Journal of the Society of Korea Industrial and Systems Engineering
Vol, 27, No. 4, pp.1－6, December 2004.

A Forecasting and Decision Model that Incorporates Accident Risks

Hee-Joong Yang · Keun-Boo Lee · Se-Ho Oh

Department of Industrial and Information Systems Engineering, Chongju University

사고 위험성을 고려한 운행중지 결정 모형

양희중 · 이근부 · 오세호

청주대학교 산업정보시스템공학과

사고 위험성을 고려한 예측 및 의사결정 모형을 구축한다. 시스템을 즉시 운행중지 할 것인지 혹은 계획된 일정 기간을 더 운행 한 후 다시 의사결정을 내릴 것인지를 판단하는 방법론에 대해 연구한다. 의사결정을 내리는데 있어서 비용 및 위험에 대한 새로운 정보가 입수되는 대로 이를 반영한다. 예측 모형을 통해 분석된 결과들을 활용해 보다 나은 의사결정을 내리는 방법에 대해 연구한다.

Keywords : bayesian decision, forecasting, safety systems

1. Introduction

In studying the operations of a safety system, such as nuclear power plants, complex chemical plants, etc., or transportation systems such as airplanes, automobiles, we must periodically decide whether to shutdown immediately, or to continue operation and then periodically repeat the analysis and decision process as additional information about new costs and risks becomes available. The length of each review period must be chosen to reflect the trade-off between computational complexity and a realistic representation of the decision process. Except for important computational issues it does not lead to any conceptual difficulties to assume that the review period is one hour or one day instead of one year. The purpose of this paper is to formulate an influence diagram and a decision tree model that predicts several levels of accidents and incorporates the necessary ingredients of plant shutdown as well as the decision to continue operation.

2. Developing a Prediction Model

2.1 Accident classifications

Although in a safety system accidents occur in innumerable ways, they may fall into only a few categories from the stand point of public safety. Evans and Hope(1984), the group of experts of the Nuclear Energy Agency in Paris (NEA(1986)), and Tat Chi Chow and R.M. Oliver(1988) proposed their classification schemes. In this paper, we classify the accidents to take care of the interaction between low and high severity accidents. To utilize the fact that one severity level accident may contain information helpful in prediction the other, we classify the accidents into different groups depending on their severity. The number of different severity groups to be classified is determined based on the purpose of the analysis and availability of information contained in data that makes such a classification possible. We start with three different severity groups : minor, significant, and severe accidents. The definition of each severity group may be different depending on the types of accidents that happen in a system which is going to be analyzed. In highway accidents for example, we may define severe accidents as accidents that involve death of lives, significant accidents as accidents that involve some number of deadly wounded passengers, and minor accidents as accidents that damage on car only without hurting passengers. We introduce another classification of accidents : level 0, and level 1, and level 2. Level 2 accidents consist of severe accidents, level 1 accidents consists of level 2 accidents and significant accidents, and level 0 accidents consists of level 1 accidents and minor accidents. Thus level 0 accidents include all precursors, level 1 accidents are a subset of level 0 accidents, and level 2 accidents are a subset of level 1 accidents. For example, of there have been 20 minor, 6 significant, and 1 severe accidents in a period, then it means there have been 27 level 0, 7 level 1, and 1 level 2 accidents in a period. In next section, we develop a forecasting model based on such levels of accidents so that the model utilizes the information contained in different levels of accidents to forecast another level of accidents. And then the forecasting model is incorporated to form a decision model that determines the most economical operating scheme.

2.2. Notations

Before we begin the analysis, we define some notations that will be used through this paper.

Notations

T : length of review period

Z : decision made at the beginning of a review period

x_j : time to next level j accidents, j=0, 1, 2

D : historical data available at the beginning of a review period

$n_0(T)$: number of level 0 accidents during a time period T

$n_1(T)$: number of level 1 accidents during a time period T

$n_2(T)$: number of level 2 accidents during a time period T

p_S : probability of one or more severe accidents in a review period

p_G : probability of one or more significant accidents in a review period

p_M : probability of one or more minor accidents in a review period

p_{NO} : probability of no accidents in a review period

p_0 : probability of level 0 accidents in a review period

p_1 : probability of level 1 accidents in a review period

p_2 : probability of level 2 accidents in a review period

C : construction cost

C_S : cost of severe accident

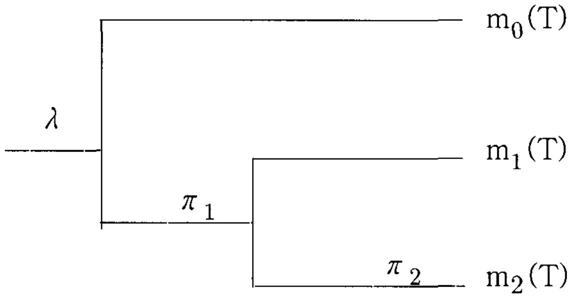
C_G : cost of significant accident

C_M : cost of minor accident

C_R : net revenue obtained from the operation of a system per a period

2.3. A Prediction Model

Based on the above classifications of accidents, we can draw an event tree in figure 1 that shows accidents initiation and escalation to more severe accidents.



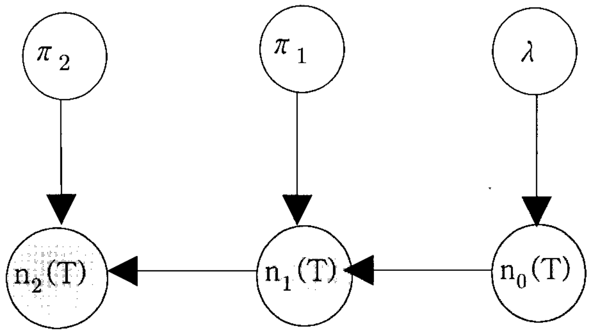
<Figure 1> An Event tree for Accident Initiation and Escalation

λ denotes the rate of initiating events, and π_1, and π_2 denote the probability of escalating to significant and severe accidents, respectively. $m_0(T)$, $m_1(T)$, and $m_2(T)$ denote number of minor, significant, and severe accidents during review period T, respectively. Then the following relationship satisfies;

$$n_2(T) = m_2(T)$$
$$n_1(T) = m_1(T)+m_2(T)$$
$$n_0(T) = m_0(T)+m_1(T)+m_2(T)$$

The event tree in figure 1 is translated into a statistically equivalent influence diagram as in figure 2. For details about influence diagrams, you may refer to Oliver and Yang (1990).

We can assume prior distributions on model parameters and likelihood on number of accidents. After observing data we get the posterior distributions, that is statistically equivalent to an arc reversal process in the influence diagram;



<Figure 2> An Equivalent Influence Diagram

$$p(\lambda,\pi_1,\pi_2|n_0(T),n_1(T),n_2(T))=p(\lambda|n_0(T))p(\pi_1|n_0(T),n_1(T))p(\pi_2|n_1(T),n_2(T)) \quad (1)$$

The influence diagram after observing data is depicted in figure 3.

The predictive distribution of time to next accident, x_j, is obtained by integration out the unobservable parameters, that is statistically equivalent to the node absorption process in the influence diagram;

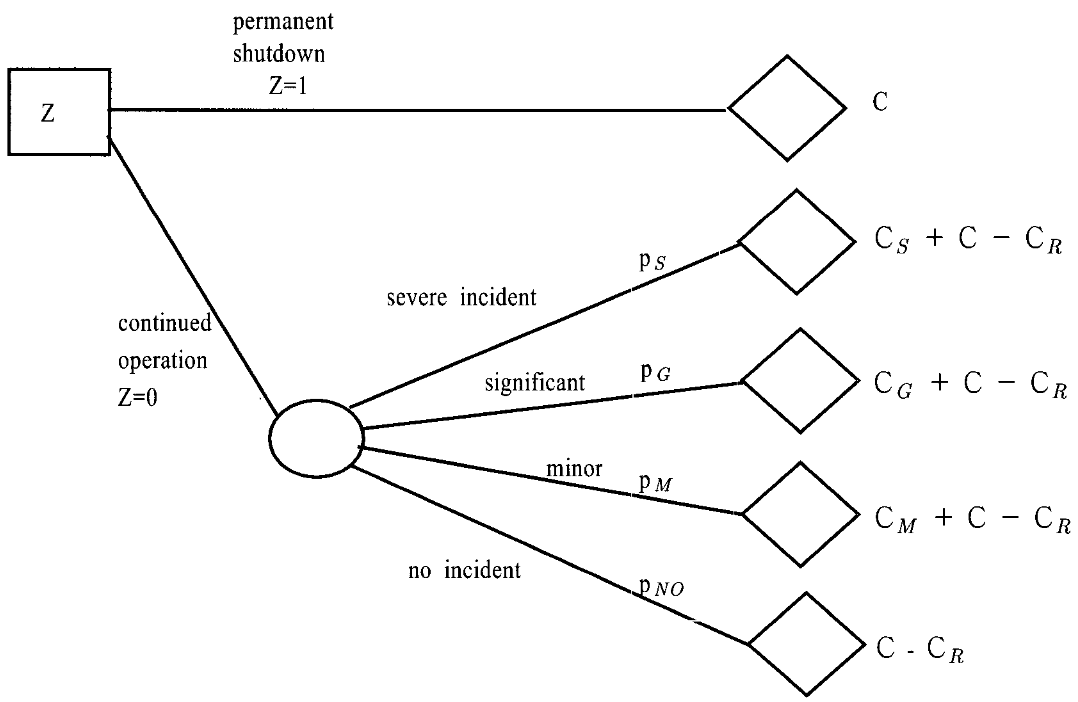
$$p(x_j|n_0(T),n_1(T),n_2(T))=\iiint p(x_j|\lambda,\pi_1,\pi_2)p(\lambda,\pi_1,\pi_2|n_0(T),n_1(T),n_2(T)) \quad (2)$$

If we let Φ denote the vector parameter (λ,π_1,π_2), and x denote the vector time to next accidents (x_0, x_1, x_2), then we can rewrite as following;

$$p(x_j|n_0(T),n_1(T),n_2(T))=\int\cdots\int p(x_j|\Phi)\,p(\Phi|I)d\Phi$$

The probability distribution of p_S, p_G, p_M, and p_{NO} can be derived from the above obtained predictive distribution of time to next incident, x_j.

$$p_S=\int_\phi\int_0^T p(x_2|\Phi)p(\Phi|I)dx_2d\Phi \quad (3)$$



<Figure 3> The Influence Diagram After Observing Data

$$p_G = \int_\phi \int_0^T p(x_1|\phi)p(\phi|I)dx_1 d\phi - p_2 \quad \cdots\cdots (4)$$

$$p_M = \int_\phi \int_0^T p(x_0|\phi)p(\phi|I)dx_0 d\phi - p_2 - p_1 \quad \cdots\cdots (5)$$

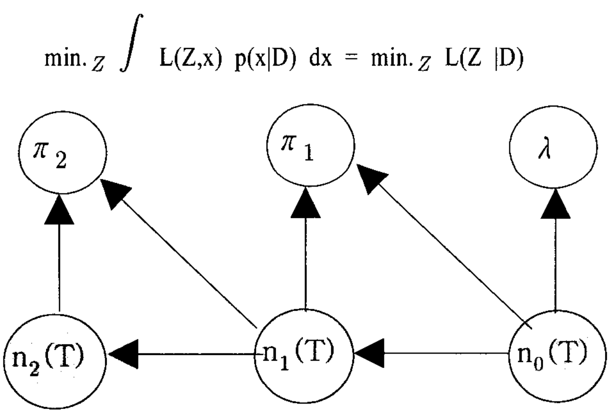
$$p_{NO} = 1 - p_0 - p_1 - p_2 = 1 - \int_\phi \int_0^T p(x_0|\phi)p(\phi|I)dx_0 d\phi \quad \cdots (6)$$

Since all the level 2 accidents are a proper subset of level 1 accidents, the integral in equation (4) must subtract the probability that a level 1 is not a level 2 accident. Similarly, the integral in equation (5) must subtract the probability that a level 0 is not a level 1 accident.

3. Incorporating with a Decision Model

Consider the influence diagram in figure 4 which represents the decision and events in a single period. L in the influence diagram denotes a loss function that evaluates a decision Z relative to x. At the beginning of the first period we decide whether to shutdown the plant permanently (Z=1) or to operate one year (Z=0). The decision is made based on the preliminary knowledge obtained from the observation of historical data. The optimal decision is obtained by choosing the option that minimizes the loss function among two alternatives; Z=1 for plant shutdown, and Z=0 for continued operation;

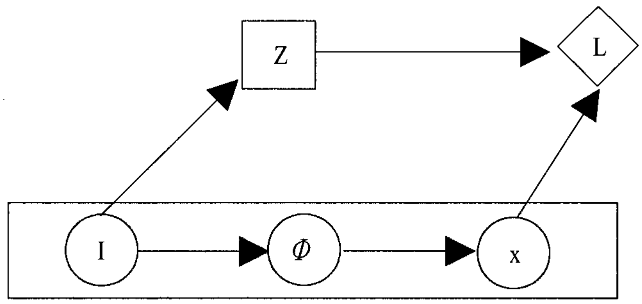
$$\min_Z \int L(Z,x)\ p(x|D)\ dx = \min_Z L(Z\ |D)$$



<Figure 4> An Influence diagram decision problem

The shaded portion of the influence diagram in figure 4 represents the typical bayesian prediction model where model parameters are updated using observed data and absorbed to get a predictive distribution as explained in the earlier section.

We can construct an equivalent decision tree model in figure 5 that explicitly shows the branches of possible decisions and associated costs. If we operate the plant for one period, the probability of minor accident is p_M. At the end of each branch, we add a cost C for construction, C_S for a severe incident, C_G for a significant accident and C_M for a minor incident, that includes cleanup, possible loss of life, treatment of survivors, damage of equipment, environmental contamination,



<Figure 5> The decision tree of one-period decision problem

and so forth. We obtain revenues, C_R, from the sale of products producted from the plant. Typically, the net revenue obtained by operation a plant for one year is small compared to the large value of C_S. The expected cost associated with continued operation is $p_M(C + C_M - C_R) + p_G(C + C_M - C_R) + p_S(C + C_S - C_R) + p_{NO}(C - C_R)$; this number can be compared with the certain cost of shutdown, C, to yield:

shutdown, if $p_0 C_M + p_1 C_G + p_2 C_S > C_R$

operate, if $p_0 C_M + p_1 C_G + p_2 C_S \leq C_R$

One should note that the optimal decision for a power plant shutdown is very much dependent on who the decision maker is. In the case of a nuclear power plant, for example, if the decision maker is the public, one may assume larger costs for accidents, with subjectively assessed large (sometimes infinite) cost of loss of lives and fear. On the other hand, if the decision makers are the managerial personnel in a nuclear power plant, the construction cost may be the dominant cost and the cost of loss of lives will be based on estimates from accidents in other fields. Even though our model can be used by either decision maker, the assessment of accident cost is highly subjective and should be the subject of much thought and discussion.

In this paper we have outlined the basic structure of a decision model and how that structure is interrelated with the forecasting models.

5. Numerical example

In this section, we illustrate a simple numerical example. Let's assume that the rate of accidents follows gamma distribution and the event occurs following poisson process. And also assume that we have reached to the following parameters based on historical data;

$\lambda_0 \sim \Gamma(5,20)$, $\lambda_1 \sim \Gamma(2,20)$, $\lambda_2 \sim \Gamma(1,20)$

We adopt the convention that if a variable λ follows a gamma distribution with parameters α and β, the probability density function is expressed as

$$p(\lambda) = \frac{\beta(\beta\lambda)^{\alpha-1}e^{-\beta\lambda}}{\Gamma(\alpha)}$$

We assume that we have observed 0 severe accident, 1 significant accident, and 3 minor accidents in 10 units of time. In other words, we have observed 4 level 0 accidents, 1 level 1 accident, and 0 level 2 accident. The posterior distributions of accident arrival rates are obtained as in equation (1) and they are also gamma because poisson is a conjugate prior of gamma distribution. Updated parameters are following;

$\lambda_0|\text{Data} \sim \Gamma(9,30)$, $\lambda_1|\text{Data} \sim \Gamma(3,20)$,
$\lambda_2|\text{Data} \sim \Gamma(1,30)$

Predictive distributions are obtained by equation (2) and they become a shifted pareto distribution;

$$p(x|\text{Data}) = \left(\frac{\beta+T}{\beta+T+x}\right)^{\alpha+n} \frac{\alpha+n}{\beta+T+x}$$

If we want the probability of each level of accident in next 10 units of time, we integrate the above equation over time and we get following;

Prob.{level 0 accident in (0,10)} = p_0 = 0.92
Prob.{level 1 accident in (0,10)} = p_1 = 0.58
Prob.{level 2 accident in (0,10)} = p_2 = 0.25

which are equivalent to p_M = 0.92-0.58= 0.34, p_G = 0.58-0.25=0.33, p_S = 0.25, and p_{NO} = 1-0.92 = 0.08. Then we can make a decision that we keep operating if $0.25C_S + 0.33C_G + 0.34C_M$ is less than C_R.

4. Summary

For a given plant design, improved decisions on when to shutdown an existing plant may be obtained by making better predictions of failure rates, by exerting efforts to collect more relevant information or by improving decision making models which put that information to best use. It is important that the models include the value of possible loss of lives and fear along with cleanup, decommissioning, relocation if the decisions derived from the model are to be useful. The decision model we have described enables us to investigate a class of optimal decisions on whether to shutdown or continue operating one period of time. The analysis and decision process is repeated at the end of each period with additional information about new costs and risks.

References

[1] Aitchison, I.R., and Dunsmore, "Statistical Prediction Analysis", Cambridge University Press, 1975.
[2] Chow, T.C., and Oliver, R.M., "Predicting Nuclear incidents", Journal of Forecasting, Vol.7, pp.49-61, 1988.
[3] Evans, N., and Hope, C., "Nuclear Power", Cambridge University Press, Cambridge
[4] NEA Group of Experts, Severe Accidents in Nuclear Power Plants : Report by an NEA Group of Experts. Nuclear Energy Agency, Organization for Economic Cooperation and Development, Paris
[5] Oliver, R.M., and Yang, Heejoong "Bayesian Updating

of Event Tree Parameters to Predict High Risk Incidents", Influence Diagrams, Belief Nets and Decision Analysis, John Wiley and Sons, pp.277-296, 1990.

[6] U.S. Nuclear Regulatory Commission, "Reactor Risk Reference Document", Office of Nuclear Regulatory Research, NUREG-1150, Vol.1-3, 1987.

[7] Yang, Heejoong, "Approximation Method in Bayesian Prediction of Nuclear Power Plant Accidents", Journal of the Korean Institute of Industrial Engineers, Vol.16, No.2, p135-147, 1990.

[8] Yang, Heejoong et.el., "A Bayesian Approach to Prediction of System Failure Rates by Criticalities Under Event Trees", International Journal of Production Economics, Vol.60, pp.623-628, 1999.

[9] Yang, Heejoong, "Forecasting and Deciding When to Shutdown a Nuclear Power Plant to Prevent a Severe Accident" Journal of the Korea Industrial and Systems Engineering, Vol.23, No.55, p25-31, 2000.