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USING BELIEF NETWORKS TO ASSESS RISK

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ABSTRACT

This paper reviews two commonly used risk assessment tools, namely weighted scores and expected value. The limitations of weighted scores have been outlined. One of the more difficult aspects of the expected value method is to determine the probability of an event. A probabilistic modeling environment called belief networks, has been proposed as an effective means of modeling the situation. An example application has been provided to show how the integrated system may work.

1 INTRODUCTION

Merriam-Webster defines risk as: 1) the possibility of loss or injury; 2) someone or something that creates or suggests a hazard; 3) the chance of loss or the perils to the subject matter of an insurance contract; 4) the degree of probability of such loss. Risk is, therefore, an issue of uncertainty. Risk reduction requires several steps: risk quantification, risk assessment, and finally, risk management. Several methods for quantifying and assessing risk have been developed including weighted scores, expected value, probabilistic modeling, and simulation.

This paper discusses two risk quantification methods commonly used in the construction industry, namely weighted scores and expected value. A new approach to probabilistic modeling is presented. Finally, an example application is discussed.

2 WEIGHTED SCORES

Weighted scores are used extensively in the construction industry to measure risk. They are used in the prequalification process (Russell and Skibniewski 1990), in bid evaluation (Alsugair 1999), and in decision making (McIntyre et al. 1998). Generally, they require the decision maker to:

1. define the risk elements or criteria
2. assign weights to each risk element reflective of the importance of the risk to the particular situation
3. for each option being assessed, score the risk element in a predetermined manner
4. multiply the scores by their weights, and sum for each option
5. compare the weighted scores and make the decision

In its most general form, weighted scores use Equation 1. In this equation, w is the weight assigned to each risk element i, x is the score assigned by the decision maker to risk elements I for each option k. In some cases, criteria or elements are categorized into major groups, j, and each group is also weighted and summed to product the total weighted score.

$$WeightedScore_k = \sum_{j=1}^{m}\left[w_j \sum_{i=1}^{n} w_{ij} x_{ijk} \right] \tag{1}$$

In the case of a contractor prequalification evaluation, shown in Table 1, the risk elements may be: 1) years in business, 2) experience with a similar type of construction, 3) bonding capacity, and 4) safety record. The decision maker reviews the criteria, and assigns weights. In this case, the weights are between 1 and 10, with 10 being the most important. These may be assessed independently or by using a multi-criterion assessment tool, such as Analytic Hierarchy Process. The method for scoring each contractor must also be determined. In this case, ranges of values for each criteria are outlined in Table 1. For each contractor, the scores for the risk elements are multiplied by the weight and summed, resulting in a total weighted score for the contractor, as shown in Table 2.

The weighted score method is very easy to understand, which explains why it is so popular in the industry. It does not restrict the number of criteria to be evaluated. On the other hand, although these two contractors acquired relatively similar scores, it cannot be assumed that they would perform equally to the well-being of the project. Contractor B has much greater experience in similar projects over a shorter period of time. It also has a better safety record than Contractor A, although it was not weighted heavily. Based on similar observations, Russell and Skibnewski (1990) outlined several shortcomings of the weighted score model.

1. The criteria and the associated weights are biased by the decision maker's experiences and preferences. This can be detrimental to the analysis process if the criteria and weights are not representative of the situation.

Table 1: Example Weighted Score for Prequalification

Criteria		***w***
Years in business		8
Score	if	
0	0-2	
1	3-5	
2	6-8	
3	9-12	
4	13-15	
5	>15	
Experience (number of similar projects)		10
Score	if	
0	0-2	
1	3-4	
2	5-7	
3	8-10	
4	11-13	
5	>13	
Bonding capacity (Letter from Surety)		5
Score	if	
0	No	
5	Yes	
Safety record (CAD-7)		5
Score	if	
0	-2.00 to -1.00	
1	-0.99 to -0.50	
2	-0.49 to -0.01	
3	0.00 to 0.33	
4	0.34 to 0.66	
5	0.67 to 1.00	

Table 2: Example Weighted Score for Prequalification

Criteria	**Contr A**	**Contr B**
Years in business	16	7
Experience	5	9
Bonding capacity	Yes	Yes
Safety record	-0.102	0.36
Score		
Years in business	5	2
Experience	2	3
Bonding capacity	5	5
Safety record	2	4
Total Weighted Score	95	91

2. A low score in one element or criterion can be counterbalanced by a high score in another, perhaps less important criteria. This may mask important contractor characteristics.
3. When a large number of criteria are used in the analysis, it is difficult for the decision maker to assign weights in a balanced and equitable manner.

In addition, the following shortcomings have been identified by the authors.

4. It is assumed that the criteria are independent, and that their effect is additive. This may not always be the case. For example, the number of years in business may be correlated to the experience with a particular construction type. Adding these scores may not be appropriate.
5. Cause and effect cannot be incorporated with confidence. The cost of a certain event cannot be taken into account other than to have the costs reflected in the weights. For example, an accident on site resulting from poor safety practices may cause work stoppage, criminal charges, and loss of project schedule.
6. Nested weights may cause the total effect of an important criterion to be diluted. Nested weights are those that are associated with larger categories of criteria, shown as w_j in Equation 1.
7. Relative assessment of decision options is not possible. It cannot be said that an option with a score of 100 is twice as good as an option with a score of 50. The scores themselves do not have meaning.
8. In the case of prequalification, it is not apparent where the limiting score should be, where those contractors with a higher score are prequalified, and those below are not.

For many risk situations, weighted scores are very useful; however, other methods are available to the decision maker for evaluating risk. This leads to the expected value method of measuring risk.

3 EXPECTED VALUE

Risk may be part of the uncertainty of the event, or uncertainty of the impact of that event. Where the impact of an event is of concern, the expected value (EV) is often used to quantify the impact. EV is defined as the product of the probability of an event occurring and the impact (cost) of that event.

$$EV(a) = P(a) * I(a) \tag{2}$$

Classical risk theory calls this the *Expected Value* of risk. The advantage of measuring impact in $ is that various types of risk, such as schedule extension measured in liquidated damages and weather measured in lost productivity, can be compared.

The EV can be evaluated by determining the probability and impact of each option. Impact costs are not overly difficult to determine, as most construction practitioners are experienced at estimating costs. Determining the likelihood of the event can cause more problems. In general, the probability can be extracted from historical records, or be based on expert opinion.

EV can be used in different ways. First, it can help a contractor determine the risk associated with an event so that an appropriate contingency maybe incorporated into the bid. For example, the probability of a snowstorm during the construction period is 35%. Should the event occur, the contractor has estimated the cost of snow removal and lost productivity at $25,000. Therefore, the risk is 35% * $25,000 = $8750. This amount can be included in the bid contingency, with the contractor knowing that over time, they will break even with their contingency budget.

Second, EV can be used to help the decision maker assess risk. The following example is based on McKim (1992). Consider a project where the contractor is responsible for the effects of weather delays, and the project has fallen 10 days behind schedule due to weather. The contract specifies liquidated damages of $10,000/day for every 2 weeks or part thereof the project is late. The project manager must decide whether to A) introduce a second shift, thereby accepting a sure loss due to additional wages but avoiding liquidated damages, or B) try to meet the contract deadline with existing labor forces, thereby avoiding the cost of extra labor, but risking the liquidated damages.

A) hire a second shift but avoid liquidated damages.
EV(a) = P(a)*I(a) where
P(a) = probability of the cost increase for the second shift = 100%
I(a) = the increased cost of the second shift = $5,000
EV(a) = $5,000

B) accept the liquidated damages
EV(b) = P(b)*I(b)
I(B) = liquidated damages = $10,000
P(b) = probability of being liable for liquidated damages = 60% (40% chance of completing the project on time with existing labor)
EV(b) = $6,000.

Option A has the lower cost, and therefore, hiring the second shift is the best action.

As the problem becomes more involved, perhaps incorporating several impact factors into each option, care must be taken to ensure the factors are independent to allow them to be added with confidence. A more sophisticated means of determining the likelihood that does not require the independence assumption may be required, depending on the complexity of the situation. A belief network may be integrated in an EV model to fulfill this need.

4 BELIEF NETWORKS - PROBABILISTIC MODELS

Belief networks are an artificial intelligence based on the conditional probability concepts of Thomas Bayes expressed in Bayes Theorem. Belief networks are graphical representations, and they consist of nodes and connecting directional arcs (arrows). The nodes represent the domain variables contained in the model, and the arcs represent conditional dependence between the variables. They are directed, acyclic graphs. The term 'directed' means the arcs have an explicit direction represented by arrows. Acyclic means that the arrows may not form a directional cycle or loop in the network.

If no arcs exist in the network, it is assumed that the variables are independent of the other variables. At the other extreme is the completely connected network where each variable is connected to all of the others. Completely connected networks are not permitted in belief networks because the requirement of acyclic graph structure would not be met. Networks that have practical application are neither unconnected nor completely connected but are referred to as partially connected. Figure 1 shows a singly connected network in which there is only one path between any two nodes. In this model, A and B are said to be parents of C, and C is a parent of E and D. Similarly, E and D are children of C. A and B are referred to as orphans because they have no parents.

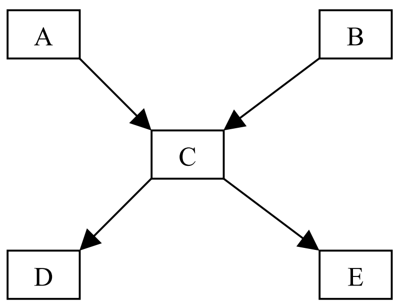

Figure 1: Singly Connected Belief Network

The arrow between A and C represents a conditional relationship between A and C, where A affects the state of C. It is often convenient to interpret the arrow as meaning that A causes C, but the issue of causation is very volatile, and the concepts of correlation should be used. For example, people once observed the correlation each morning that the rooster would crow and that the sun would rise. They concluded that the rooster caused the sun to rise! While this may seem humorous now, it was seen as very logical then.

The addition of one more arrow to Figure 1 would create a multiply connected network, as shown in Figure 2. Here, there are 2 paths between nodes B and E: straight from B to E, and from B to C and then to E.

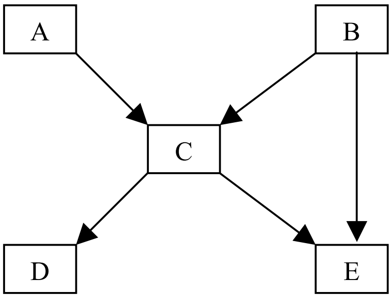

Figure 2: Multiply-Connected Belief Network

The distinction between singly- and multiply-connected networks is their ease of solving. Singly-connected networks may be solved through manipulations of Bayes' Theorem and other probability calculus techniques. Multiply connected networks are NP-Hard. To address this problem, several techniques, such as clustering and simulation, have been developed to solve them and these have been incorporated into software systems available academically or commercially. These developments have resulted in great interest in this modeling environment over the past 10 years.

Belief network applications allow the user to instantiate or enter evidence of known conditions from the existing situation into the network. This information is evaluated in the network and the probabilities of the nodes with unknown states are recalculated. The user may then extract the updated probability of any node. This symmetry is an important characteristic of belief networks that permits flexibility in the development and application of networks. The variables associated with a risk may be modeled in a comprehensive manner, resulting in greater confidence in probabilistic assessment.

Belief networks are well suited to applications of risk because they are capable of capturing uncertainty. In addition, the information required to develop a network can be extracted from data as well as from experts in the field. Development of a belief network requires 5 main steps.

First, define the relevant variables. This requires understanding of the problem and the scope of the model.

Second, define the states of the variables. While variables can have any number of states, binary states are most common, such as true/false, yes/no, male/female. The states can also be numeric or descriptive, but they must be discrete.

Third, define the relationship between the variables. Arrows are drawn between the variables to represent conditional dependence relationships. It is important to keep the number of arrow to a reasonable number to reduce the number of probabilities required in the next step. There are no constraints about the way in which the variables interconnect or where they join in the network. The only constraint is that cyclic relationships must be avoided.

Fourth, define the conditional probabilities of the relationships. This requires a probability to be determined for each node for each combination of states of its parent. In the case of orphan nodes, only the priori (unconditioned) probability is needed. Probabilities may come from data or from experts. There are entropy calculations that provide a measure of the information gained by joining two variables.

Finally, verify and validate the network. The identification of weak relationships in the model and understanding whether they should exist is an important part of the validation of the network. This can be achieved by testing it through several scenarios to ensure the results are appropriate and acceptable.

Another way of looking at it is to say that there are two parts to a belief network: the qualitative part and the quantitative part. The qualitative part is primarily developed in the first stages of the network. This is the stage where the variables and their states are defined. The qualitative part of the network is needed for the next two stages of development: relationship identification and quantification. In reality, deciding where the arrow should be is both qualitative and quantitative. Quantification of the relationships means assigning conditional probabilities.

The advantages of using belief networks to model risk are as follows.

- Belief networks are excellent modeling environments for situations where there are conditional or influential relationships.
- Belief networks can integrate data and expert opinion seamlessly.
- The structure of a network is very intuitive, and domain experts do not need to understand the background technology to be able to participate in knowledge elicitation.
- The models are symmetric in that evidence can be entered at any node, and all remaining nodes are recalculated. There is no direction constraint on the logic once it has been developed.

The limitations of belief networks in practical terms are as follows.

- It is often difficult to collect data and/or expert knowledge in a consistent and unbiased manner, and translate it to nodes, arrows, and probabilities.
- The current software for the development of networks cannot handle continuous variables, but that is slowly changing.

5 EXAMPLE APPLICATION

The risk scenario was based on the failure of large equipment that could result in the release of pollutants and contamination of adjacent lands. The owner had traditionally used a weighted score system with nested weights for three main risk categories. It was found that the system had several serious shortcomings. The most important was that the model did not consider risk as a series of events. For an environmental contamination to occur, an equipment had to fail. That failure also had to result in the loss of fluid. Finally, that fluid had to escape the site and get into the adjacent lands.

It was decided to develop a probabilistic model of the scenario, and to use the model to feed into an expected value assessment model. The model shown in Figure 3 is an extraction of the entire model. The mechanisms of failure have not been included due to space considerations.

The model may be reviewed in the following manner. Note that variables that relate directly to a node in the network are indicated by *italic*. Starting at the upper right corner, the *Equipment Failure* can result in the loss of fluid. It is assumed that the fluid at this point will only affect the owner's property. The event of an *Environmental Spill*, which implies that the fluid has entered adjacent lands, is dependent on the *Response Time* of the company personnel, the *Containment* system at that site, the *Distance to the Property Line*, and, of course, the event that there has been a *Loss of Fluid.*

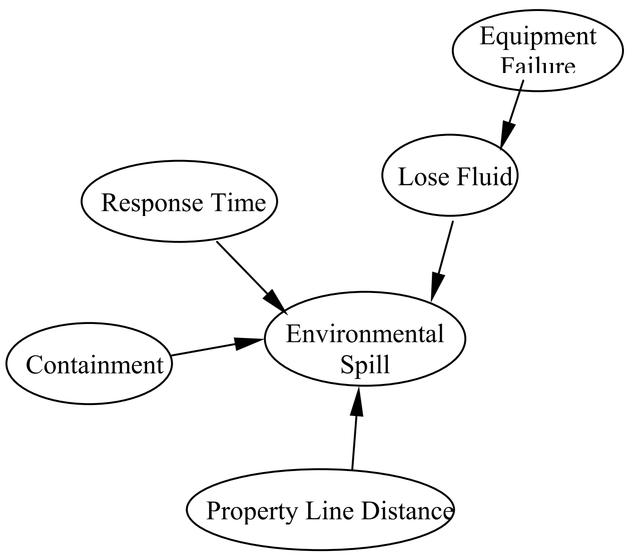

Figure 3: Belief Network for Equipment Failure

It is important to note that the parents of *Environmental Spill* do not contribute linearly to the spill event. For example, if *Lose Fluid* or *Equipment Failure* is false, then the states of the other parents are irrelevant i.e. *Environmental Spill* is also false. The conditional dependence of the events are logically and effectively incorporated in the model.

The information required to develop the network, including variables, relationships, and probabilities, was provided by experts, as these failures do not occur often enough to have reliable data from which to base the network. Once the specific equipment characteristics were entered into the network, the probability of *Environmental Spill* was calculated and entered into the EV model. Based on the characteristics of the adjacent site, the cost of remediation was estimated, and the expected value of the event was calculated using Equation 3.

$$\begin{aligned}EV = P(\text{Lose Fluid}) * I(\text{Site Remediation}) +\\ P(\text{Environ'l Spill}) * I(\text{Environ'l Remediation})\end{aligned} \quad (3)$$

The company found the information very useful. First, the resulting EV for each site allowed them to understand the risk they were taking, or not taking, buy improving site conditions. Second, if the EV for one site was double that of another, it truly meant that the risk was double. Finally, the probabilities of each event could be analyzed to determine the best strategy to take to reduce their total risk. Equipment sites could be ranked with confidence based on their EV.

The belief network model permitted the decision makers to model the real world in a logical and realistic manner. Mechanisms of failure, not shown here, allowed the experts to share their knowledge and understand how others perceived these events. On the other hand, the weighted scores modeled the expert's willingness to accept risk and how that risk was associated with certain equipment characteristics.

6 CONCLUSIONS AND RECOMMENDATIONS

Risk management is becoming a very important part of business management. Many methods are used to assist the decision maker, with varying degrees of success. It is important to use a method that provides the most effective information to the decision makers, and that they understand the biases and limitations of the system they are using.

Glenn Shafer, a researcher in probabilistic reasoning, has said that 'Probability is not about numbers. It is about the structure of reasoning.' This application has shown that the structure of reasoning is extremely important when events are conditionally dependent

The following recommendations are for improvements of the model. On the most part, these recommendations relate to the availability of data with which to assess the transformers and their stations.

First, the probabilities in the belief network model can be improved with time. Although there is confidence in the values provided by the experts, up to date data may help to refine the analysis.

Second, quantitative site data are more valuable than qualitative or categorical data. Categorical data identify a group of values rather than a value itself. While this was convenient for the weighted scores method, it limits future model improvements. Therefore, it is recommended that quantitative data be collected whenever possible.

It is believed that the proposed risk assessment model is a significant improvement over the previous weighted scores method. It addresses many of the concerns and provides a defensible system.

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