$ = N(1- p_c). If (10) is the sole binding constraint then (17) holds alone as an equality and $n^* <$ min($c^{-1}(C_0)$, N(1- p_c)). On the other hand, if n^* $<$ min($c^{-1}(C_0)$,N(1- p_c)) then neither (18) nor (19) can hold implying (17) holds alone as an equality and (10) is the sole binding constraint.

The implications of Proposition 1 can be made more transparent by considering conditions under which (17) holds as an equality at the solution to (9) - (13).

Proposition 2 provides the desired result.

Proposition 2: A robust protocol is potentially advantageous in detection problems for which the failure cost does not exceed inordinately the cost of complete inspection of the proportion of the population of vessels associated with the failure probability, i.e., $L \not\gg c(N(1 - p_c))$.

Proof: Expressing (17) as an equality, solving for p, and maximizing the result as a function of n gives the following necessary and sufficient conditions:

$$L - c\left(N\left(1 - p_c\right)\right) = (N - n)c'(n) - c(n) \tag{22}$$

$$c'(n) < (1/2)(N - n)\, c''(n) \tag{23}$$

In view of Proposition 1, unless (22) and (23) are solvable for some n, then a robust protocol cannot be advantageous. According to (22), marginal 'failure' cost of incomplete inspection at N(1 - p_c) equals marginal 'physical' cost of incomplete inspection at n. According to (23), marginal physical inspection cost at n must be rising more slowly than marginal physical cost of inspecting the rest of the population of vessels. If the left-hand side of (22) is inordinately large, it will exceed the right-hand side and prevent (17) from holding as an equality ruling out a potential advantage for a robust protocol.

Assuming p_c is small, Proposition 2 suggests that problems for which the cost of complete inspection of a large proportion of the population of vessels does not differ inordinately from the failure cost, are those problems where pursuing the robust optimal decision may be beneficial for risk-averse decision makers. The result of Proposition 2 suggests that problems with catastrophic economic consequences relative to complete inspection costs for a large proportion of vessels cannot be pursued fruitfully with a robust protocol. In such cases, use of a failure probability approach or simply expending a budgeted amount will correspond to the solution to (9) - (13). In other cases, use of (9) - (13) may yield benefits as suggested by the numerical illustration in the preceding section.

CONCLUDING REMARKS

Current invasive-species inspection policy in the United States is based on sampling intensity to meet a detection probability requirement given the size of the population to be sampled. Such policy does not incorporate economic criteria, which may be increasingly important as inspection techniques grow more sophisticated and costly. Moreover, existing criteria may be infeasible as the population of shipments grows with increasing trade due to limited inspection resources.

Robust satisfying as exemplified by the info-gap theory may provide a feasible alternative to current inspection policy that recognizes both resource constraints and inherent uncertainty in the inspection process. The method described in this chapter provides for maximum robustness and, in the illustration given here, does so at a fraction of the cost of a non-economic inspection policy. Of particular interest is the realization that the information requirements associated with application of the info-gap approach are much less than those associated with a more traditional risk assessment and management approach. Avoiding the need for what may be costly risk assessment may well lower the bar for required information for policy by a non-trivial amount. Of course, if risks are known, then the traditional risk management framework may be used to advantage.

It is important to remain mindful that, in practice, decisions related to detection of invasive species contained in trade shipments are characterized by both important consequences and severe uncertainty. The hybrid info-gap model, extended to incorporate risk considerations for purposes of performance, provides an opportunity to manage both risk and uncertainty through robustness. Efficiency gains from robust protocols depend on problem characteristics and will be appropriate on a case-by-case basis. Extensions of the info-gap model described here to incorporate inspection errors such as failures to detect and false alarms are possible.

NOTES

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