

## **On the Tools of Decision Trees and Influence Diagrams for Assessing Severe Accident Management Strategies**

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### **중대사고관리전략의 평가를 위한 의사결정수목과 영향도에 관한 연구**

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#### **Abstract**

Accident Management involves all measures to prevent core damage and retain the core within the reactor vessel, maintain containment integrity and minimize off-site releases. The accident management approach includes: (1) advanced evaluation of candidate strategies, (2) development of procedures to execute appropriate actions efficiently, and (3) identification and provision for materials, tools, and possible modifications to the plant system that may be needed for such execution. When assessing accident management strategies, its effectiveness, adverse effects and its feasibility, including information needs and compatibility with existing procedures, must be considered. The objective of this paper is to introduce analytical tools of decision trees and influence diagrams to develop a framework for modeling and assessing severe accident management strategies. The characteristics associated with these tools are presented. Based on decision trees and influence diagrams, the framework is applied to a simple example associated with a single decision.

#### **요 약**

사고관리란 사고발생시에 이용가능한 모든 자원, 즉 인원과 설비를 효율적으로 활용함으로써 발전소를 안전상태로 회복시키거나 사고의 피해를 완화시키기 위한 제반 활동을 말한다. 사고관리의 접근방식은 첫째, 후보사고관리방안의 사전 평가, 둘째, 효과적으로 적절한 조치를 수행하게 하는 세부 절차서의 개발, 그리고 셋째, 그러한 조치수행에 필요한 도구와 자원의 준비, 실현 가능한 원전 시스템의 변경등을 포함한다. 사고관리 전략을 평가할 때에는 그 전략의 효율성뿐만 아니라 부작용, 타당성, 필요한 정보, 기존 절차서와의 양립성 등을 종합적으로 고려하여야 한다. 이 논문의 목적은 여러가지 사고관리 전략을 모델링하고 평가하기 위한 체계를 개발하기 위한 의사결정 수목과 영향도의 해석도구를 소개하는 것이다. 이 해석도구와 관련한 여러가지 특징들이 제시되었으며 이 해석도구에 근거하여 세워진 사고관리 전략의 평가체제가 간단한 예제문제에 적용되었다.

## 1. Introduction

Accident management usually encompasses the actions taken by reactor operators during an accident to prevent core damage, to terminate the progress of core damage, if it begins, to maintain containment integrity as long as possible, and to minimize off-site releases [1]. It provides an extension of the defense-in-depth safety philosophy for core melt accidents. The emergency operating procedures of pressurized water reactor nuclear power plants extend up to the time of inadequate core cooling, but have not been specifically developed for conditions involving significant core damage. Accident management can be considered as a bridge between preventive actions initiated before the start of inadequate core cooling and the protective actions taken at the time off-site releases occur. There are many actions the operating staff can take to prevent or mitigate the consequences of severe accidents, many of which can be accomplished with little or no modification to existing plant features.

The accident management approach includes: (1) advanced evaluation of candidate strategies, (2) development of procedures to execute appropriate actions efficiently, and (3) identification and provision for materials, tools, and possible modifications to the plant system that may be needed for such execution. When assessing accident management strategies, its effectiveness, adverse effects, and its feasibility, including information needs and compatibility with existing procedures, must be considered. A lot of uncertainties associated with severe accident management are identified [2, 3]. The key uncertainties involve issues related to phenomena, operator actions, instrumentation and systems availability.

In order to include the various uncertainties in assessing the viability of a potential severe accident management strategy, a framework is required. Decision trees and influence diagrams can be used as tools for this purpose. In this paper, these tools are introduced for the framework for modeling and

assessing severe accident management strategies given the key uncertainties.

## 2. Decision Trees and Influence Diagrams

The decision tree is a graphical and mathematical representation of a decision problem. It is a connected tree with two types of nodes (i. e., decision and chance) and two types of branches (i. e., probabilistic and alternative). It is a common tool for decision problems (the event tree, which is widely used in probabilistic safety assessments (PSA), is a decision tree without decision nodes, but only chance nodes). An advantage of the decision tree is the explicit representation of the decision structure, which directly shows the decision maker the value of each possible outcome, i. e., all the possible scenarios that could occur. Despite their widespread use, decision trees have two significant drawbacks. First, decision trees grow exponentially with problem size and, for realistic problems, they rapidly become unwieldy. Second, decision trees have no provisions for the explicit representation of the probabilistic dependency between node variables.

Influence diagrams, on the other hand, are networks consisting of nodes and two types of directed arcs (conditional and informational) that represent the conditional dependence between the random quantities and the timing of information and decision. Nodes are of four types: decision, chance, deterministic, and value nodes. According to convention, decision node (representing decision point) has a square or rectangular shape; chance node (representing uncertain quantities) is circular; deterministic node (representing functions of the values of predecessor nodes) has a double circle shape. The shape of the value node is not standardized; it may be a diamond shape or a rectangle with rounded corners, depending on the analyst.

Influence diagrams are much simpler in terms of problem representation; they can show probabilistic

dependencies between directly related nodes; they make it convenient for the decision maker to add and delete nodes and arcs depending on the goals of the problem; and finally, they are useful in the rapid identification of important variables. It is, of course, possible to construct a decision tree directly from an influence diagram. Following paragraphs are brief descriptions on the influence diagram and corresponding decision tree. Further details on influence diagrams may be found in References 4 to 7.

Figures 1 through 3 show three possible cases associated with a decision problem. Each involves one node of each type: decision, chance, and value. In Figure 1.a, the value depends on the random variable (chance node), which itself depends upon the decision. The equivalent decision tree, Figure 1.b, shows that the decision node does not directly affect the value. For example, let D represent whether or not to depressurize the primary system, and C represent whether in-vessel steam explosions occur or not. The probability of a steam explosion depends on the vessel pressure, hence  $p_1 \neq p_2$ . However,

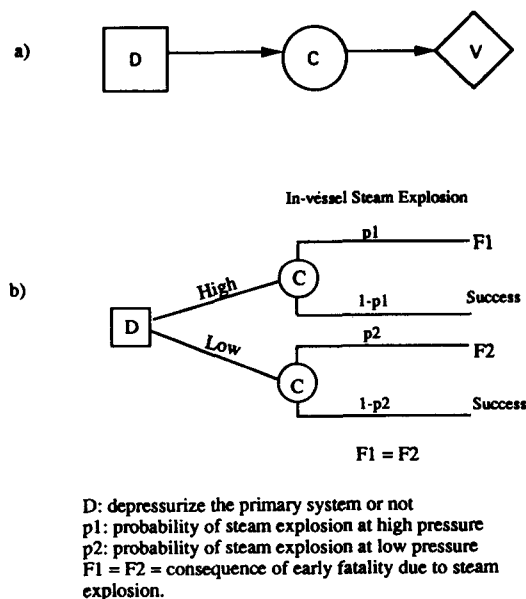


Fig. 1. Three Cases with Decision, Chance, and Value nodes ( $p_1 \neq p_2$ ,  $F_1 = F_2$ ).

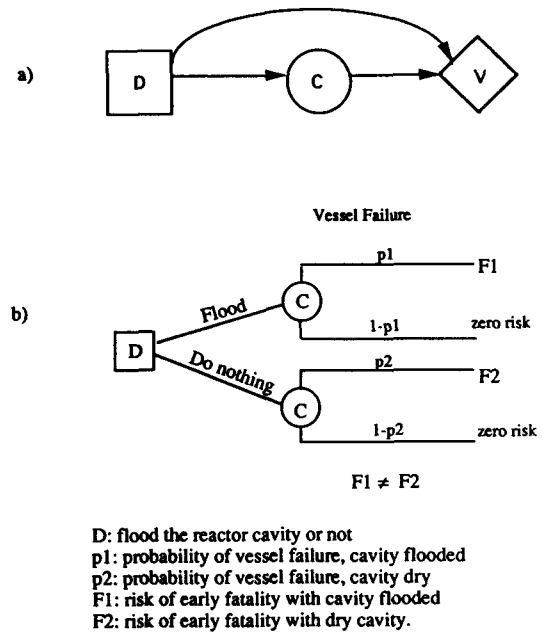


Fig. 2. Three Cases with Decision, Chance, and Value nodes ( $p_1 \neq p_2$ ,  $F_1 \neq F_2$ ).

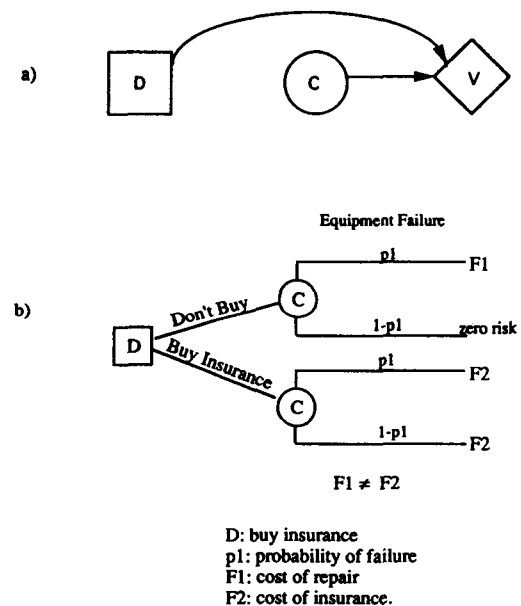


Fig. 3. Three Cases with Decision, Chance, and Value nodes ( $p_1 \neq \text{const}$ ,  $F_1 = F_2$ ).

since  $F1$  is assumed equal to  $F2$  (the consequence of early fatalities due to a steam explosion), the value node only depends on the chance node,  $C$ .

Figure 2.a is similar to Figure 1.a, but here the value depends upon both the decision and the random variable (chance variable), which depends on the decision. The equivalent decision tree is also shown in Figure 2.b. For example, let  $D$  represent whether or not to flood the reactor cavity and  $C$  represent whether the vessel fails or not. Since the probability of vessel failure depends on the decision  $p1 \neq p2$ , and consequence  $F1$  is assumed not equal to  $F2$  (the consequence of early fatalities), the value node depends on both the chance node  $C$  and the decision node  $D$ .

In Figure 3.a, the value depends on both the decision and the chance node, but the random variable is independent of the decision. Consider the insurance example. Let node  $C$  represent whether or not the electronic component will fail during its lifetime. The decision can be graphically structured as shown in Figure 3.a. The probability of system failure is independent of whether or not one buys insurance, but the cost ( $F$ ) is dependent on the purchase of insurance and the probability of failure, as shown in Figure 3.b. Note that the bottom branch can be collapsed because once insurance is purchased, the cost is the same irrespective of the system failure.

In many cases, decision trees and influence diagrams will contain more than one decision. Figure 4.a shows an influence diagram in which two decisions are modelled, i. e., whether or not to flood the reactor cavity and whether or not to depressurize the primary system. The equivalent decision tree is shown in Figure 4.b. Since the two decision nodes in Figure 4.a and 4.b are not separated by a chance node, they can be collapsed into one decision having four outcomes, i. e., flood the cavity only, depressurize the primary system only, do both, and do neither, as shown in Figure 5.a and Figure 5.b.

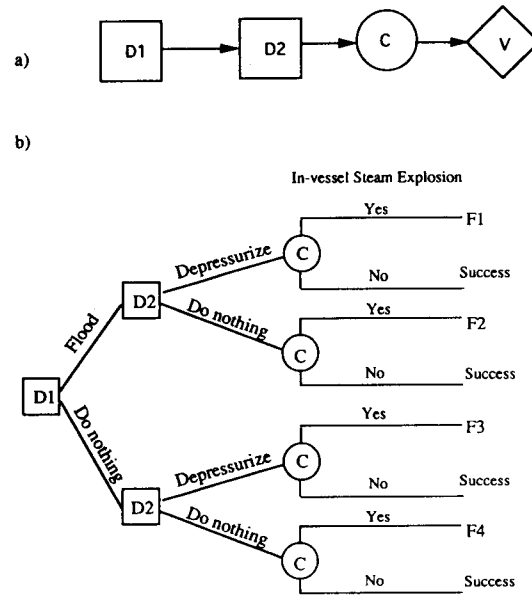


Fig. 4. Influence Diagrams and Decision trees Associated with Multiple and Sequential Decisions.

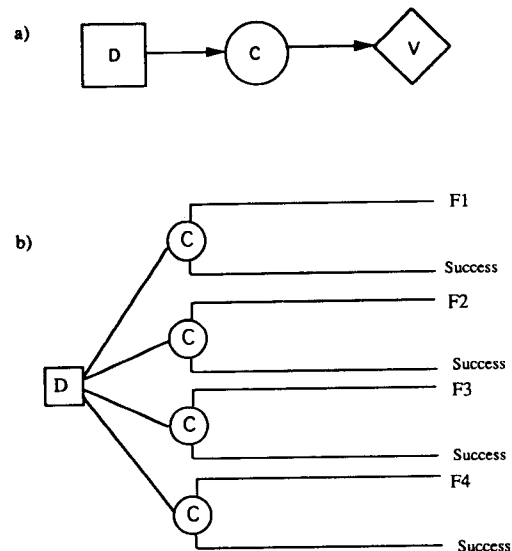


Fig. 5. Influence Diagrams and Decision trees Associated with Multiple and Sequential Decisions.

As shown in Figure 6, a sequential decision problem may have chance nodes between the decision nodes. For example, let  $D1$  represent the decision of

whether or not to flood the reactor cavity, D2 represent whether or not to inject water into the vessel, and chance node C represent whether or not AC power is recovered. In this case, since vessel injection of water depends on the recovery of AC power (which is represented by the chance node), two decision nodes cannot be collapsed into a single node, and still preserve the logic of the original diagram. The equivalent decision tree is also presented in Figure 6.b.

If decision node D1 precedes decision node D2 in a regular influence diagram, then node D1 and all of its informational predecessors should be informational predecessors of node D2. Figure 6.c shows the addition of a "non-forgetting" arc. Informational arcs toward node D2 denote that the decision maker knows the outcome of node C, as

well as decision D1 when decision D2 is made.

The chance nodes in the decision tree and the influence diagram describing severe accident management have two basic types of uncertainty: that due to stochastic variability and that due to inadequate knowledge or data (state-of-knowledge uncertainty). Some of the chance nodes represent phenomenological events that are deterministic in nature, i. e., they will always occur or never occur given the states of the predecessor nodes; we just cannot predict which. The uncertainty associated with such nodes is purely state-of-knowledge and the distribution that characterizes that uncertainty is a split fraction over the two possible states, namely the event will always occur (with a probability of 1.0) or never occur (with a probability of 0.0). Using the terminology of Ref. [8], the model of the world contains no uncertainties in this case.

A few nodes, however, represent phenomenological events that are stochastic in nature, i. e. they will occur with a rate of occurrence  $\lambda$ , but, due to inadequate data, the value of  $\lambda$  is uncertain. In this case the distribution that describes the state-of-knowledge uncertainty is a continuous probability density function (pdf) over the possible values of the rate of occurrence of the event. Using the terminology of Ref. [8], the model of the world contains stochastic uncertainties. Sometimes the distinction between a deterministic event and a stochastic event is not that clear cut, and we are uncertain whether an event is purely deterministic or whether there is some stochastic variability associated with it.

### 3. Evaluation

In general, once constructed, both decision trees and influence diagrams can be quantified and solved in order to evaluate decision strategies. Solving the decision tree or the influence diagram means to compute the expected values associated with the attributes of the value node, given the possible decisions. Decision trees utilize the concept of

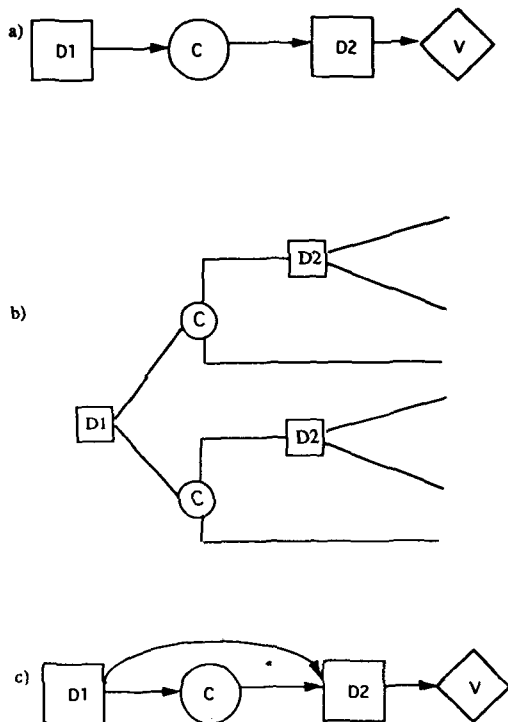


Fig. 6. Influence Diagrams and Decision trees Associated with Multiple and Sequential Decisions.

"rollback" to solve a problem. This means starting at the right-hand terminus with the highest expected value of the tree and working back to the current or beginning decision point to determine the decision or decisions that should be made.

Evaluation of the influence diagram is straightforward by utilizing four operations. The detailed explanation of these basic operations are given in Ref. 4 and 5, and are summarized as follows;

- (1) Arc reversal: Given an influence diagram containing an arc from a chance node  $X$  to another node  $Y$ , but with no other directed path from  $X$  to  $Y$ , this arc can be reversed to point from  $Y$  to  $X$ . In the modified diagram, both  $X$  and  $Y$  inherit each other's conditional predecessors.
- (2) Sink node removal: Any node in the influence diagram can be converted into a sink node by a suitable sequence of arc reversal operations. A chance node that has no successors can be eliminated.
- (3) Chance node removal: Two nodes with a directed arc from  $X$  to  $Y$  can be replaced by a single node. The condition for this operation is that  $Y$  must be the only successor of  $X$ .
- (4) Decision node removal: A decision node is removed by optimization, i. e., by selecting the decision alternative that maximizes (or minimizes) the expected value.

In order to show how these operations are applied, an example associated with a used car buyer is made as follows. The buyer can decide whether or not to buy a used car. There are two choices, D (Do not buy) and B (Buy). The car can be of either good quality, or bad quality. It is assumed that the buyer knows from experience that the chance of good quality is 0.7, and of poor quality 0.3.

There is a close friend of the decision maker, who is a mechanic. The mechanic checks the quality of the car for his friend without cost. If the car is of good quality, there is 0.7 probability that the mechanic will recognize it (or say "good"), there is 0.2 probability that he will say "so-so (medium)", and

there is 0.1 probability that he will say "poor". If the car is of poor quality, the probabilities of the mechanic recognizing it as good, medium, and poor are 0.15, 0.25, and 0.6, respectively. We shall assume the buyer's objective is to maximize the expected satisfaction value.

The following satisfaction values are assumed as follows. The buyer gets satisfaction 100 if the car is of good quality and he buys it. He gets 0 if the car is of poor quality and he buys it. The rest are in-between values. He gets 70 if the car is of poor quality and he does not buy it, while he gets 20 if the car is of good quality and he does not buy it.

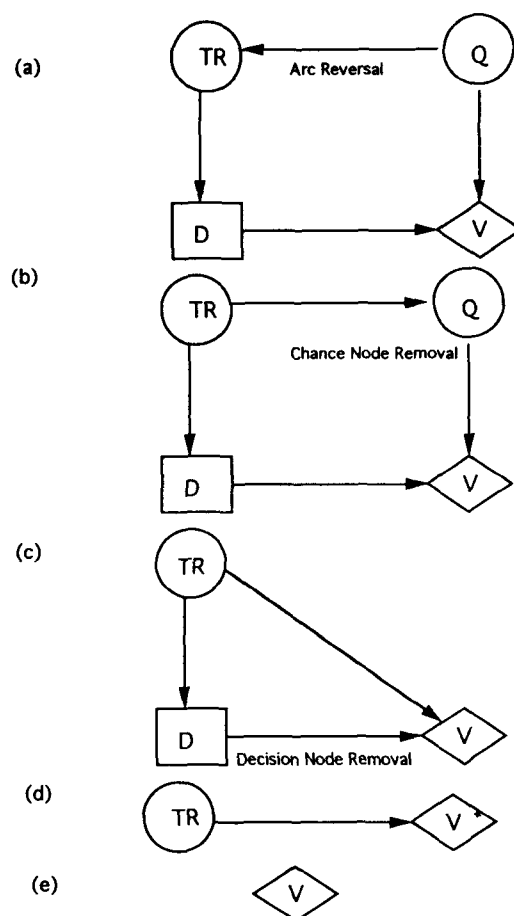


Fig. 7. Evaluating the Influence Diagram for Buying a Used car.

The equivalent influence diagram is shown in Figure 7.a, where node TR and Q represent the mechanic's judgement and the condition of the car, respectively. The influence diagram operations described above are shown in Figure 7.b-7.e. Since node Q has two successors, the operation of chance node removal cannot be applied. In order to reduce two successors to one successor, the operation of arc reversal is applied. Since the influence diagram contains an arc from the chance node Q to another node TR, but with no other directed path from Q to TR, the operation of arc reversal can be applied, as presented in Figure 7.b. Then node Q is absorbed into the value node, as shown in Figure 7.c. The decision node D is removed by maximizing the expected value of the satisfaction, as shown in Figure 7.d. The process ends when all predecessors to the value node have been removed (Figure 7.e). The detailed calculations are as follows :

Let  $Q_1$  = event "the car is good"

$Q_2$  = event "the car is poor"

$TR_1$  = event "the mechanic judged the car is good"

$TR_2$  = event "the mechanic judged the car is medium"

$TR_3$  = event "the mechanic judged the car is poor"

$D_1 = D$  = Decision not to buy the car

$D_2 = B$  = Decision to buy the car.

Then :

$$P(Q_1) = 0.70 \quad P(Q_2) = 0.30$$

$$P(TR_1/Q_1) = 0.70 \quad P(TR_1/Q_2) = 0.15$$

$$P(TR_2/Q_1) = 0.20 \quad P(TR_2/Q_2) = 0.25$$

$$P(TR_3/Q_1) = 0.10 \quad P(TR_3/Q_2) = 0.60$$

The probabilistic notation for the value is given by :

$$V(D_1/Q_1) = 20 \quad V(D_2/Q_1) = 100$$

$$V(D_1/Q_2) = 70 \quad V(D_2/Q_2) = 0.$$

In order to find  $P(TR_i)$  associated with Figure 7. b, the arc reversal operation is applied as follows :

From the definition of the joint probability

$$P(TR_i) = \sum_{j=1}^2 P(TR_i / Q_j) P(Q_j) \quad (1)$$

Using the Bayes' theorem

$$\begin{aligned} P(TR_1) &= P(TR_1 / Q_1) P(Q_1) + P(TR_1 / Q_2) P(Q_2) \\ &= 0.7 \times 0.7 + 0.15 \times 0.3 = 0.535. \end{aligned}$$

Similarly,

$$\begin{aligned} P(TR_2) &= P(TR_2 / Q_1) P(Q_1) + P(TR_2 / Q_2) P(Q_2) \\ &= 0.2 \times 0.7 + 0.25 \times 0.3 = 0.215 \end{aligned}$$

$$\begin{aligned} P(TR_3) &= P(TR_3 / Q_1) P(Q_1) + P(TR_3 / Q_2) P(Q_2) \\ &= 0.1 \times 0.7 + 0.60 \times 0.3 = 0.250. \end{aligned}$$

And to find  $P(Q_i / TR_i)$ , Bayes' theorem is applied again.

$$P(Q_i / TR_i) = \frac{P(Q_i) P(TR_i / Q_i)}{P(TR_i)} \quad (2)$$

$$P(Q_1 / TR_1) = \frac{0.7 \times 0.7}{0.535} \approx 0.92$$

$$P(Q_1 / TR_2) = \frac{0.7 \times 0.2}{0.215} \approx 0.65$$

$$P(Q_1 / TR_3) = \frac{0.7 \times 0.1}{0.250} = 0.28$$

$$P(Q_2 / TR_1) = \frac{0.3 \times 0.15}{0.535} \approx 0.08$$

$$P(Q_2 / TR_2) = \frac{0.3 \times 0.25}{0.215} \approx 0.35$$

$$P(Q_2 / TR_3) = \frac{0.3 \times 0.6}{0.250} \approx 0.72.$$

Figure 7c and 7d represent removal of node Q and its absorption into the value node. Then we need  $V(D_1 / TR_1)$ ,  $V(D_1 / TR_2)$ ,  $V(D_1 / TR_3)$ ,  $V(D_2 / TR_1)$ ,  $V(D_2 / TR_2)$ ,  $V(D_2 / TR_3)$ .

Using Eq. (2)

$$V(D_1 / TR_1) = \sum_{i=1}^2 V(D_1 / Q_i) P(Q_i / TR_1)$$

$$= 20 \times 0.92 + 70 \times 0.08 = 24$$

$$V(D_1 / TR_2) = \sum_{i=1}^2 V(D_1 / Q_i) P(Q_i / TR_2)$$

$$= 20 \times 0.65 + 70 \times 0.35 = 38$$

$$V(D_1 / TR_3) = \sum_{i=1}^2 V(D_1 / Q_i) P(Q_i / TR_3)$$

$$= 20 \times 0.28 + 70 \times 0.72 = 56$$

$$V(D_2 / TR_1) = \sum_{i=1}^2 V(D_2 / Q_i) P(Q_i / TR_1)$$

$$= 100 \times 0.92 = 92$$

$$V(D_2 / TR_2) = \sum_{i=1}^2 V(D_2 / Q_i) P(Q_i / TR_2)$$

$$= 100 \times 0.65 = 65$$

$$V(D_2 / TR_3) = \sum_{i=1}^2 V(D_2 / Q_i) P(Q_i / TR_3)$$

$$= 100 \times 0.28 = 28$$

Hence,

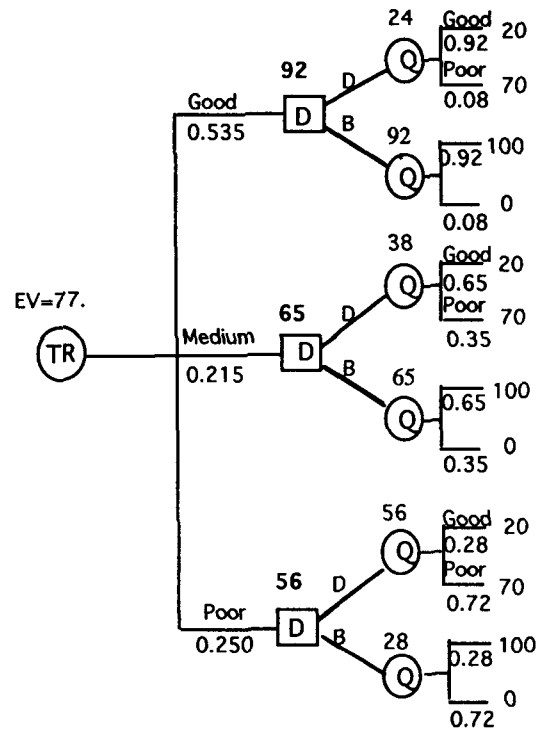
if  $TR_1$  occurs, the decision is  $D_2$ , "Buy"

if  $TR_2$  occurs, the decision is  $D_2$ , "Buy"

if  $TR_3$  occurs, the decision is  $D_1$ , "Do not buy".

This is where one can stop since guidance for making the decision is given above. Figure 7.d represents degree of satisfaction associated with the decision optimization. Figure 7.e shows total expected value; i. e., the satisfaction, which in this case is 77.

The same result can be obtained from an evaluation of the equivalent decision tree, as shown in Figure 8, and can be interpreted as follows: If the friend says "good" or "so-so", then buy; if the friend says "poor", do not buy. As shown above, the



B = Buy D = Don't Buy

$P(Q | TR) = \{0.92, 0.65, 0.28\}$  by Bayes' Formula

Fig. 8. Equivalent Decision tree for Figure 7.

decision tree is more clear in representing outcome states and policy results than the influence diagrams.

#### 4. An Example

When assessing a severe accident management strategy five criteria should be considered [9]:

- the feasibility of the strategy,
- the effectiveness of the strategy,
- the possibility of adverse effects,
- information needs, and
- compatibility with existing procedures

For the cavity flooding strategy considered in the example, the feasibility is essentially a question of whether or not the operators will be able to fill the



cavity up to the required level in appropriate time. The effectiveness has to do with whether or not there is sufficient heat transfer to keep the molten core in the vessel. A possible adverse effect is a steam explosion, if the strategy should be feasible but not effective, i. e., the core penetrates the vessel, and finds water in the cavity, which otherwise would not be there. Information needs refers to instrumentation availability, and compatibility considers the impact on existing rules and procedures.

Figure 9 shows a case with adverse effects. The lower branch, "Do Nothing", is the risk associated with employment of standard emergency operating procedures. The upper branch, flood cavity, has three chance nodes. The first chance node  $C_1$  represents the question of feasibility; whether or not the operators can fill the cavity up to the required level in time. The second chance node  $C_2$  represents effectiveness; whether or not the water will keep the vessel cool enough. The third chance node  $C_3$  represents adverse effects; whether or not there will be a steam explosion if the strategy is not effective. Note that this last question can also apply to the feasibility issue as well. The branch "flooding not successful" may also lead to the potential adverse effect (regarding a steam explosion) if the cavity is partially filled with water.

Early containment failure can be attributed to two phenomena : direct containment heating and

ex-vessel steam explosions. From Ref. [10], the following values for the risks ( $F_i$ ) and the probabilities ( $P_i$ ) are derived :

- |               |  |
|---------------|--|
| $F_1 = 0$     | If there is no vessel failure, the conditional probability of early containment failure, $P_{ed} = 0$ .                |
| $F_2 = 0$     | If the vessel fails and the melt is quenched, $P_{ed} = 0$   |
| $F_3 = 0.01$  | If the vessel fails and there is an ex-vessel steam explosion, but no direct containment heating, $P_{ed}$ is reduced. |
| $F_4 = 0.025$ | If flooding is not successful; same as "do nothing".   |
| $F_5 = 0.025$ | Given in NUREG-1150; "do nothing" [11].  |
| $P_1 = 0.41$  | The probability that the option is not feasible; that the arrival of water is not timely.                              |
| $P_2 = 0.098$ | The probability that the option is not effective, given the water is there in time.                                    |
| $P_3 = 0.5$   | The probability of an adverse effect; i.e. of an ex-vessel steam explosion, given water in the cavity.                 |

An influence diagram for this example is shown in Figure 10.a. The value of the consequence depends on the decision node (D) and three chance nodes ( $C_1$ ,  $C_2$ , and  $C_3$ ) which are defined in Figure 9. The nodes  $C_2$  and  $C_3$  are not directly dependent on the decision because the probabilities of occurrence of a steam explosion and of vessel failure just depend on the success probability of cavity flooding, which, in turn, just depends on the decision node. Since the probability of a steam explosion is affected by the occurrence of vessel failure, the node  $C_2$  depends only on the node  $C_1$ .

The evaluation process for this diagram is as follows.

The value ( $V$ ) is a vector given by:

$$V = [f(F_1, F_2, F_3, F_4), F_5] \quad (3)$$

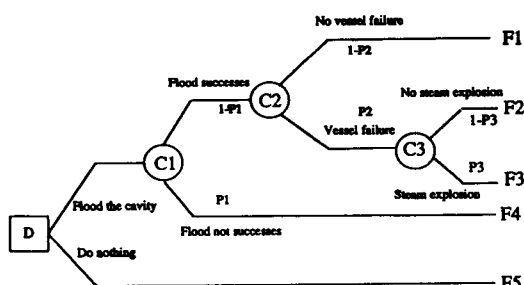


Fig. 9. Decision Tree for PWR Cavity Flooding Example.

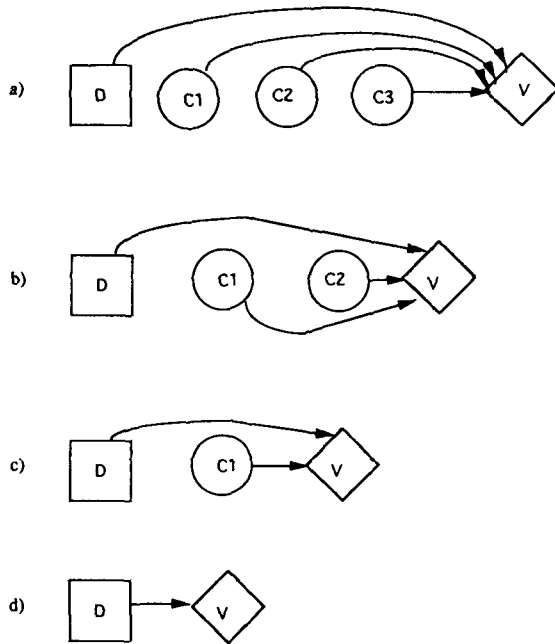


Fig. 10. An Influence Diagram Equivalent to Figure 9 and Reduced Diagrams.

where the function ( $f$ ) for cavity flooding has four elements ( $F_1, F_2, F_3, F_4$ ) as noted in Figure 9. It is possible to remove  $C_3$  by chance node removal, one of the operations for influence diagrams.

A chance node can be removed if its only successor is the value node. This chance node is then removed by conditional expectation. The value becomes :

$$Y = [f(F_1, F_2 (1 - P_3) + F_3 P_3, F_4), F_5] \quad (4)$$

where the function ( $f$ ) for cavity flooding now has three elements.

Note that the node  $C_2$  in Figure 10.b becomes a direct predecessor of the value node in this elimination process. Now this chance node,  $C_2$ , can be eliminated by chance node removal and the value becomes :

$$Y = [f((1 - P_2) F_1 + P_2 (F_2 (1 - P_3) + F_3 P_3), F_4), F_5] \quad (5)$$

In the same manner, the node  $C_1$  in Figure 10.c now becomes a direct predecessor of the value node,

and can also be eliminated resulting in the value being given by :

$$Y = [P_1 F_4 + (1 - P_1) \{ (1 - P_2) F_1 + P_2 (F_2 (1 - P_3) + F_3 P_3) \}, F_5] \quad (6)$$

Figure 10.d illustrates the final diagram, which has just two nodes. By comparing the value of each alternative, the optimal decision can now be made. Using Equations (6), the expected values can be evaluated as follows :

$$EV(\text{Do Nothing}) = 0.025$$

$$EV(\text{Flood Cavity}) = 0.011.$$

In this example, and on an expected value basis, one would choose to flood the cavity, in spite of the potential for adverse effects. This is the same as the value obtained from the decision tree evaluation.

For the probabilities of the input variables with the distributions in Eq. (6), a sample size of  $N$  observations can be used to propagate the uncertainty in the variables through the decision model. The result is two output distribution, one for each decision alternative. There are several methods developed for the propagation of uncertainty; e. g., Monte Carlo simulation and Latin Hypercube sampling [12, 13]. How each variable is sampled is determined by what kind of uncertainty is associated with it. Deterministic variables are sampled zero-one. This means that every sample observation contains either the value of 0 or the value of 1 for the occurrence probability of the event modeled by the node in question. And the fraction of the observations containing the value of 1 is determined by the split fraction that characterizes the state-of-knowledge uncertainty about the occurrence of the event in question. For nodes that model stochastic events, the continuous distribution of the occurrence frequency of the event in question is sampled. Every sample observation then results in a point value of the event occurrence frequency. The detailed calculation is beyond the scope of this paper.

### 5. Conclusion

In this paper, decision trees and influence diagrams have been introduced as tools for modeling and assessing severe accident management strategies. Some candidate strategies are complex, involving both beneficial and adverse effects, and subject to large uncertainties. The influence diagram represents a valuable tool for showing probabilistic dependencies among many factors involved. The decision tree, equivalent to the influence diagrams, represents a second way of illustrating complex relationships. It is the explicit representation of the decision structure, which directly shows the decision maker the value of each possible outcome.

Both tools are demonstrated to be used as the basis for the framework for assessing severe accident management strategies. This framework is very flexible in that it can be applied to any kind of accident management strategy for any sequence.

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### References

1. USNRC, "Staff Plans for Accident Management Regulatory and Research Program," SECY-89-012 (Jan. 1989).
2. W.E. Kastenberg, editor, "Summary of a Workshop on Severe Accident Management For PWRs," NUREG/CR-5781, UCLA (November 1991).
3. W.E. Kastenberg, editor, "Summary of a Workshop on Severe Accident Management For BWRs," NUREG/CR-5780, UCLA (November 1991).
4. R.D. Shachter, "Evaluating Influence Diagrams," *Operations Research*, 34, No. 6, p. 871 (1986).
5. M. Jae and G. Apostolakis, "The Use of Influence Diagrams for Evaluating Severe Accident Management Strategies," *Nuclear Technology*, 99, p. 142, August (1992).
6. M. Jae, A. Milici, W.E. Kastenberg, and G. Apostolakis, "Sensitivity and Uncertainty Analysis of Accident Management Strategies," *Nuclear Technology*, 104, p. 13, August (1993).
7. R.M. Oliver and J.Q. Smith, *Influence Diagrams, Belief Nets and Decision Analysis*, John Wiley and Sons (1990).
8. G. Apostolakis, "The Concept of Probability in Safety Assessments of Technological Systems," *Science*, 250, 1359 (Dec. 1990).
9. D.J. Hanson, H.S. Blackman, O.R. Meyer, L.W. Ward, "Developing and Assessing Accident Management Plans for Nuclear Power Plants," NUREG/CR-609, Vol. 1, EG&G Idaho, Inc. (August 1992).
10. M. Jae, "The Use of Influence Diagrams for Evaluating Severe Accident Management Strategies in Nuclear Power Plants," Ph. D. Thesis, p. 35, University of California, Los Angeles, USA (1992).
11. USNRC, "Severe Accident Risks: An Assessment for Five Nuclear Power Plants," NUREG-1150, Vol. 1 & 2 (June 1989).
12. J.M. Hammersley and D.C. Hanscomb, "Monte Carlo Methods," London: Methue (1964).
13. R.L. Iman and M.J. Shortencarier, "A FORTRAN 77 Program and User's Guide for the Generation of Latin Hypercube and Random Samples for Use with Computer Models," NUREG/CR-3624, SAND83-2365, Sandia National Lab., Albuquerque, NM (1984).