Decision Analysis Approach Model to Maximize Students Cognitive of Environmental Problems

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***Abstract*— A learner is a cognitive system that develops by students information and knowledge-processing activities. To maximize the learners cognitive development, knowledge-intensive environments are essential particularly for achieving environmental knowledge. This paper proposes a model based on decision analysis approach in such a way could evaluate students cognitive development toward environmental problem**

***Keywords*— Decision analysis, education, cognitive, environmental knowledge**

I. INTRODUCTION

A learner is a cognitive system that develops by his own information and knowledge-processing activities. To maximize the learner's cognitive development, knowledge-intensive environments are essential to help him explore a situation, construct his own concepts, and discover general laws by his own problem-solving activity [1]. The lecturer, as knowledge facilitator, has an extremely complex problem on his hands. Before deciding exactly what course of action to take, he needs to consider many issues, including suitable environments and the uncertainties involving students abilities and school resources.

Decision analysis provides effective methods for organizing a complex problem into a structure that can be analyzed [2]. In particular, elements of a decision structure include the possible courses of action, the possible outcomes that could result, the likelihood of those outcomes, and eventual consequences to be derived from the different outcomes. Figure 1 shows a flowchart for the decision analysis process. For illustration, assume a lecturer needs to make a decision on which tutoring method to apply for motivating a class of under-achievers in engineering mechanics. A few alternatives may be considered: drill and practice, peer tutoring, hands-on activity, and on-line tutoring. Thereafter, variables associated with the alternatives are identified. The variables may be uncertainties such as students interest, their abilities, and availability of computer resources. Utility functions are assessed in order to model the way the lecturer values different outcomes and trade-off competing objectives.

Decision analysis tools such as influence diagrams [2, 3] and decision trees [4, 5] are then used to model the problem for determining a preferred alternative. For complex models, computer software such as DPL [6] is available to auto-mate the computation. Additional analysis such as sensitivity study [7] may be performed to answer `what if' questions such as: "*If a computer resource is available, does it imply that on-line tutoring leads to a better student motivation?*". If the answer is positive, then the lecturer may want to consider obtaining more information on that variable prior to making the decision.

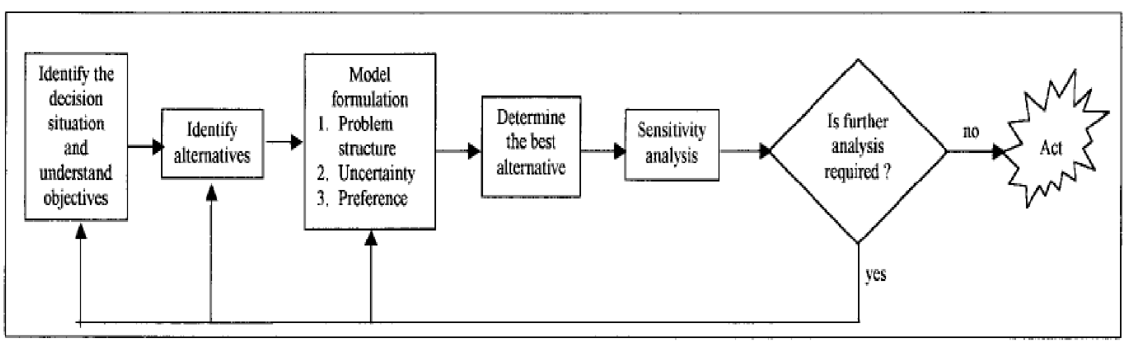

Fig. 1. Decision analysis cycle.

Figure 1 also shows that the lecturer may return to the previous steps of the decision analysis process. It may be necessary to refine the objectives or to include objectives that were not previously considered. When new alternatives are identified, the model structure, the uncertainties and preferences may also need to be modified. This process may go through several iterations before a satisfactory solution is found. The final solution that contains the essential components is known as the requisite model [8]. The approach allows inclusion of personal judgments about uncertainties and values [9] for making good decisions.

Consider a team of academic staff who are to formulate a school promotion strategy, where some decisions they may be making include type of advertisement, duration of advertisement, and extensiveness of staff involvement. If the decision is on type of advertisement, then possible alternatives may be newspapers, magazines, Internet, radio, television, road show, and open house exhibition. Variables that may affect the alternatives are budget, links with outside organizations, staff interest, accessibility of each media to the public, and interest areas of potential applicants. How these variables (deterministic or stochastic) may affect the alternatives has to be identified. The team has to agree on what value they consider important before a most satisfying alternative can be determined. For example, attracting applicants with the desired academic qualifications could be the most important objective.

The issues of uncertainties, subjective judgments, and trade-offs in values are further discussed in the following sections to provide the readers with essential decision-theoretical foundation before they walk through a case study. We have selected the case study to illustrate how a module team may apply the decision-theoretical approach to determine policy that maximizes student learning in tutorials.

II. Probability Assessment

Uncertainty in decision problems is represented by probability. Besides interpreting probability in terms of long-run frequency, one can consider it to represent an individual's degree of belief that a particular outcome will occur. There is no correct answer when it comes to subjective judgment: different people have different beliefs and hence will assess different probabilities. However, as long as the probability axioms [10] are not violated, decision-theoretical approach being normative rather than descriptive it is able to explain the course of action.

One of the methods to assess probabilities adopts a thought-experiment strategy [11] in which the decision-maker compares two lottery-like games, each of which can result in a prize (A or B). Consider the situation to assess the students probability distribution for the number of hours (uncertain variable X) he spent in extra-curricular activities. The probability wheel (see Fig. 2) is used to determine the size of the unshaded sector in which the lecturer is just undecided between the two options:

1. Spins the wheel and wins \$100 or nothing.
2. Checks the real value of x (assuming it can be done) such that if $x \leq 2$, he wins \$100, otherwise he gets nothing.

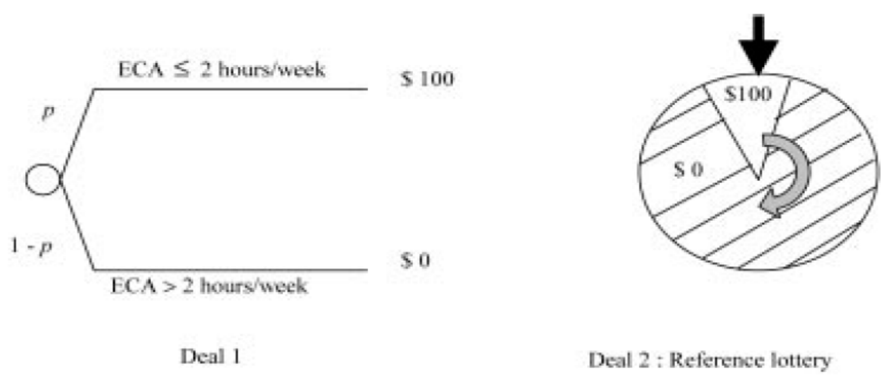

Fig. 2. Probability assessment with equivalent-lottery method.

If p is the value indicated by the wheel, then $P\left(x \leq 2|\xi\right)$ where "ξ" refers to background knowledge that the decision-maker brought to bear on assessing the uncertainty. This process is repeated for different values of x. The cumulative probability distribution can be plotted as shown in Figure 3a.

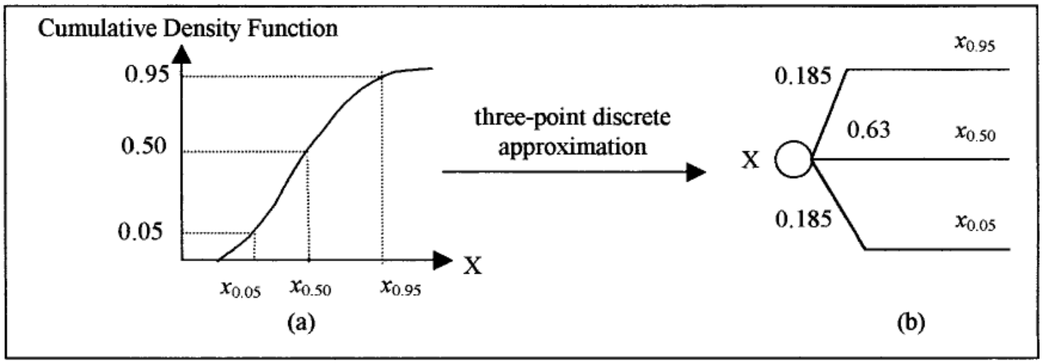

Fig. 3. Pearson-Tukey method.

Another method for probability assessment is to use theoretical probability models [12, 13] and their associated distributions. For example, if we believe that the cognitive abilities of students follow the familiar bell-shaped curve, which is the normal distribution, then we may use the distribution to generate probabilities. Such probability modeling is just as subjective as a directly assessed probability distribution because judgment is being made that students abilities can be adequately represented using the theoretical model. When historical data is available it is possible to use it to construct probability distributions [14]. We can use the data to understand and model relationships among variables.

The way to use a continuous distribution in a decision tree is to approximate it with a discrete distribution. A few representative points in the distribution are selected and assigned specific probability values. A simple approach (see Fig. 3) known as the Pearson-Tukey method [15] uses the 5, 50, and 95 percentiles as the representative points. In assigning probabilities, the 50 percentile gets a probability of 0.63, and the 5 and 95 percentiles each has a probability of 0.185.

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III. Preference And Risk Attitudes

In this section, we examine the representation of the decision makers preference or their attitude towards risk. Examples of risk taking are willingness to try new or unproven tutoring methods such as on-line assessment, video conferencing, and peer tutoring. Modeling a persons preference by assessing their utility function is a subjective procedure much like assessing subjective probabilities [16].

A utility function can be specified in terms of a graph or in a mathematical expression. Tradition-ally, the utility function has been used to translate dollars into a utility (or satisfaction) unit. Individuals who are sensitive to risk are called risk-averse [17].

Some examples of mathematical expressions that have the general concave shape (opening downward) are:

$$U(x) = a\log\left(x\right) \quad (1)$$

$$U(x) = a - be^{-\frac{x}{\rho}} \quad (2)$$

$$U(x) = x^{a} \quad (3)$$

where a and b are constants that can be determined using boundary conditions, while ρ is the risk tolerance [5, 18] value. x is any quantity where the satisfaction of possessing it is expressed in the utility function.

Not everyone displays risk-averse behavior all the time. A convex (opening upward) utility curve indicates risk-seeking behavior. Alter-natively, an individual can be risk-neutral. Risk neutrality is reflected by a utility curve that is a straight line. A person who is risk-neutral does not care about risk of the alternatives that he or she faces.

Utility scales can also be used for measuring how satisfaction varies with non-monetary objectives including:

1. Quality of classroom facility
2. Students motivation
3. Lecturers preparation time
4. Students pass rates
5. Classroom air quality
6. Lecturers morale
7. Recreational opportunities
8. Students travelling time to school, etc.

An approach to elicit a decision makers utility scale for non-monetary objectives is known as the probability-equivalent assessment technique [11]. The best and worst possible outcomes for a prospect are first identified. A utility score of 0 is assigned to the worst and 1.0 to the best outcome. Next, the intermediate values (x_i, p_i) are determined using a reference gamble. The (x_i, p_i) values are plotted on a graph as a contin-uous curve.

While most non-monetary objectives have the natural order of more being better, some require that fewer are better. Consider the case where the objective is to maximize students learning through the use of information technology, the utility function for the number of students to a computer is a decreasing curve. Because a utility function incorporates a decision-makers attitude towards risk, he or she may choose the alternative that maximizes their expected utility [19, 20]:

$$\max_j \sum_{i=1}^{n} u_i p_i^j \tag{4}$$

where p_i^j is the preferred probability of j^{th} decision which deals with outcomes $\underline{A}_i$ (worse prospect) and $\overline{A}_i$ (best prospect); and u_i is the preference probability (or utility) of outcome A_i.

IV. Structuring Values

The chance node represents uncertainty associated with students ability and it has three possible outcomes. The table besides `Critical thinking' node shows that if the decision for assessment is open book, the satisfaction (utility) depends on the outcome of students ability. Open book assessment places greater emphasis on higher order cognitive skills (such as application and evaluation) than does closed book assessment [21]. Students who are trained for open book assessment are more aware of critical thinking techniques and will be likely to use it. However, it requires greater efforts and training for students to master higher order cognitive skills, which may not be currently available. Consequently, students grades are likely to be better for closed book assessment than open book assessment as reflected by the higher utility values for the former option. The mathematical expression besides the final value node indicates the trade-off between the two intermediate objectives as represented by the constants k_1 and k_2. The next section illustrates the method to estimate these constants and to determine the preferred alternative in this decision problem.

A. Multiple Attribute Utility and Preferred Decision

A method to assess the constants (k_1 and k_2) is known as Saaty's Eigenvector Method [22]. Consider the example, assuming the decision maker decides that attribute 1 (Grades) is half as important as attribute 2 (Critical thinking), then the A matrix is: $\begin{bmatrix} 1 & \frac{1}{2} \\ 2 & 1 \end{bmatrix}$

Through solving the matrix for eigenvectors $k_1 = \frac{1}{3}$ and $k_2 = \frac{2}{3}$.

In general, for an outcome that has m objectives, the multiple attribute utility is given as:

$$\begin{aligned} U(x_1, \ldots, x_m) &= k_1 U_1(x_1) + \ldots k_m U_m(x_m) \\ &= \sum_{i=1}^{m} k_i U_i(x_i) \end{aligned} \tag{5}$$

where $k_i \geq 0$, $\sum_{i=1}^{m} k_i = 1$, $0 \leq U_i \leq 1$

A necessary and sufficient condition for Equation (5) to hold is that the m attributes (also known as stochastic variables) are mutually utility independent [23].

It is created to understand how the preferred alternative is determined. First, the options represented by branches from a decision (square) node must be such that the decision-maker can choose only one option. Second, each chance (circle) node must have branches that correspond to a set of mutually exclusive and collectively exhaustive outcomes. Third, the decision tree represents all of the possible paths that the decision-maker may follow through time. The preferred alternative is found by selecting the maxi-mum utility at the decision node, after the expected utility has been computed at each chance node.

V. Conclusions

The modeling effort illustrated in the case study combines the pedagogical experience possessed by the lecturers and the decision-theoretical methodology. On the one hand, lecturers experience is brought to bear on determining the decisions to make, available alternatives, nature of uncertain variables and their relationship (whether dependent or independent), probabilistic and preference assessments, and trade-off among values. On the other hand, it relies on a series of activities associated with the decision-theoretical approach to build a requisite model.

Sensitivity analysis is used to simplify the model by reducing stochastic variables to deterministic values. The requisite model consists of two sequential decisions and stochastic variables that influence decisions. In addition, conditional probabilities and utility values for different outcomes are included in the model. With the help of decision-theory software, the model is solved for the preferred policy to enhance students learning. When information on computer resources, students effort and lecturer's preparation time is available either singly or in combinations, it can lead to higher satisfaction so that the recommended policy improves students learning.

This study has illustrated that decision analysis provides a normative rationale for achieving clarity of action under complex and uncertain decision situations. Although good decisions do not guarantee optimal outcomes all the time, a decision-theoretical approach ensures no unforeseen surprises. This paper has also shown how lecturers could construct graphical models for decision-making, in particular on selection of tutoring methods to maximize student learning. Subsequently, lecturers can take action for different situations with greater confidence that is gained through a clearer understanding of the problem.

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