# 10

# Scope and concepts of risky decision making

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## Objectives

From this chapter the reader should gain knowledge of:

- the basic steps in the decision-making process
- the concepts of decision theory, taking into account the risk attitude of the decision maker(s)
- the various choice criteria, such as expected utility model, stochastic efficiency criteria and expected monetary value
- Bayes' theorem and the economic value of information

## 10.1 Introduction

The economic success of animal health management is closely related to the way in which decisions are taken and implemented. The decision-making process is essentially a five-step procedure:

1. defining the problem or opportunity;
2. identifying alternative courses of action;
3. gathering information and analyse each of the alternative actions;
4. making the decision and take action; and
5. evaluating the outcome.

The first step is probably the most important one. When problems are not recognized, continuing losses may occur, particularly with subclinical diseases and reduced fertility. Monitoring systems especially within herd health programs are increasingly used to register, and to help identify, these problems. Once a problem has been defined, it will seldom be the case that there are no reasonable solutions or actions to be taken (step 2). It will be more common that the number of alternatives has to be limited, so that each can be examined thoroughly. For documenting and examining the potential effects of the various alternative actions (step 3), it will not be feasible to have only actual field data available. Computer simulation has long been recognized as a complementary approach and is particularly attractive when real-life experimentation would be impossible, costly or disruptive.

Whichever way, and to whatever extent, the information has been provided, the fourth step is always taken, either consciously (by choosing the 'best' option) or not (which implicitly means a continuation of the available strategy). Evaluating the outcome of actions taken (step 5) brings the decision maker back to the first step, thus making the process a **cyclical** one.

Decision making in animal health management has to deal with several factors over which the decision maker has little or no control, making the outcome of actions uncertain. Different criteria can be applied to what is called 'decision making under risk'. Some of those criteria are discussed below and illustrated with an example.

## 10.2 Components of a risky decision problem

Traditional analyses of decision making have distinguished two types of imperfect knowledge: **risk**, when the probabilities of the uncertain outcomes are known, and **uncertainty**, when they are not. However, this distinction is of little practical use and is discarded by most analysts today. Probabilities can be 'known' only for the so-called stationary stochastic processes, ie, for events where there is variability but where the sources and nature of the variability remain constant through time. Such processes are rare in practical decision making. In modern discussions and analyses, therefore, the terms risk and uncertainty are used more or less interchangeably.

Any **risky decision** involves five components: acts, states, probabilities, consequences and a choice criterion (Anderson *et al.*, 1977). **Acts** ($a_j$) are the relevant actions available to the decision maker. They constitute the relevant set of mutually exclusive alternatives among which a choice has to be made. Examples of acts in animal health management are 'treat' or 'do not treat' an animal, or 'keep' or 'replace' a specific animal. The possible events or **states of nature** ($\theta_i$) must also be defined by a mutually exclusive and exhaustive listing. Examples of states of nature are 'good', 'average' or 'poor' rainfall, or 'severe', 'normal', 'small' or 'no' outbreaks of a certain disease. The essence of a risky decision problem is that the decision maker does not know for certain which state will prevail. Some state variables are intrinsically continuous (eg, herd health status), but generally a discrete representation (such as good, average or bad) will prove adequate. **Prior probabilities** ($P_i$) reflect the degrees of belief held by the decision maker about the chance of occurrence of each of the possible states. Such probabilities are considered subjective or personal in nature. Example probabilities for a disease problem can be as follows: a probability of 0.2 for a 'severe' outbreak, 0.3 for a 'normal', 0.25 for a 'small' and 0.25 for 'no' outbreak of a certain disease. Depending on which of the uncertain states occurs, choice of an act leads to some particular **consequence**, **outcome** or **payoff**. Finally, some **criterion of choice** is necessary to compare the possible consequences of any act with those of any other act. One such criterion is the expected monetary value (EMV), defined as the summation of the possible money outcomes multiplied by their probabilities.

Consider a simplified case in which a farmer can choose between two acts, ie, herd health programs $a_1$ and $a_2$. The payoffs of the programs are expected to differ according to the actual health status of the herd. These 'states of nature' can be good, average or bad, with an estimated (subjective) probability of 0.2, 0.6, and 0.2 respectively. Results are summarized in Table 10.1.

*Table 10.1 Payoff matrix for two herd health programs (US$)*

| States of nature ($\theta_i$) | P($\theta_i$) | Program $a_1$ | Program $a_2$ |
|---|---|---|---|
| Herd health good ($\theta_1$) | 0.2 | 1000 | -10000 |
| Herd health ave. ($\theta_2$) | 0.6 | 4000 | 5000 |
| Herd health bad ($\theta_3$) | 0.2 | 9000 | 19000 |
| Expected monetary value | | 4400 | 4800 |

When taking into account the mean outcome (ie, expected monetary value) to compare the alternatives, program $a_2$ is the preferred one. This choice, however, does not hold for the situation should the herd health status be good, thus making this a classical example of risky choice.

## 10.3 Subjective expected utility model

One of the most widely applied models for studying decision making under risk is the subjective expected utility (SEU) model (Anderson *et al.*, 1977). Using the model, actions are ordered according to the beliefs and risk attitudes of the decision maker. Each outcome is assigned a utility value (ie, preference), according to a personalized, arbitrarily scaled **utility function.** The utility values for each possible outcome of an action are weighed by their (subjective) probability and summed across outcomes. The resulting expected utility is a preference index for that action. Actions are ranked according to their levels of expected utility with the highest value being preferred. Farmers' attitudes towards risk vary depending on their objectives and financial resources, for instance. Most farmers, like other people, tend to be risk averse.

Suppose that a farmer's utility function for gains and losses is adequately represented by:

$$U(x) = x - 0.005x^2 \quad \text{for } x \leq 50$$

where $x$ denotes thousands of US dollars.

This function makes it possible to convert the money values for each of the alternatives in Table 10.1 to utility values (U):

$$U(a_1) = 0.2U(\text{US\$1000}) + 0.6U(\text{US\$4000}) + 0.2U(\text{US\$9000})$$
$$= 0.2(0.995) + 0.6(3.920) + 0.2(8.595) = 4.270$$

$$U(a_2) = 0.2U(\text{US\$ -10 000}) + 0.6U(\text{US\$5000}) + 0.2U(\text{US\$19 000})$$
$$= 0.2(-10.5) + 0.6(4.875) + 0.2(17.195) = 4.264$$

So, taking into account the risk-averse attitude of the farmer makes program $a_1$ the preferred one, ie, yielding the highest subjective expected utility.

The implementation of the SEU model requires the risk preferences of decision makers (ie, the utility function) to be known. The notion of certainty equivalent is central to the measurement of these preferences, and hence to the elicitation of the utility function. When given a choice between (a) payment of US$1000 for sure versus (b) a chance of winning US$5000 with a probability of 0.25, for instance, most people will opt for (a), even though (b) has a higher expected monetary value. The **certainty equivalent** (CE) of a risky prospect then is the value which the decision maker is just willing to accept in lieu of the risky prospect. So, the relationship between the CE and the expected monetary value (EMV) of the outcomes tells something about the decision maker's attitude towards risk. If the person is averse to risk, which is normally the case, (s)he will assign a CE less than EMV. For people that have a preference for risk CE will be greater than EMV, while in the case of risk indifference CE = EMV.

Methods of eliciting utility functions involve asking people to specify their CEs for specified risky prospects. According to Anderson *et al.* (1977), the simplest recommended method is based on considering an Equally Likely risky prospect and finding its Certainty Equivalent. In using this so-called **ELCE-method**, the first step is to find the CE for a hypothetical 50/50 lottery with the best and worst possible outcomes of the decision problem as the two risky consequences. The next step is to find the CE for each of the two 50/50 lotteries involving the first-established CE and the best and worst possible outcomes. This process of establishing utility points is continued until sufficient CEs are elicited to plot the utility function. In order to obtain meaningful values it is important to provide enough realism for this type of game setting (Smidts, 1990). Moreover, worthwhile outcomes require utility functions to be described in a mathematically sound way, thus making the choice of the function form very important.

## 10.4 Other choice criteria

Utility functions may not always be easy to elicit. Many authors, therefore, have suggested alternative rules that might be used, leaving it to the individual decision maker to decide what criterion is the most appropriate given his/her own specific situation (Barry, 1984).

A first group of criteria includes those that do not require probability estimates:

- **Maximin** is a criterion that arises from a very pessimistic or conservative risk attitude. Each action is judged solely on its worst outcome, and the one that maximizes the minimum gain is selected. In the example of Table 10.1 the minimum gains of the two programs are US$1000 and -10 000 respectively, with program $a_1$ being the preferred one according to this criterion.
- **Minimax** regret is similar to the previous criterion but it argues that the 'correctness' of a decision be measured by the amount by which the outcome could have been increased, had the decision maker known some information beforehand, and then selects the action with the smallest maximum increase (ie, regret). This is a criterion which has in mind judgment by hindsight. When choosing program $a_2$ in Table 10.1 the maximum possible

regret is US$11 000 (ie, US$1000 - (-10 000), in case herd health turned out to be good), while with program a1, this is US$10 000 (ie, US$19 000 - 9000, if herd health was bad). So, program a1 is now the preferred one.

- **Maximax** simply amounts to scanning the outcome matrix to find its largest value and then taking the corresponding action. This is a totally optimistic criterion, and similar to the approach of a gambler. In Table 10.1 this would result in program $a_2$ being taken (ie, US$19 000 being the largest payoff).

A second group of criteria includes more than one single value of the outcome distribution and, therefore, do require probability estimates:

- **Hurwicz α index rule** allows for a weighed average of the minimum and maximum outcome per action, and then selects the action with the highest weighed average. In formula:

$$\text{Max } [I_j = \alpha(M_j) + (1-\alpha)(m_j)]$$

where $\alpha$ is supplied by the decision maker subject to $0<\alpha<1$, $M_j$ equals the maximum gain of action j, and $m_j$ equals the minimum gain of action j. Should $\alpha = 0.5$, then the outcome in Table 10.1 is 0.5 x 9000 + (1-0.5) x 1000 = US$5000 for program $a_1$ and 0.5 x 19 000 + (1-0.5) x -10 000 = US$4500 for program $a_2$. Program $a_1$ then is preferred.

- **Laplace principle of insufficient reason** selects the action with the highest expected outcome, based on equal probabilities for all outcomes. Unlike the previous criteria it takes into account the outcomes for all events, but still ignores that one event may be (considered) more likely than the other. For the example in Table 10.1 this turns out to provide an equal outcome for the two programs, ie, (1000 + 4000 + 9000)/3 = US$4667 for program $a_1$ and (-10 000 + 5000 + 19 000)/3 = US$4667 for program $a_2$.
- **Expected Monetary Value** is probably the best-known criterion, and is defined as the summation of the possible levels of outcome multiplied by their probabilities. If there are m possible states for the $j^{th}$ action with the $i^{th}$ state denoted $\theta_i$, having outcome $O_{ij}$ and probability $P_i$, then the expected monetary value of the outcome is given by:

$$EMV(O_j) = P_1O_{1j} + P_2O_{2j} + ... + P_mO_{mj} = \Sigma P_iO_{ij}$$

It assumes that the decision maker's satisfaction is measured by the level of profit, which in fact is a special linear case of the more general expected utility model (ie, assuming risk neutrality of the decision maker). The outcome for the two programs in the example was already given in Table 10.1, with program $a_2$ being the preferred one in this case.

None of the previous criteria, however, takes account of any 'utility-based' trade-off between the average outcome of each strategy and its variance. That is why **stochastic efficiency criteria** (the third group to be considered) are proposed as a useful alternative, at least for cases where probabilities are reasonably well defined. Stochastic efficiency rules satisfy the axioms of the expected utility model but do not require precise measurement of risk preferences. However, as opposed to the complete ordering achieved when risk preferences are known, they provide only a partial ordering (King & Robison, 1984). Stochastic efficiency rules are implemented by pairwise comparisons of cumulative distribution functions of outcomes (y) resulting from different actions.

- **First-degree stochastic dominance (FSD)** holds for all decision makers who prefer more to less (ie, whose first derivative of the utility function is positive). No assumptions are made about risk preferences of the decision maker, which widens the possibilities of application but limits its discriminatory power. Graphically, these conditions mean that the cumulative of the dominant (ie, preferred) distribution must never lie above the cumulative of the dominated distribution. In Figure 10.1, for example, F(y) dominates G(y) by FSD, but neither F(y) nor G(y) can be ordered by H(y).

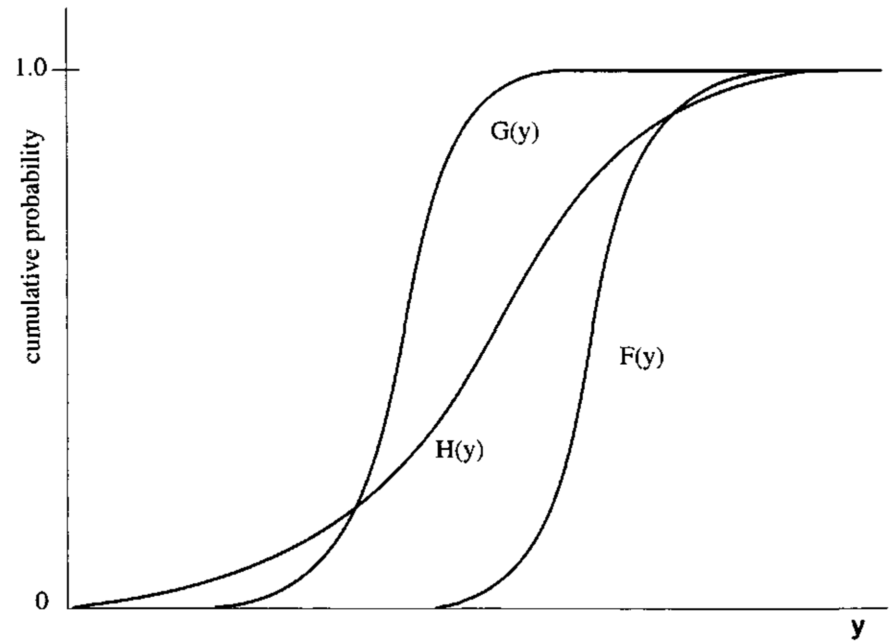


*Figure 10.1 First- and second-degree stochastic dominance*

- **Second-degree stochastic dominance (SSD)** assumes that decision makers, in addition to preferring more to less, are risk averse, with utility functions having positive, nonincreasing slopes at all outcome levels. Under SSD, an alternative with the cumulative distribution F(y) is preferred to a second alternative with cumulative distribution function G(y) if

$$\int F(y)\,dy \leq \int G(y)\,dy$$

for all possible values of y, and if the inequality is strict for some value of y. SSD has more discriminatory power than FSD, but still may not effectively reduce the number of alternatives. Graphically, because the accumulated area under F(y) in Figure 10.1 is always less than or equal to that under either G(y) or H(y), only F(y) is in the so-called SSD-efficient set of these three alternatives. When only G(y) and H(y) are considered, neither one dominates the other by SSD, since the accumulated area under G(y) is less than the area under H(y) for low values of y, while the opposite condition occurs at high values of y.

- **Stochastic dominance with respect to a function (SDWRF)** is a more discriminating efficiency criterion that allows for greater flexibility in reflecting preferences, but also requires more detailed information on those preferences. Formally stated, SDWRF establishes necessary and sufficient conditions under which the cumulative function F(y) is preferred to the cumulative function G(y) by all decision makers whose risk attitude lies anywhere between specified lower and upper bounds. The method is flexible enough to include and investigate the impact of any specified value (King & Robison, 1984).

PC-software has become available to perform the stochastic efficiency analyses (Goh *et al.*, 1989). This was also used to carry out the analyses for the example given in Table 10.1. Results are summarized in Table 10.2, together with the outcome of the previously discussed criteria.

*Table 10.2 Outcome according to the various decision criteria (US$). The preferred programs are underlined or indicated with an **

| | Herd Health Programs | |
|---|---|---|
| **Criteria** | $a_1$ | $a_2$ |
| Maximin | <u>1000</u> | -10000 |
| Minimax regret | <u>10000</u> | 11000 |
| Maximax | 9000 | <u>19000</u> |
| Hurwicz $\alpha$ rule ($\alpha = 1/2$) | <u>5000</u> | 4500 |
| Laplace principle of insufficient reason | <u>4667</u> | <u>4667</u> |
| Expected monetary value | 4400 | <u>4800</u> |
| FSD | * | * |
| SSD | * | * |
| SDWRF (with risk aversion assumed to be): | | |
| - low | * | * |
| - considerable | * | |
| - high | * | |

Table 10.2 shows that choices appear to vary considerably among the criteria. The more risk averse types of criteria lead to choice of program $a_1$, while with the expected monetary value criterion (assuming risk neutrality) program $a_2$ is preferred. Under the so-called 'gambling' approach (ie, maximax), program $a_2$ is preferred even more strongly. The Laplace criterion (using equal weights for all outcomes) does not discriminate between the two programs. The same applies to most of the stochastic dominance criteria under

consideration. At higher levels of risk aversion (ie, with higher boundaries for the risk aversion interval), however, program $a_1$ is preferred again.

## 10.5 Bayes' theorem

Most farmers formulate subjective probabilities about uncertain decisions at a point in time. If additional information comes available, the farmer has to revise or update the probabilities. Many farmers appear to revise their subjective probabilities in an informal manner when they receive weather reports, national production estimates, data on domestic use and exports, price predictions, and other data that may affect their operation. Such probability revisions can be accomplished in a logical and mathematically correct manner by applying Bayes' theorem. Bayes' theorem is an elementary theorem of probability developed by the eighteenth-century English clergyman Thomas Bayes. This theorem is normally developed in introductory courses of statistics, and its logical validity is demonstrated in many books on decision theory (Anderson *et al.*, 1977; Barry, 1984; Boehlje & Eidman, 1984)

In Table 10.3 the major components that are needed to explain Bayes' theorem are summarized, some of which have been introduced already earlier in this chapter.

*Table 10.3 Summary of the major components of a risky decision problem*

| | |
|---|---|
| $a_j$ | = the $j^{th}$ *act* or action available to the decision maker |
| $\theta_i$ | = the $i^{th}$ *state of nature* or possible event |
| $P(\theta_i)$ | = the *prior probability* of occurrence of $\theta_i$ |
| $x_{ij}$ | = the *consequence, outcome* or *payoff* that results if $a_j$ is chosen and $\theta_i$ occurs |
| $z_k$ | = the $k^{th}$ possible *forecast* from an experiment |
| $P(z_k \vert \theta_i)$ | = the *likelihood probability* of $z_k$ occurring given that $\theta_i$ prevails |
| $P(\theta_i \vert z_k)$ | = the *posterior probability* of $\theta_i$ given forecast $z_k$ |
| c | = the *cost* of the forecast device generating the set $\{z_k\}$ of possible forecasts |

Suppose that the farmer in the example of Table 10.1 can obtain a prediction from the veterinarian of the probabilities of the events $\theta_i$. The veterinarian may give k possible forecasts (k levels of the predictor; $z_k$). Since predictions of uncertain phenomena such as price and yield levels for agricultural production are less than perfect, it is important to consider the veterinarian's accuracy of the predictions in revising the prior probability estimates. The likelihood of obtaining a particular forecast, given the event that occurred $P(z_k|\theta_i)$, can be obtained by utilizing data on previous forecasts (z) of the veterinarian and the actual outcomes ($\theta$). Then Bayes' theorem can be used to combine the prior probabilities $P(\theta_i)$ of the farmer and the data on the accuracy of the prediction $P(z_k|\theta_i)$ to estimate the posterior probabilities $P(\theta_i|z_k)$. The posterior probabilities indicate the probability that an event will occur given the prediction that has been made. Bayes' theorem can be expressed as:

$$P(\theta_i|z_k) = P(\theta_i)\ P(z_k|\theta_i) / \Sigma_i\ [P(\theta_i)\ P(z_k|\theta_i)] = P(\theta_i,z_k) / P(z_k)$$

In words, the first of these formulas says that the posterior probability of the $i^{th}$ state, given that the $k^{th}$ prediction has been made, is equal to the product of (1) the prior probability of the state, and (2) the likelihood probability of the prediction given the state, divided by all such products summed over all the states. As the second formula indicates, the numerator at the right-hand side is, by definition, just the joint probability of $\theta_i$ and $z_k$, while the denomi-nator is the unconditional probability of occurrence of the particular prediction $z_k$. In general, Bayes' formula can be considered a posterior probability (density) being proportional to prior probability (density) times likelihood. Bayes' theorem hinges on the definition of conditional probability (P(A|B) = P(A and B) / P(B)).

Now we continue our example on selecting the best animal health program (Table 10.1). The farmer asks the veterinarian for advice. Based on past history, the farmer determined the accuracy of the predictions of the veterinarian. They are outlined in Table 10.4. The data indicate, for example, that if $z_1$ (good herd health) was predicted by the veterinarian in the past, a good herd health was found in 80% of the cases, an average herd health in 15% of the cases, and a bad herd health was never found. The values in other columns of the conditional probability matrix are interpreted in a similar manner.

*Table 10.4 Likelihood probabilities of the veterinarian*

| | Likelihood probabilities $P(z_k\|\theta_i)$ | | |
|---|---|---|---|
| **State of nature ($\theta_i$)** | $z_1$ | $z_2$ | $z_3$ |
| Herd health good $\theta_1$ | 0.80 | 0.20 | 0.00 |
| Herd health average $\theta_2$ | 0.15 | 0.70 | 0.15 |
| Herd health bad $\theta_3$ | 0.00 | 0.20 | 0.80 |

The farmer now wants to combine the predictions received with the prior probabilities using Bayes' theorem. The joint probabilities required for the numerator of Bayes' theorem have been calculated and recorded in Table 10.5. For example, $P(\theta_1)\ P(z_1|\theta_1) = 0.2 \times 0.80 = 0.16$. After completing the calculation of the joint probabilities, the denominator of Bayes' theorem can be calculated by summing each column. For example, $P(z_1) = \Sigma_i\ P(\theta_i)\ P(z_1|\theta_i)$ $= 0.16 + 0.09 + 0.00 = 0.25$. Notice that summing the $P(z_k)$ for all values of k equals 1.

*Table 10.5 Calculation of the joint probabilities*

| | Joint probabilities $P(\theta_i)\ P(z_k\|\theta_i)$ | | |
|---|---|---|---|
| **State of nature ($\theta_i$)** | $z_1$ | $z_2$ | $z_3$ |
| Herd health good $\theta_1$ | 0.16 | 0.04 | 0.00 |
| Herd health average $\theta_2$ | 0.09 | 0.42 | 0.09 |
| Herd health bad $\theta_3$ | 0.00 | 0.04 | 0.16 |
| $P(z_k)$ | 0.25 | 0.50 | 0.25 |

Following Bayes' theorem, the posterior probabilities can be calculated by dividing the joint probabilities by the unconditional probability of $z_k$. For example, $P(\theta_1|z_1) = 0.16 / 0.25 = 0.64$. The posterior probabilities are given in Table 10.6.

*Table 10.6 Calculation of the posterior probabilities*

| | Posterior probabilities $P(\theta_i|z_k)$ | | |
|---|---|---|---|
| **State of nature ($\theta_i$)** | $z_1$ | $z_2$ | $z_3$ |
| Herd health good $\theta_1$ | 0.64 | 0.08 | 0.00 |
| Herd health average $\theta_2$ | 0.36 | 0.84 | 0.36 |
| Herd health bad $\theta_3$ | 0.00 | 0.08 | 0.64 |

The posterior probabilities replace the prior probabilities estimated in Table 10.1. However, here are three sets of posterior probabilities, one for each predicted health situation ($z_k$). The next step is to calculate the EMV for each action using each set of posterior probabilities. For this, we first have to recalculate the payoff matrix taking into account the costs (c) of obtaining the prediction. Suppose that c equals US$200.

The results obtained, which are based on the payoff values of Table 10.1 and information cost of US$200, are shown in Table 10.7. For instance, the EMV of program $a_1$ given forecast $z_1$ is calculated as 1000 x 0.64 + 4000 x 0.36 + 9000 x 0.00 - 200 = US$(2080 - 200) = US$1880. Further inspection of Table 10.7 indicates that $a_1$ has the highest EMV for prediction of $z_1$ (denoted by underlining), while $a_2$ has the highest EMV if $z_2$ and $z_3$ are predicted. Thus the optimal strategy $s^*$ for the farmer is $\{a_1, a_2, a_2\}$, meaning the farmer will maximize EMV by selecting program $a_1$ if $z_1$ is predicted, and selecting program $a_2$ if either $z_2$ or $z_3$ is predicted. This optimal strategy $s^*$ is also called Bayes' strategy.

*Table 10.7 EMVs based on posterior probability of θi given forecast zk and information cost c*

| | Forecast | | |
|---|---|---|---|
| **EMV**[a] | $z_1$ | $z_2$ | $z_3$ |
| Program $a_1$: $EMV(a_1|z_k)$ | <u>1880</u> | 3960 | 7000 |
| Program $a_2$: $EMV(a_2|z_k)$ | -4800 | 4720 | 13760 |

[a] Calculated as $EMV(a_j|z_k) = \Sigma_i [(x_{ij} - c) P(\theta_i|z_k)]$

## 10.6 Value of information

It is reasonable to ask whether the use of the predictor will increase the farmer's EMV. Moreover, there is a charge for veterinary services (cost c of the prediction). A farmer will like to know whether the increase in EMV exceeds the cost of the service. These questions can be answered by comparing the EMV using the optimal strategy with the predictor (Bayes' strategy) and the EMV for the optimal action without the predictor. If this value is negative, then the additional information provided by the forecast is not worth purchasing. The maximum price that should be paid for the forecast is given by the value of c for which these two EMVs (with and without the additional information) are exactly the same.

Now consider the case of a perfectly forecasting veterinarian. Since a **perfect predictor** is never wrong, it implies a posterior probability distribution of unity for some state of nature and zero for the rest. Thus, using a prime to denote perfection, there is a one-to-one correspondence between the $k^{th}$ perfect forecast signal $z_k'$ and some state of nature, say $\theta_i$, so that we can denote the $k^{th}$ perfect forecast by $z_i'$. Further, by Bayes' theorem $P(z_i') = P(\theta_i)$. With a perfect forecast device the optimal act can always be chosen. This results in the EMV of a perfect predictor. The EMV of perfect information can then be calculated as the difference between the EMV of the perfect predictor and the EMV without the predictor (ie, without additional information).

Let us return to our animal health example. The EMV of the optimal strategy with the additional information from the veterinarian, the Bayes' strategy $s^*$ $\{a_1, a_2, a_2\}$ equals US$6270 (see Table 10.8). As the EMV of the optimal decision without the predictor ($a_2$) is US$4800 (see previous section and Table 10.8), the EMV of the forecast device turns out to be US$6270 - 4800 = US$1470. Because this value is positive, the additional information expected from the forecast device is worth purchasing.

*Table 10.8 Value of information (in US$)*

| |
|---|
| EMV of optimal decision ($a_2$) without additional information: |
| $\text{Max}_j\,[x_{ij}\,P(\theta_i)] = -10\,000 \times 0.2 + 5000 \times 0.6 + 19\,000 \times 0.2 = 4800^a$ |
| EMV of optimal (Bayes') strategy ($s^* = \{a_1, a_2, a_2\}$) with additional information: |
| $\Sigma_k[\max_j \text{EMV}(a_j \vert z_k)]\,P(z_k) = 1880 \times 0.25 + 4720 \times 0.50 + 13\,760 \times 0.25 = 6270^b$ |
| EMV forecast device: 6270 - 4800 = 1470 |
| EMV of the optimal strategy based upon perfect predictor ($z_i'$): |
| $\Sigma_i\,[\max_j \text{EMV}(x_{ij} - c \vert z_i')\,P(\theta_i) = 800 \times 0.2 + 4800 \times 0.6 + 18\,800 \times 0.2 = 6800^c$ |
| EMV of perfect predictor: 6800 - 4800 = 2000 |

[a] See Table 10.1 for $P(\theta_i)$ and $x_{ij}$

[b] See Table 10.5 for $P(z_k)$ and Table 10.7 for $s^*$ and the corresponding EMVs

[c] See Table 10.1 for $P(\theta_i)$ and $x_{ij}$; c = US$200

The EMV of the optimal strategy based upon a perfect predictor is also determined in Table 10.8. The EMV of such perfect information is US$6800. So, the EMV of the perfect predictor is US$6800 - 4800 = US$2000. This makes the efficiency of our predictor relative to a perfect predictor, both assumed to cost US$200, (1470 / 2000) x 100% = 73.5%.

**Exercise**

*Work through the example on decision analysis, a left-displaced abomasum case, in Chapter 19. For three different strategies, the payoff matrix is given. You have to find the best strategy according to different criteria: the EMV, the maximin, the minimax regret and the maximax criterion (as discussed in section 10.4). In the next part of the model you can practise working with a utility function and 'translating' this into risk attitude (see section 10.3). Lastly, the model leads you through the Bayes' theorem (see section 10.5) and calculations will be made on the value of information (see section 10.6). The time needed for this exercise is approximately 60 minutes.*

## 10.7 Multiperson decision making

The model of risky choice, as outlined above, relates primarily to a situation where there is one decision maker whose beliefs and preferences are to be used in the analysis and who bears the consequences of the choice. Often, however, more than one person will be involved in any decision and/or affected by the consequences. Unfortunately, the extension of the methods of decision analysis to multiperson decision problems is not a simple matter. Three multiperson decision situations can be considered of particular importance in agriculture: (1) group choice situations, wherein a number of people are collectively responsible for a decision, (2) situations with many individual and independent decision makers, and (3) social choice situations, where the power of decision rests with government or one of its agencies, but where many people are affected by the consequences. The last one especially relates to compulsory programs for contagious disease control and, therefore, will now be discussed in more detail.

Policymakers often tend to react in a risk-averse fashion, fearing the personal consequences of being seen to have made decisions that turned out bad. The uncertainties of particular public projects or programs, however, are often rather insignificant when measured against the total performance of the economy. That is why economic theory teaches that governments make the best economic choice among risky projects by using risk-neutral decision rules, such as the expected monetary value criterion (Little & Mirrlees, 1974). There are two major reasons to consider risk-related decision rules to be appropriate for the choice among projects: (1) when they are unusually large, eg, affecting 10% or more of national income, or (2) when their consequences are not spread widely, and fairly evenly, among the population. The latter will often apply to contagious disease outbreaks, since losses primarily affect producers' income, especially on farms and in those areas that are actually affected by the disease (Berentsen *et al.*, 1990). A better insight into the potential consequences of the various decision rules and risk attitudes may be helpful anyway to provide useful information for a more thoughtful and rational decision-making approach. Stochastic dominance with respect to a function is commonly considered the most promising approach in this type of analysis, but requires at least some information on the policymakers' preferences concerning the outcomes. Empirical research to determine these preferences in agriculture has been sparse so far.

## 10.8 Concluding remarks

Risk and uncertainty are undoubtedly important in animal health management. Advice and modelling that are to support decisions in this area, therefore, should include appropriate (subjective) probability estimates for the relevant variables under consideration. Decision analysis and Bayes' theorem are considered worthwhile approaches for ensuring that farmers get advice and make decisions which are consistent with (a) their personal beliefs about the risks and uncertainties surrounding the decision, and (b) their preferences for the possible outcomes. It can also help to provide a more rational basis for decision making in the public domain, and to determine the economic value of additional information to reduce and/or predict the risks and uncertainties. **A good risky decision, however, does not guarantee a good outcome.** That would only be possible with perfect foresight (ie, in the absence of uncertainty). It does assure, however, that the decision made is the best possible one given the available information.

Appropriate decision rules are considered a major component of a risky decision problem (Boehlje & Eidman, 1984). The most widely used expected monetary value criterion does not always tell the whole story, as shown in the - simplified - example in this chapter. Less advanced criteria (such as maximin or minimax) are considered not to be appropriate from a theoretical point of view. Utility functions make it possible to provide the most comprehensive approach, including a trade-off between the average outcome and its variation, but will not always be easy to carry out and apply in actual field advice. Stochastic dominance criteria are commonly considered promising tools in this type of analysis. User-friendly software has become available to make the application of this type of advanced criteria much easier and accessible (Goh *et al.*, 1989).

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