Practical Uses of Decision Analysis: A Case Study on Feedlot Production Medicine

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Introduction to Decision Theory

We live in a changing world, a world in which we make choices without full knowledge of the effects those changes will have on the outcomes of our decisions. Every choice we make opens future options, while at the same time closing off others. We can exercise control over some events, such as in ordering a culture or prescribing a treatment; however, many events are beyond our control. Culture results are not known until we run them and response to treatment is unknown until therapy is under way. But despite the uncertainties, we must make decisions.

For the majority of choices in life, decisions can be made without much introspection. A decision may not be important enough to warrant analysis, or its outcomes are so easy to rank, the choice is obvious. Occasionally, however, situations arise where the consequences of each choice are not obvious. At these times we need systematic methods to estimate future events, consequences of actions, likelihoods of occurrences, and the end results of the many scenarios facing us.

The Function of Decision Analysis

Decision Analysis (DA) techniques can improve clinical reasoning through three inherent properties of the method. These qualities force us to be (1) explicit, (2) quantitative, and (3) prescriptive in our reasoning processes (1,2).

The *explicitness* comes through by DA compelling us to formulate a problem by its component parts. We must consider the time relationships of a diagnostic or therapeutic work-up in detail. It also obligates us to recognize the areas about which we are unsure. The DA process requires us to make *quantitative* statememts about probabilities, even if the precision only relates to how little we know about an event. We are also prodded to examine endpoints, how we (and the client) will value differing outcomes, and how to approach risk and risk aversion.

The end result is a systematic view that allows decisions of known strength or weakness. Hence, the process is *prescriptive*; it allows us to prescribe a course of action from among the many choices available to us. It has this power because it is formally explicit in problem description, and quantitatively rigorous in establishing values and probabilities.

As with any formal system, DA techniques can be broken down into a series of steps or elements. Each step builds upon previous activities. Certainly, not all clinical problems will require performing all of the steps, but this general outline will serve in most instances.

Elements of a Decision Analysis Problem

1. Identify and bound the decision problem
   - Define alternative actions
   - Define possible future clinical states
   - Other considerations (non-monetary)

2. Structure the decision problem
   - Decision tree representing the logic and timing of the problem:
     - Clinical starting point
     - Choices available in approaching the problem
     - Probabilistic events
     - Outcomes
3. Characterize needed information
   - Uncertainties
   - Outcome values
4. Choose a preferred course of action
   - Synthesize structure and available information
   - Quantification
   - Sensitivity analysis

Identify the Problem

At times the most difficult part of the process is defining the problem at hand. Is a respiratory disease outbreak a problem with nutrition, shipping, processing, purchasing choices, handling, or some combination of all these factors? The choices made in this phase of DA are often the result of a compromise between theory and practicality.

We can usually do more than is practical, and often need more data than is possible due to monetary or time constraints. Suffice it to say that, in general, the more time spent delineating and defining the problem and the important factors to evaluate, the better will be the final model

and the decisions generated from that model.

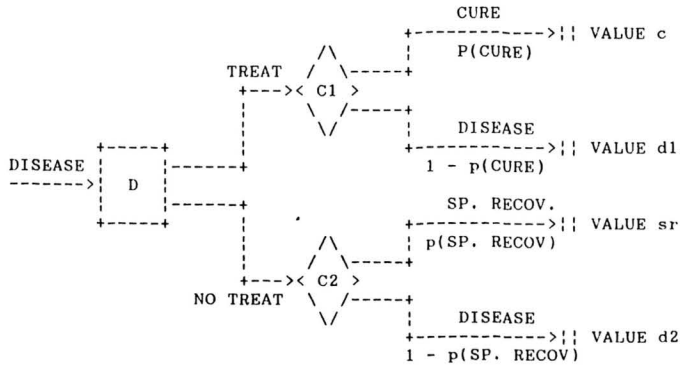
In some situations defining clinical states may be complete with only "sick" and "normal". However, other situations may call for more refined categories such as "full recovery", "partial recovery", "recovered but relapsed", "no recovery", and "death". Other considerations, such as any prognostic value of tests for herd-level decisions, animal welfare, and regulatory limits can sometimes play a role in determing the final choices made.

Structuring Clinical Decisions Under Uncertainty

In structuring a decision problem we aim to keep the different types and timing of events in proper sequence. In the process of evaluating complex decisions, each contingent on information available at that specific time, we form a "road-map" of our decision flows, often in the form of a decision tree.

The decision tree below displays the three basic parts of any decision diagram. By convention, decision flow diagrams are read from left to right. The first point to note is that it branches at each alternate event or node, making a winding trail of the sequential events that comprise one potential path. Second, the tree explicitly lists the probabilities of each event, forcing us to consider the uncertainty inherent in the choices. Third, it quantitatively describes the outcome values we placed upon the endpoints of the different branches, again, obliging us to evaluate the outcomes and the best means of achieving, or prescription for attaining, a given desired outcome.

DECISION TREE #1 - Hypothetical decision process for treating a disease. The choice between intervention (TREAT) and no intervention (NO TREAT). The outcomes considered in this example are therapeutic success (CURE), recovery without intervention (SP. RECOV.), and failure to respond to either selected action (DISEASE). Each outcome has a unique chance of occurring (P(xxx)) and a separate endpoint value (VALUE x). The decision tree components are more fully described below.



Branch Point Nodes

Decision Nodes (Depicted by the square labelled D)

Earlier we discussed two kinds of clinical events: those we control, and those we don't control. The decision nodes indicate the points in the process where the decision maker can have an effect on the outcome, by making a decision. In a clinical setting this usually mean either choosing to gather more information or opting for a treatment protocol. The actions branching from a decision node must be exhaustive of the actions available from that point. Decision nodes are depicted, by convention, as squares along the branches of a decision tree.

Chance Nodes (Depicted by the "diamonds" labelled C1 and C2).

Chance nodes are normally depicted as circles along a tree's branches. For printing reasons, here they are diamonds. They portray the uncertain points in the process, the events which we cannot control. These can be how a blood test will turn out, or list the possible results of a given treatment. Branches off a chance node describe all the events possible at that point (their combined probabilities sum to 1.0) each with a unique and explicit probability. These give decision trees probabilistic power, plus they explicitly state the working probabilities.

Paths (Depicted by the dashed lines)

A path, in decision theory parlance, represents a stream of events over time. Usually a path is bounded on one end (the end signifying the start of the process) by a decision node, and at the other by a final outcome event. In between these two markers can be any number of decision nodes and chance nodes. Each path in a tree is unique, made up by a special combination of decisions and probabilities. Each path represents the alternative choices and events that can occur.

Outcomes Values (Listed as "VALUE x" to the far right of the tree)

For a decision diagram to be of use, the various endpoints must be differentiated from each other. Usually this is done by assigning a cash value to each endpoint. A healthy laying chicken has some value, as does a market pig, or a bred cow. How much value depends on the individual situation described by the path that led to the outcome in question, or by some overall rule or pricing scheme outside the decision process. But not all endpoints are best described in strictly economic terms. For example, an endpoint may be best described as "80% two year survival" as opposed to "20% two year survival". When dealing with wildlife, herd-level decisions, or pets, this is likely to be true.

Adjusting for Probabilities and Non-Economic Concerns

If you had only a 20% chance of receiving a $500 bill,

it is unlikely you would be willing to pay $500 for that chance. This is because the expected monetary value (EMV), a measure of the action's "average" return, is only $100. This is the product of an event's intrinsic value and the likelihood of the event occurring.

In general, the EMV of a path is found by multiplying the probability of that event coming to pass against the outcome value for that path. If everyone behaved perfectly rationally in making decisions, then all decision trees would be solved by using EVM's. But we don't, so they aren't.

Means of "adjusting" EMV's to a situation not well described by pure cash values involve Utility Theory. This is a discipline of its own aimed at scaling values of completely disparate items and concepts such as quality of life, and perceptions of risk, danger, and challenge.

In the field of food animal medicine a powerful set of consumer utility values is found when describing "organically raised beef", "range fed chickens", and consumer perceptions of food safety and quality. Other considerations, such as social values (is a manatee worth only what one could get by rendering it?), can impact an outcome value. Utilities can be very complex to develop, and very powerful tools in decision analytic problems.

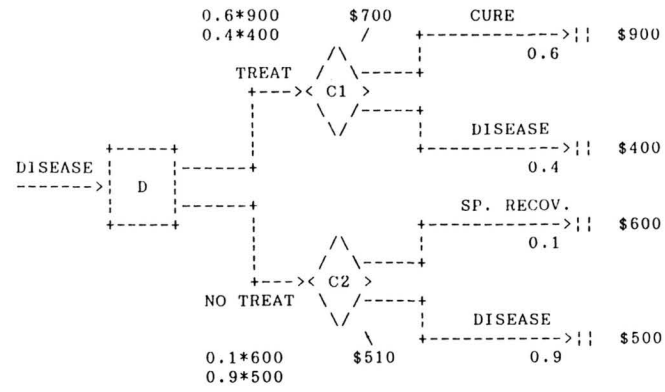
Building Decision Trees

The first step in building a tree is to diagram the events in sequence. Start with an event you influence, i.e., a decision node. Depending on the problem at hand, the next node could be a chance node, another decision node (if so, combine the two into one node - they represent only one decision if nothing happens between them), or a terminal node (an end point). From chance nodes, branches may again go to any of the three types of nodes.

The process continues, with each node representing some singular occurrence in a whole series of events. Eventually the path ends at a terminal node, as many terminal nodes as there are unique paths in the diagram.

The tree is solved in reverse chronological order (right to left). Outcome end values are multiplied by their respective probabilities. All branches that exit a node are similarly evaluated, and the results are summed across branches, creating the overall EMV of that chance event.

DECISION TREE #2 - Continuation of hypothetical decision process for treating a disease. Probabilities of each chance event have been added (0.6 = 60% chance of CURE, given the animal was TREATed) as have endpoint values (a CUREd animal is worth $900). Expected Monetary Values of the chance nodes are determined by multiplying the endpoint values against their respective probability of occurrence (60%*$900 + 40%*$400 = $700).



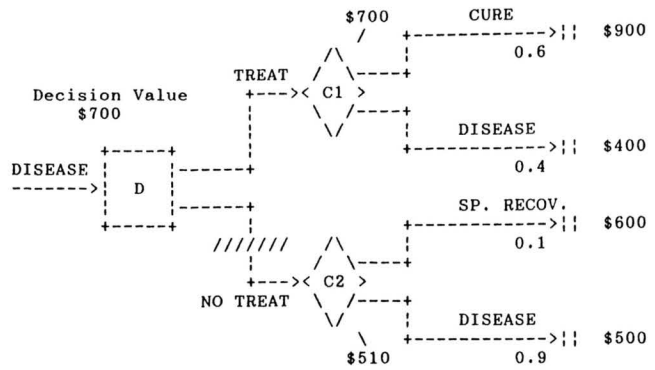
The process of multiplying probabilities against outcome values is called averaging out (as it produces a weighted average of the values at the tips of the paths radiating from a given node), and is simply a collapsing of the probabilities at chance nodes.

This averaging out continues until the decision maker "backs up" to a decision node. Just as was the case in drawing the tree, in analyzing the diagram a decision must now be made. The decision maker must choose between the chance nodes radiating from a decision node, the criterion being to select the branch that has the highest EMV, pruning out the other, suboptimal, paths.

The surviving EMV, by definition the most advantageous value, is then assigned to that decision node. This pruning process is called folding back a tree. Unlike the demonstration tree shown here, most clinical situations require a number of decisions to be made. In such a scenario, the next node to the left of an intermediate decision node will be another chance node, and it is treated just as were the chance nodes in the previous paragraph; its value will be the value of the decision node just selected.

Eventually, the process backs up the tree to the original decision node. Simply fold back at that point, selecting the most advantageous of the branches radiating therefrom. That branch is the optimal choice to make from that first decision point. The subsequent optimal path that follows forms the best clinical strategy to take, given the beginning conditions.

DECISION TREE #3 - Conclusion of the hypothetical decision process for treating a disease. The EMV's for the two chance events are subjected to the decision rule of taking the highest EMV. The appropriate choice is to select the TREAT option, as it is worth, on average, $190 more ($700-$410 = $190) to us than the NO TREAT option. The choice is depicted by drawing a series of slashes across the non-selected path.



Sensitivity Analysis of Decision Trees

When a formal structure is laid over a problem, it is advisable to test the findings by conducting a sensitivity analysis. This is accomplished by systematically varying the structural assumptions and probabilities within the diagram to see if the conclusions change. The process can be tedious if done by hand, however electronic spreadsheets perform the task easily. All analyses in this paper were accomplished using the LOTUS 1-2-3[R] electronic spreadsheet (9).

If the decision resulting from a decision tree does not change over a broad range of likely probabilities, the tree is "stable". If the decision changes, that is, if the tree is not stable, then one must be careful making recommendations. An unstable tree may represent true instability in the situation, or may simply be pointing to the weakest points in our knowledge, a capability drawn from the explicit nature of a decision tree's structure.

TABLE 1. SENSITIVITY OF THE MODEL ON PROBABILITIES OF OUTCOMES FOR THE HYPOTHETICAL DECISION PROCESS ON TREATING A DISEASE

New Chance of CURE	New Chance of DISEASE	Expected Monetary Value of the TREAT Chance Node
0.8	0.2	720 + 80 = $800
0.6	0.4	540 + 160 = $700
0.4	0.6	360 + 240 = $600
0.2	0.8	180 + 320 = $500

New Chance of SP RECOV	New Chance of DISEASE	Expected Monetary Value of the NO TREAT Chance Node
0.8	0.2	480 + 100 = $580
0.6	0.4	360 + 200 = $560
0.4	0.6	240 + 300 = $540
0.2	0.8	120 + 400 = $520

As demonstrated in the table above, the model appears stable when estimated treatment success rates remain at, or above, 40%, even if the spontaneous recovery rate reaches 80%. That is, with the endpoint values as listed in the decision tree, the EMV for TREAT, given P(CURE) = 0.4, exceeds the EMV of NO TREAT, given P(SP RECOV) = 0.8. This is evidence that the decision tree is stable with regards to probability estimates. I will leave it to the reader to perform the sensitivity analysis on changing the end point values.

Application of Decision Analysis Techniques: Case Study on Feedlot Production Medicine

Problem Description

Feedlot veterinarians are often faced with making a decision on mass medicating a group of steers. The situation usually arises within a week of the animals' arrival, and often the inciting event is management's recognition of the onset of respiratory disease in some animals in the group.

Mass medication has its proponents and its dectractors. Proponents claim it 1) can save labor costs, 2) could lessen stress, 3) may halt inapparent disease before permanent damage is done, and 4) might prevent future losses. Detractors argue it 1) may expose animals to un-needed antibiotics, 2) could produce high medication costs, 3) can promote resistant organisms. and 4) might increase rates of chronic poor-doers and their losses.

Both arguments are prefaced with qualifiers -- can, could, may, might -- acknowledging that interactions of disease severity and incidence, together with responses to treatment, determine a program's value. Hence, at certain times and conditions either camp can be correct. The choice depends upon many chance events; the kind of situation for which decision analysis was developed.

Identify the Decision Problem

The decision is whether to mass treat animals showing respiratory disease within several days of arrival. We specify four outcomes, based on mass medication or none: (1) steers remain healthy through the feeding period, (2) steers contract respiratory disease but recover after treatment, (3) steers contract disease, are treated, yet become chronically ill, and (4) steers die from respiratory disease in spite of treatment.

For this example, assume the operation grows out holstein steers with an average incoming weight of 300 pounds (range = 260-350), shipped in from other farms. Records indicate performance of animals from different sources varies, so that data will be included. Records also indicate incoming weight and month of arrival play a role in respiratory mortality, so that data will also be included in the decision process. Lastly, assume we are dealing with two feedlots under the same ownership, but with differing facilities and personnel. This will affect disease rates and treatment responses, so data on which lot is involved in the choice should be included.

In summary, the interactions believed to effect the feedlots' incidence of respiratory mortality are: 1) incom-

ing weight, 2) season, 3) farm of origin, and 4) arrival feedlot. Our records analysis will determine if our common sense is correct. Once we know disease incidence probability, we can apply known costs to calculate the relative returns under a variety of scenarios.

We have standard feedlot data on average costs of medicating hospitalized animals and on the results after treatment (3-6). We assume these costs will be constant over time and treatment. While this may be a false assumption, it is the best we can get from feedlot records, and can be tested by sensitivity analysis. We also can develop the average carrying costs, average feed consumption, the average market values of different classes of animal (TABLE 2), and the returns to management for either lot. These average values are calculated in this problem using the methods described by Tim Jordan (7), in his paper from these proceedings.

TABLE 2. COSTS TO BE ENTERED INTO THE DECISION TREE. Data adapted from USDA and Texas Cattle Feeders five year averages.

	DOLLARS
Avg Value Of Healthy Animals ($/Cwt)	65.94
Cost To Produce Healthy Animal	360.84
Value Of Healthy Animal, Full Gain :	659.40
Avg Value Of Chronic Animals ($/Cwt)	45.00
Cost To Produce Chronic Animal	140.00
Value Of Chronic Animal, No Gain :	180.00
Cost To Mass Medicate, Per Head :	1.50
Average Cost To Treat & Cure :	13.60
Average Cost To Treat a Chronic Animal :	52.00

Structure the Decision Problem

Structuring the decision problem is often the easiest part of the process. The tree diagram itself will be simple, starting with the decision to mass medicate on the far left, and ending on the far right with the categories of outcomes (TREATED, OK; TREATED, CHRONIC; TREATED, DIE; NOT TREATED, OK) for both the non-mass medication option and the mass medication option. The probability codes for each possible option-specific outcome are:

P[DZ]: The probability of respiratory disease occurring without mass medication.

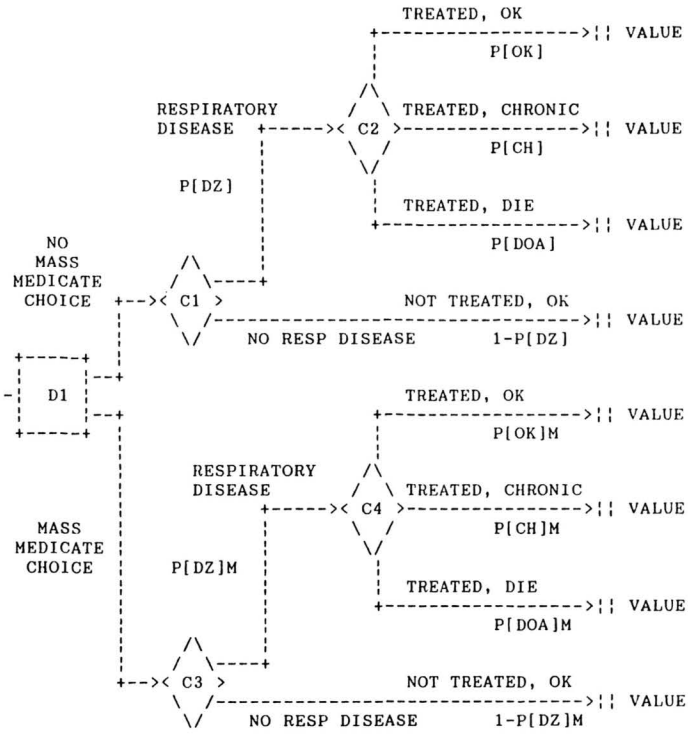
P[OK]: The probability of full recovery post treat ment without mass medication.

P[CH]: The probability of becoming a chronic ill case without mass medication.

P[DOA]: The probability of dying despite treatment without mass medication.

Probabilities listed in the decision tree with an "M" following them describe the same events as above, but reference the situation when mass medication is undertaken.

MASS MEDICATION DECISION TREE # 1



However, much information must still go into the decision, specifically with regards to choosing valid probabilities of disease and the economic efficiency of response to treatment.

Characterize the Informaton Needed

The decision is based on predictions of perfomance which are, themselves, founded upon past experience. Hence, we need to distill information from the data presented in the feedlots' records. For this example we will use data from a study of spring and summer respiratory mortality in 42 truckloads (6536 animals) for two Oklahoma feedlots which grow out Holstein steers brought in from calf raising units in Southern California (8). The paper evaluated respiratory mortality by incoming weight, farm of origin, month, and feedlot for one year. It was shown that incoming weight graphically broke into two categories, animals which were less than 300 pounds and animals which were greater than 300 pounds. This categorization of weight is sufficient for our purposes of making a treatment decision.

The table below is excerpted from the above reference. Note that the information is not anything out of the ordinary for normal feedlot records. It lists respiratory mortality in lots of 160 calves each by feedlot, by season, by farm of origin, and by weight category. This is the non-mass medicated performance data we need for our decision. What we must do is convert it into factor-specific estimates of respiratory mortality rates.

TABLE 3. DATA ON FEEDLOT, SEASON, INCOMING WEIGHT, AND ORIGIN FOR RESPIRATORY MORTALITY IN HOLSTEIN STEERS. 42 cases total. Data excerpted from Sizelove, 1987.

LOT	MO	WT	ORIG	MORT%	LOT	MO	WT	ORIG	MORT%
1	5	1	2	3.8	2	5	2	2	2.0
1	5	2	2	0.0	2	5	2	2	2.0
1	5	2	4	3.3	2	5	2	4	2.7
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:

LOT = Feedlot involved (1,2)
MO = Arrival Month, May-Sept. (5,6,7,8,9)
WT = Weight class (1=<300#, 2=>300#)
ORIG = Source farm (1,2,3,4)
MORT% = Respiratory mortality of group

Most spreadsheets and nearly all statistical software will perform multiple regressions on data such as Table 3. Multiple regressions allow us to estimate associations between an outcome variable (MORT%) and proposed factors (LOT, MO, WT, and ORIG).

Sometimes one gets a reasonable fit of the equation to the data, defined as a high value for Adjusted R^2 (the amount of variation in MORT% accounted for by changes in the other variables). If the fit is not good, one can transform the variables by taking logarithms or powers and rerunning the regressions. It can be done by hand with spreadsheets, or some of the statistical software will do it automatically. Again, LOTUS 1-2-3^R (9) was used for this paper.

By trial and error the best fit for this data set was found to use LOT, MO, and WT, plus the natural logarithm of ORIG, regressed against the natural logarithm of MORT%. The resulting equation:

$$\ln MORT\% = 1.86 + -0.23(LOT) + 0.05(MO) + -0.70(WT) + 0.48(\ln ORIG)$$

gives an adjusted R^2 of 0.755 -- a good fit and is also significant ($P < 0.0001$). The regression gives us the ability to account for 75% of the variability in respiratory mortality for a group of animals coming into either feedlot at any combination of month, weight, and farm of origin supported by our data. This is the probability P[DOA] in the decision tree.

Assigning the other probabilities is more problematical. One of the difficult numbers to capture is the amount of disease that will be decreased by use of mass medication. Unfortunately, it is one of the most important numbers. Ideally we would run a clinical trial to determine this value, however, clinical trials are long-term, expensive procedures. Few practitioners have the time, funding, and capabilities to run clinical trials. Hence, we will make estimates for this figure and then see how sensitive the decision is to changes in this figure.

For the ratio of chronic animals to deaths, we will use a 2:3 figure (7). Further, the work of Sizelove indicated that we will need to look at a "best-case" scenario (animals shipped in May to the second of the two feedlots, weighing in at over 300 pounds, and coming from the first of four source farms) and a "worst-case" scenario (animals shipped in September to the first feedlot, weighing less than 300 pounds, and coming from the fourth source farm) to describe the ranges of respiratory outcome we are likely to face.

Lastly, we need to be concerned about the effects the program will have on the pull-rate. Often pen riders assume that after mass medication they need not be as conscientious in pulling ill animals, allowing the disease process to advance, and causing pulled animals to have a lower response to treatment. Training personnel to be more sensitive to the signs of respiratory disease can overcome this problem. We will evaluate this potential complication of the program by rerunning the scenarios with new probabilities.

Choose a Preferred Course of Action

The first scenario to be evaluated is the "best-case" scenario indicated above. We assume no special yard personnel training took place, so the animals pulled have more severe respiratory disease. The disease severity will result in a treated case fatality rate 50% greater than that expected in the non-mass medicated scenario. The list of probabilities so calculated and a tally of actual numbers is given in Table 4.

TABLE 4. PROBABILITIES OF RESPIRATORY DISEASE FOR TWO MASS MEDICATION STRATEGIES, BEST CASE SCENARIO WITHOUT TRAINING. Scenario is comprised of: May shipping of 300 pound and greater calves from Farm number 1 to Yard number 2. No special personnel training. Tally assumes population size at start is 1,000 animals. Data from Sizelove and Jordan.

	VALUE	TALLY of 1000
Disease rate without mass med.	30.0%	300 ILL
Response to treatment, OK	92.7%	278 RESPOND
Response to treatment, Chronic	2.9%	9 CHRONICS
Response to treatment, Death	4.4%	13 DEATHS
Disease rate with mass med.	15.0%	150 ILL
Response to treatment, OK	89.1%	134 RESPOND
Response to treatment, Chronic	4.4%	7 CHRONICS
Response to treatment, Death	6.6%	10 DEATHS
Ratio of Chronics to Deaths	2:3	
Disease reduction by mass medication	50.0%	

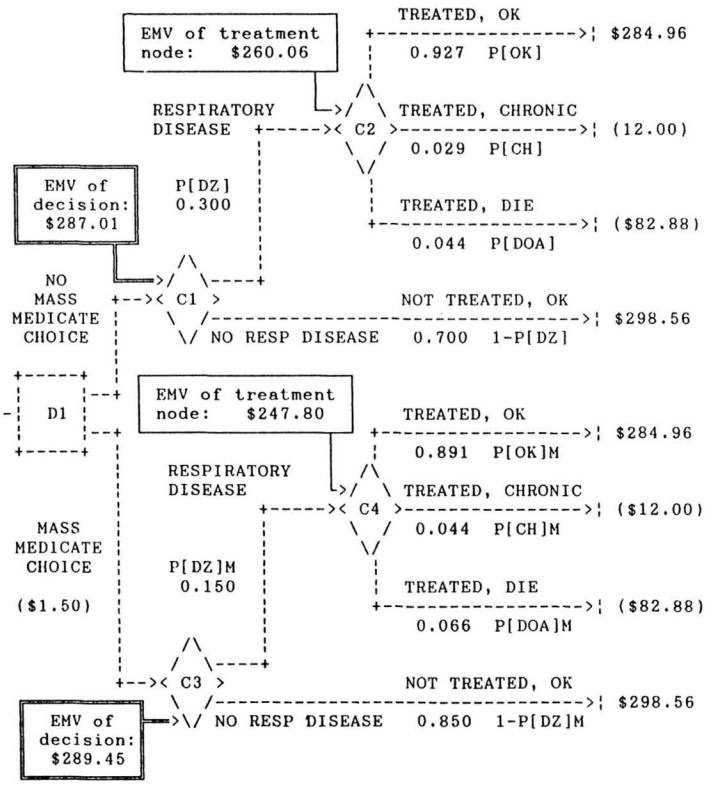
The "Response to treatment, Death" for the non-mass medicated strategy was calculated using the regression equation from the Sizelove data adjusted for predicted overall disease rate. "Response to treatment, Chronic" is calculated from the "Ratio of Chronics to Deaths" applied to the case fatality rate. "Response to treatment, OK" is deduced by subtracting the probabilities of getting a chronic animal and of having the animal die, from 1.0.

The case fatality rate for the mass medication strategy was assumed to be 50% greater than the rate of the non-mass medicated strategy, due to the disease detection problem if no training is employed, as described above. The "Response to treatment, ..." values were then calcu-

lated as for the non-mass medicated strategy. When training is employed, "Response to treatment,..." in the mass medicated animals will equal that of the non-mass medicated group.

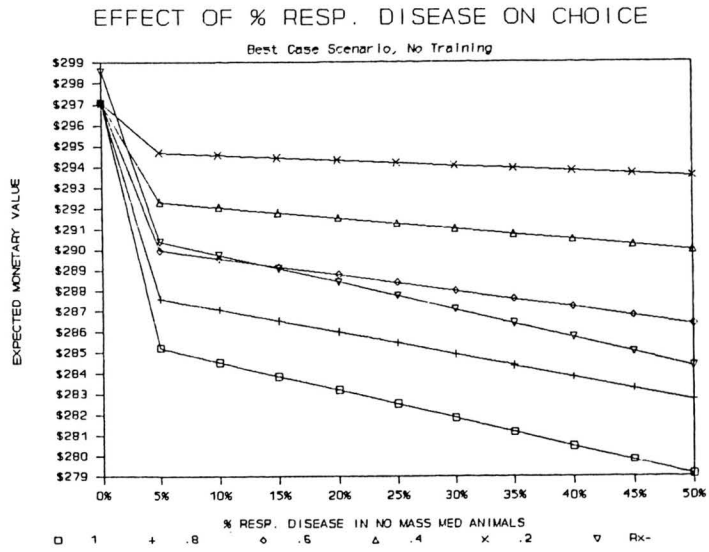
The decision tree (below) for this specific scenario indicates that the mass medication strategy is preferred over the non-mass medication strategy. However, the mass medication strategy's EMV ($289.45) is only 1% greater than the EMV for the non-mass medicated strategy ($287.01). Depending on decision tree results when the opposing strategies are this close can be dangerous. We know our estimates are likely not accurate to 1%. Sensitivity analysis on the basic assumptions is a must in such cases.

MASS MEDICATION DECISION TREE #2. Best case scenario (May, Yard 2, >300#, Farm 1) without personnel training. Probability data from Table 4.



Sensitivity analysis was performed on the expected probability of disease in non-mass medicated animals, and on the reduction in disease from mass medication. This is performed by systematically altering each variable's value and solving the decision tree for each new combination. Needless to say, this is tedious and time consuming if done by hand. With an electronic spreadsheet, however, the feat is easily accomplished. The results are shown in Figure 1.

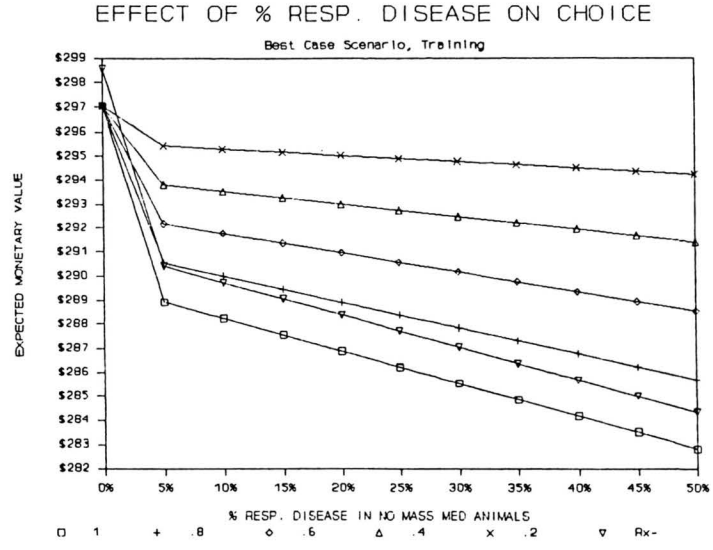
Figure 1. Effect of expected disease rate and mass medication (MM) efficacy, SCENARIO 1a. Numbers indicate disease rate in MM animals compared to non-MM animals (1 = same disease rate, .8 = disease rate in MM = 80% of non-MM), Rx- = values for non-MM.



The sensitivity analysis on this "best case scenario without training" suggests that with a 40% reduction in disease incidence a mass medication strategy will break even when respiratory disease is expected to reach 15% if no mass medication is employed. If mass medication reduces disease by 60%, or more, it will pay even if the expected non-mass medication disease rate is only 5%. The EMV differences observed, however, are less than 3% in most cases, so the decision is still not clear cut.

If a disease detection training program is added to the

Figure 2. Effect of expected disease rate and mass medication (MM) efficiency, SCENARIO 1b. See Figure 1 for legend.



"best case scenario" the picture changes. No longer does the mass medication strategy suffer from inadequate case detection and a resultant lowered treatment response. This affects overall program efficacy, as show in Figure 2.

Improving disease detection greatly improves program efficacy. A mass medication protocol, with training, need only reduce disease incidence by 20% to break even at an expected disease rate of 5% to 10% in non-mass medicated animals. The decision tree not only gives us general recommendations, it predicts the difference in economic potential for an innumerable variety of scenarios. If we expect the disease rate without mass medication to be 40 out of 100, and the mass medication program will decrease this by 40% (i.e., to 24 of 100), then we expect to net $3.70 ($289.30-$285.60) more, per head, by applying the mass medication program.

Another way to use the results in making a decision to mass medicate is to estimate the most likely disease prevalence without mass medication. Should that value be more than 10%, and should the mass medication program be capable of lowering clinical cases by one in five, then mass medication will, on average, more than pay for itself. Now the practitioner has objective values with which to make a decision regarding a specific situation.

Note that this does not imply mass medication will *always* pay under the above circumstances. It suggests that mass medication will give preferable results if applied several times. That is, on average, applying a mass medication program that includes personnel training, will more than pay for itself.

What would happen if the "best case" did not occur? By Sizelove's data, the scenario with the greatest expected respiratory mortality was shipping light calves in September from Farm #4 to Yard #1. Calculation of the probabilities as done above for the best case scenario follows:

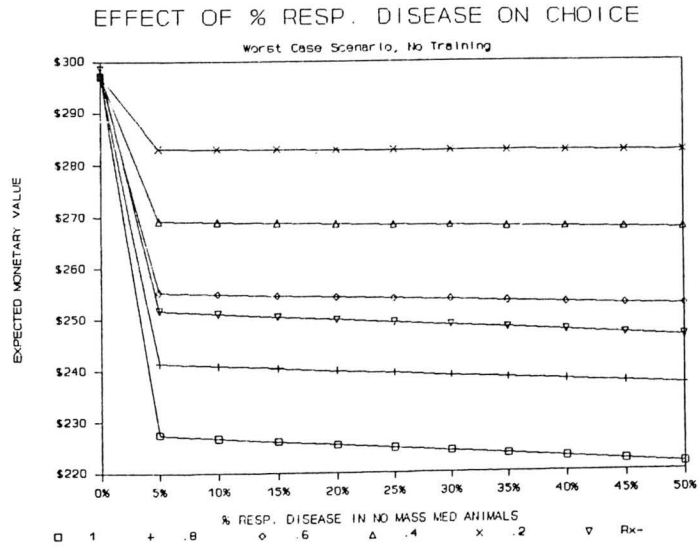
The ratio of chronic animals to dead animals is kept the same as previous. Similarly, the case fatality rate in mass medicated animals is 50% higher than the non-mass medicated animals. This results in the overall mortality for the non-mass medicated group to be 8.2%, compared to 1.32% for the best case scenario.

TABLE 5. PROBABILITIES OF RESPIRATORY DISEASE FOR TWO MASS MEDICATION STRATEGIES, WORST CASE SCENARIO WITHOUT TRAINING. Scenario: Sept. shipping of <300 # calves from Farm 4 to Yard 1. No special personnel training. Tally assumes starting herd size of 1,000. Data from Sizelove and Jordan.

	VALUE	TALLY of 1000
Disease rate without mass med.	30.0%	300 ILL
Response to treatment, OK	54.7%	164 RESPOND
Response to treatment, Chronic	18.1%	54 CHRONICS
Response to treatment, Death	27.2%	82 DEATHS
Disease rate with mass med.	15.0%	150 ILL
Response to treatment, OK	32.4%	49 RESPOND
Response to treatment, Chronic	27.1%	41 CHRONICS
Response to treatment, Death	40.6%	61 DEATHS
Ratio of Chronics to Deaths	2:3	
Disease reduction by mass medication	50.0%	

Using the costs and prices developed in Table 2, and the probabilities derived from Table 5, the decision tree for the worst case scenario, without training can be solved. Since it is of greater practical interest to examine the sensitivity analysis, we will go straight to that without re-drawing the decision tree, though the reader is encouraged to do so.

Figure 3. Effect of expected disease rate and mass medication (MM) efficiency, SCENARIO 2a. See Figure 1 for legend.



Note that the worst case scenario yields expected monetary values much lower than does the best case scenario depicted in Figure 1. Despite this, the break-even point for mass medication efficacy is similar to the best case scenario.

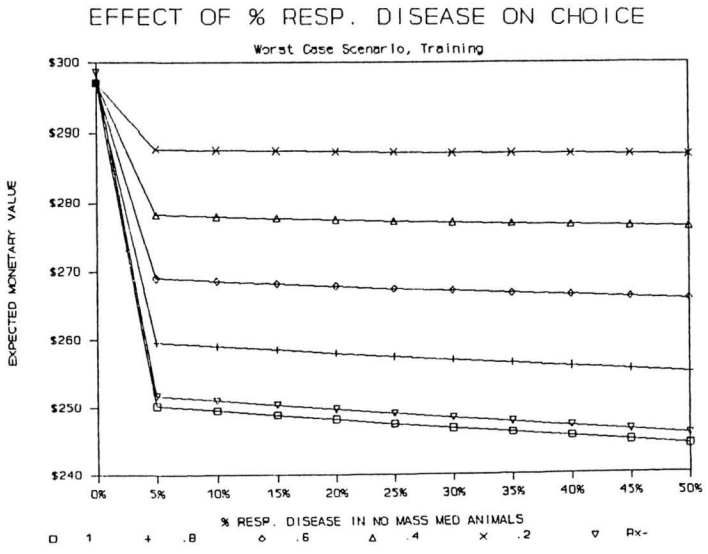
It appears, then, that expected mortality rate does not play a major role in making the decision, as break-even occurs at close to the same value for each. This is useful information, for estimating mortality is one of the analyses' "soft" numbers; a value about which we could not be certain.

Instead, the relative performance of the mass medication program versus no program, a number we can reliably test for after trying the program on a few lots, is the deciding factor. This is confirmed by viewing the outcomes for the worst case scenario when a disease detection training program is employed:

As with the best case scenario, when training is employed, a mass medication program need only reduce disease incidence by a few percentage points to break-even; only the line where mass medication has no effect on disease rate is consistently below the non mass medication line. Any disease reduction greater than a few percent is profit, the whole point of the exercise.

A full analysis of the mass medication problem would

Figure 4. Effect of expected disease rate and mass medication (MM) efficiency, SCENARIO 2b. See Figure 1 for legend.



next approach a number of questions. What if the ratio of chronic to dead animals varied? How sensitive is the outcome to the fixed relationship between case fatality rates in the no training scenarios? What if mass medication costs were higher than modeled? How much could we afford to bring up efficacy in the no training situations.? How do prices affect the outcomes? What kind of a premium could we afford to offer for the lower risk, heavy weight calves? Conversely, at what price do lightweight calves, in spite of their higher risks and lower EMV's, become cost-effective against heavier calves? Are there other market or biological factors that should be included?

The questions and scenario-specific examples could go on almost indefinitely. The potential for exploring the intricate relationships and dependencies within a complex system such as this one is immense, limited only by the user's interests, and the quality of the supporting database.

Conclusion

Medicine has often been described as part "art" and part "science". The science aspect has always been easy to define: It is the whole made up of anatomy, pharmacology, surgery, etc., etc. But the art side of medicine is difficult to explain, for it is not clear how to partition the whole into its parts, or even to describe what we mean by the word "art".

Most of us would agree that it is most clearly demonstrated by those clinicians who "just seem to know" the best treatment, the best questions, the best methods, for solving problems. Such practitioners seem to use a sixth sense to ferret out what is important from what is not. Often, if asked how a decision was made, they will not be able to tell. We call it "art" because some people seem able to do much of this almost intuitively, and because we haven't attempted to formalize the processes. Having never attempted to describe the process, in a sense, we assumed it could not be described.

Experience seems essential in order to be a true "medical artist". We assume life experiences can be organized into a library of signs, symptoms, actions, and reactions. When faced with a problem the person searches through the library to find a past situation that is similar. When it is found, the degree of similarity is assessed and the practitioner then uses the information to create a protocol aimed at solving the difficulty. The "art" of practice, then, really involves ordering the characteristics of a problem, collating the information available to clarify perceptions of future environments and decision alternatives, creating consistency in the approach by ranking outcomes by some value system, and balancing these facets into a system for making choices.

Qualitatively, what we call the "art" of medicine is decision analysis. The mental library referred to above provides relative rankings of likelihoods (or probabilities) of the situation at hand being a manifestation of one disease over another. The inferences are then used to rank outcomes and pick what appears to be the best solution out of many options.

Unfortunately, experience is only the term we use to refer to our past mistakes. Many of us cannot afford to commit that many mistakes and still hope to be able to practice. Plus, experience is of no value, and can even be an impediment, when faced with a completely new situation. If you doubt that, just think about the time it takes an adult versus a 10 year old to learn to program a video cassette machine.

Decision analysis is a powerful tool for those of us not lucky enough to be artists in the practice of medicine. It can also be the foundation for solving very difficult and complex problems, those problems where intuition,and hence the "artists', tend to fail. Like any tool used in practice, decision analysis can be misused -- such as by putting too much faith in any particular assumption or in the data used to build a tree -- but methodical implementation and analysis can largely protect from that drawback.

As our clients become more sophisticated, and as our animal agriculture operations and markets become more intensively managed, we will face more of these complex situations daily. We call them "production diseases". Another tool to help us make sense out of the changes the world presents us with is most welcome.

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Abstracts

A survey of caesarean operations on cattle in general veterinary practice

J. H. Cattell, H. Dobson

Veterinary Record (1990) **127,** 395-399

The animal most frequently requiring operation for dystocia in this survey of 133 cases was the Friesian/Holstein heifer. In 38 per cent of cases the reason for surgery was an oversized calf and in 84 per cent the operation was performed on the farm of origin. The majority of the dams were operated on while standing, using a left flank incision, and under paravertebral or field infiltration with local anaesthetic solution. Exteriorisation of the uterus did not appear to be essential except when the calf was dead. Ninety-five per cent of the calves alive in utero and 91 per cent of the dams survived, although 30 per cent of the dams suffered ill-health afterwards. In nine cases neither dam nor calf survived. The fertility indices of those which were rebred were not markedly affected, but milk production was reduced by an estimated 12 per cent of the potential yield.

Bovine endometritis: Comparative efficacy of alfaprostol and intrauterine therapies, and other factors influencing clinical success

R. D. Murray, J. D. Allison, R. P. Gard

Veterinary Record (1990) **127,** 86-90

A comparative study of the treatment of 306 severe, moderate, or mild cases of bovine endometritis was carried out over two calving seasons. The cases were treated with alfaprostol, or an intrauterine antibacterial preparation, or with a combination of both therapies. There was no significant difference between the efficacies of these treatments, and a single injection of alfaprostol was effective in 74 per cent of the cases treated. The effectiveness of the treatments was related to the degree of self-cure of the endometritis after parturition, the luteral activity at the time of treatment, and farm management factors affecting the health and condition of the calving cows.

Clinical efficacy of chlortetracycline hydrochloride administered in milk replacer to calves

J. C. Braidwood, N. W. Henry

Veterinary Record (1990) **127,** 197-301

Two similar groups of 14 calves were housed and fed identically in individual pens on a calf-rearing farm. The groups were balanced for weight and immunological status as determined by zinc sulphate turbidity values. When an outbreak of enteric and respiratory disease occurred one group was treated with 20 mg chlortetracycline hydrochloride/kg bodyweight daily for seven consecutive days, by adding the active ingredient to the milk replacer, while the other group was left untreated. Both groups received additional therapy as required. The calves were examined daily during the period of treatment and the clinical observations were assessed and analysed statistically. There was a significant difference between the clinical scores of the two groups on the second day of treatment (P 0•5) and on all subsequent days (P 0•01) indicating that the calves receiving chlortetracycline hydrochloride were less affected by the disease outbreak. The abnormal enteric and respiratory signs were associated with several potential pathogens including bacteria, viruses and protozoa. The treatment was therefore effective against enteric and respiratory disease involving several organisms.

Sympathico-adrenal effects of endotoxaemia in cattle

R. Boosman, C. W. A. A. M. Mutsaers, S. J. Dieleman

Veterinary Record (1990) **172,** 11-14

Intradermal injection of 46 *ug E coil* endotoxin had no effect on the plasma cortisol and noradrenaline concentrations of four dairy cows. Mean values were similar to normal values reported in the literature. Intravenous injection of 75 ug of endotoxin on the following day caused a massive increase in plasma cortisol concentrations which lasted for seven hours. Plasma noradrenaline concentrations increased rapidly after the intravenous administration of endotoxin and remained high for at least one hour. A possible relationship between endotoxaemia and the pathogenesis of acute laminitis is discussed.