A DECISION SUPPORT SYSTEM
FOR THE EVALUATION OF GEOLOGIC EXPLORATION PROGRAMS

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1 Introduction.

Most of the risks in underground construction are either directly or indirectly related to the main underlying random variable: the project's geology. This is particularly true for all the risks associated with the direct construction cost items, such as excavation and support. Uncertainty in predicting geologic conditions often leads to postulating worst conditions and thus to conservatism in design and construction. Research has shown that the designer and the contractor are very sensitive to their perception of what the impacts of such risks may be on their organization (Levitt et al., 1979; Ioannou, 1980, 1984; Qaddumi, 1981). In particular, designers have adopted the strategy of "defensive engineering" or "design conservatism", and contractors have been accused of including large contingencies in their bids, or of resorting to excessive claims litigation over "changed conditions".

A reduction in the currently high cost of underground construction can be achieved by investing in subsurface exploration programs that provide both the designer and the contractor with sufficient geologic information during the preconstruction phase. As of yet, however, the problem of determining the optimal level of investment in exploration has not been resolved. This is also the case for the related problem of determining the configuration of the most effective exploration program given a particular exploration budget. This paper describes the development of a decision support system that can be used for evaluating the merits of different exploration alternatives. This is accomplished by estimating the effect of additional information on design and construction decisions and hence on the total project cost.

2 The Geologic Prediction Model.

Design and construction decisions in tunneling depend on such parameters as rock type, joint density, faulting, joint appearance, degree of weathering, and groundwater characteristics. In defining a set of design-construction options prior to construction, the variability of these parameters has to be taken into account. This can be done

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through the geologic prediction model, the output of which is a probabilistic description of the geologic parameters of interest.

The underlying model of geologic variability is the continuous-space, discrete-state Markov process. This model represents one of the most powerful analytical techniques that have been used to date for the purposes of geologic prediction (Krumbein, 1969; Chan, 1981; Ioannou, 1984; Kim, 1984). In particular, the development of the geologic prediction model is based on the following assumptions:

- It is possible to define a set of geologic parameters which, for all practical design and construction purposes, provide a complete description of a project's geologic conditions. Each of the parameters necessary for the description of geology is associated with an enumerable (as opposed to continuous) domain of feasible values. Since any number of discrete states can be assigned to each parameter, the decision maker can approximate continuous state parameters to any degree of accuracy.[2]
- In the absence of location-specific information linking certain parameter states with particular locations (along the alignment of the project) each of the parameters describing the geology undergoes state transitions (i.e. changes in value in the direction of the project's axis) according to the probability laws of a discrete-state, continuous-space Markov process.
- If strong probabilistic dependencies exist between geologic parameters, then a natural hierarchy must be used to define different Markov processes for the dependent parameters. For example, if the degree of jointing is presumed to be strongly dependent on rock type, then different processes must be defined for rock jointing depending on the prevailing rock type.
- Location-specific observations from additional subsurface exploration are used to update the individual Markov processes for each parameter according to Bayes theorem.

The resulting model has been compared against the following general requirements and has proven to be satisfactory (Chan, 1981; Ioannou, 1984):

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2. Some parameters are naturally discrete (for example, "rock type" can be granite, schist, limestone, etc.) while others are continuous (for example, "joint density" as measured by RQD can be anywhere from 0% to 100%). It is common practice, however, to discretize these parameters (for example, "joint density" may be classified as "severe" or "not severe") a fact that greatly simplifies the mathematical model.

1. Tunnel profiles generated by the model must be compatible with general expectations on the actual profile.

2. The model makes full use of all available information be it general or project-specific.

3. Geologic predictions can be updated as exploration proceeds and more information is gathered.

4. The prediction and updating processes should be capable of including subjective judgment when necessary.

5. The model must be complete. All relevant geologic parameters and the entire ranges of their possible states must be included. Furthermore, it must be flexible enough to accommodate parameters whose importance increases through subsequent exploration.

In its simplest form, and within homogeneous geologic regions, the model treats each geologic parameter as an independent random process with a single-step memory. Thus, the a priori description for each process is based on two parameters: P_{ij} = probability of entering state j when a transition is made out of state i, and the so-called transition intensity coefficients c_i. The latter are easier to understand if one considers that under the Markovian assumption of single-step memory, the state extents (i.e. the lengths of tunnel within which a geologic parameter occupies a particular state i) follow an exponential distribution with parameter c_i. Thus, c_i = average extent of state i.

The transition intensity coefficients and the transition probabilities for each geologic parameter can be estimated by either statistical or judgmental procedures. A complete description of these techniques, as well as a discussion of how to handle differences in the opinions of several experts, is beyond the scope of this paper and can be found elsewhere (Chan, 1981). However, it must be pointed out that an attractive feature of this probabilistic method for geologic prediction is that it can make explicit use of information that is not specific to the project site. Thus, information about the geology from nearby locations or from geologic maps can readily be used for estimating the initial Markov process parameters.

In addition to general information, which basically describes the geology in the greater vicinity of the project, the geologic prediction model makes use of location-specific information. The latter is usually in the form of observations from exploration programs. Depending on the exploration method used and the geologic parameter being examined, these observations may be deterministic in nature (for example, "the rock type 500 ft. ahead of the tunnel portal is schist") or they may lead to probabilistic assessments. In the latter case, one may use direct encoding of subjective judgment to make a posterior statement about the parameter state probabilities (for example, "the rock type 700 ft. away from the tunnel portal is granite with probability 0.8 or quartzite with probability 0.2") Alternatively, one can use the likelihood function (reliability matrix) associated with the method providing the observation to compute the posterior parameter state probabilities using Bayes theorem and the parameter state probabilities of the Markov process. The limiting state probabilities of the latter, of course, serve as the vague prior.

Apart from philosophical issues, the main difference between the two procedures is that the first requires the use of an expert geologist every time a new observation is made available, whereas the second can be automated as a computer routine. In the process of evaluating future exploration programs, however, it is necessary to update the parameter state probabilities based on a large number of simulated observations; thus, the former approach is practically infeasible. As a result, the geologic prediction model updates the parameter state profiles and the interval transition probabilities by applying Bayes theorem to the corresponding probabilities of the Markov processes (the prior) using the reliability matrices associated with the available observations.

3 The Design-Construction Model.

The objective of this model is to transform the updated probabilistic geologic parameter profiles into a predicted sequence of design-construction alternatives. This transformation must reflect:

1. The existing level of geologic uncertainty, which is a function of the available geologic information.
2. The conservatism (risk aversion) traditionally exhibited by the engineer and the contractor based on the amount of risk they have to bear.

To satisfy these requirements the design-construction model employs the concepts of "ground classes" and the "threshold probability".

Ground classes have been extensively used in tunneling for describing the ground characteristics pertinent to the design and construction of underground structures (Einstein et al., 1983; Chan, 1981; Ioannou, 1984; Kim, 1984; Deere et al., 1969). The underlying ideas behind this concept are:

1. The ground at a particular location can be adequately described by a set of geologic parameter states (a

"geologic vector"); the number of parameters and the number of (discrete) states for each parameter can be arbitrarily large, depending on the geology and the desired modelling accuracy.

2. There exists a finite set of design-construction methods (excavation and support combinations) CM_i (i=1,...,n) of which at least one (i.e., CM_n) is adequate for the construction of every possible set of geologic conditions within the extent of the project at hand. These methods can be arranged according to their cost in such a way that a more expensive method can be used in all the geologic conditions for which a less expensive method is adequate. In other words, the least expensive design-construction method CM_1 can always be substituted by $CM_2,...,CM_n$, whereas CM_n cannot be substituted by any other method.

3. A ground class GC_i (i=1,...,n) is defined as a collection, or set, of geologic vectors that describe all the possible geologic conditions for which the adoption of design-construction method CM_i is the most economical alternative.

It is clear from this definition that ground classes provide the link between the states of geologic parameters and the possible design-construction methods that may be possibly adopted.

Furthermore, it should also be clear that the transformation from geologic parameter vector profiles to ground class profiles is quite straightforward. The parameter vector profiles express the probability that the geologic parameters jointly assume a particular combination of states along the alignment of the tunnel. If the parameters are assumed to be independent, then this is simply the product of the individual parameter state probabilities. Thus, at each point along the tunnel there exists a joint state probability for each vector. The sum of these probabilities for all the vectors belonging to the same ground class yields the ground class state probability at that point. This process can be repeated for all ground class states and all points to obtain the complete ground class profile. The latter simply expresses the likelihood that the ground will be in a particular ground class (state) at each point along the tunnel.

The next step involves the transformation of a ground class probabilistic profile into a sequence of design-construction methods. This step is necessary in order to predict the impact of additional exploration on design and construction and the resulting consequences on project cost. The main problem, however, is that it is virtually impossible to predict the decision making behavior of the designer and/or the contractor under conditions of uncertainty by using a prescriptive model of rational behavior. Describing the geology in probabilistic terms is not enough; one has to also take into account:

- How the consequences of the geologic risk are shared between the project participants (owner, designer, contractor); this primarily depends on the spirit and wording of the design and construction contracts, as well as on the owner's reputation for dealing with such matters in the past.

- The relative magnitude of the risk consequences depending on the type, size and location of the project.

- The designer's and contractor's attitudes towards risk depending on firm size, reputation, work backlog, availability of other projects, the desirability of the project at hand, general economic conditions, market penetration strategies, etc.

Furthermore, a "prescriptive" model would require that the owner entity bearing the cost of preconstruction exploration, should also have the technical capability of predicting design and construction decisions, which is not usually the case. The most efficient and realistic method for bypassing these problems is for the owner to make use of the engineer as a design-construction expert and adopt a model that "describes" rather than "prescribes" how designers and contractors make decisions. The model presented below is based on the findings of previous research in this area (Qaddumi, 1981; Ioannou, 1980; 1984) and uses the concept of hypothesis testing.

From the definition of ground classes it is apparent that there is some non-zero probability for any ground class to exist at any location along the alignment of a project. Using the ground class numbering convention above, and assuming that n ground classes (corresponding to n design-construction methods) have been defined, ground class 1 (i.e., GC_1) represents the most favorable geologic conditions that may be encountered, whereas ground class n (i.e., GC_n) represents the most adverse conditions. As a result, if a particular design-construction method CM_i is chosen for a certain segment of a project, there is some finite probability that this method may in fact prove to be inadequate. The only exception to this rule is the most conservative and hence most expensive design-construction method CM_n. Since the latter cannot always be specified for the whole length of the work, the choice of design-construction methods can be considered as a typical example of a "calculated risk".

To this effect, the designer (acting as the owner's expert representative) sets up the null hypothesis that method i is indeed adequate. The alternative hypothesis, of course, is that method i is inadequate and that a more conservative method has to be used:

Null Hypothesis H_0: Method i is adequate.

Alternate Hypothesis H_1: Method i is inadequate.

The typical decision rule used in hypothesis testing is the following:

Decision Rule: Reject the null hypothesis in favor of the alternate if, based on the information available (i.e., the observations provided from a subsurface exploration program), the probability of making a Type I Error is more than "alpha", "the level of significance".

In this case, however, making a Type I Error merely implies excessive conservatism, because rejecting the null hypothesis automatically means that a more conservative method will be considered. Making a Type II Error is much more serious, because it defeats safety by accepting the null hypothesis that method i is adequate when in reality a more conservative method should be used. The probability of a Type II Error is commonly known as "beta" = the "threshold probability".

As a result, the above decision rule should be modified to reflect the importance of the Type II Error:

Decision Rule: "At any point along the alignment of the tunnel, use the least conservative method whose probability of being inadequate, based on the available information, is less than the acceptable threshold probability."

From an operational point of view, the application of the threshold probability rule can be best illustrated using the example ground class cumulative profile in Figure 1. Each curve in this figure corresponds to a particular ground class i and represents the probability that the true ground class is at least as favorable as class i. For example, at location t_o there is a 0.88 probability that the true ground conditions are at least as favorable as ground class 2; this simply equals the sum of the state probabilities for classes 1 and 2 at that location. By definition, this figure also gives the probabilities that CM_i (i=1,2,3) are adequate; for example, the probability that CM_2 is adequate at location t_o is also 0.88. The complement of the cumulative profile gives the probability that CM_i (i=1,2,3) is inadequate. If a horizontal line is drawn below the top of the cumulative profile, at a distance equal to the threshold probability, one immediately gets the least conservative acceptable sequence of design-construction methods as defined by the the points of intersection of the threshold probability line and the ground class curves. This sequence represents the expected design and construction decisions as a function of the threshold probability.

The determination of the threshold probability, however, is not a trivial or intuitive task. For this reason, the designer is not required to provide a blind input of this parameter; instead, color graphics are used to portray the computed ground class profile, thus permitting experimentation with different levels of conservatism. For each level of the threshold probability the corresponding sequence of design-construction methods is computed and presented in graphics form. The objective of this interaction is to allow the user to specify a threshold probability that reflects his own philosophy and risk preference. This step is a fundamental requirement for the general acceptance of the system by practicing engineers; it is also the main feature that distinguishes a decision-support system from an optimization model.

On the other hand, the threshold probability must not be based exclusively on the designer's risk exposure and risk attitude. Under current practice, the designer usually serves as the specifications writer for the owner-contractor contract. Thus, it is not uncommon for the designer to possess information relevant to the contractual sharing of risk between the owner and the contractor. This information must be used in specifying the threshold probability so that it also reflects the contractor's exposure and behavior under risk. Because of their strong dependence, the interaction between design and construction decisions cannot be directly modelled since it involves the conditional prediction of behavior which cannot be easily quantified and for which there are no objective data.

On the basis of the above discussion and for the purposes of developing a decision support system for the evaluation of exploration, the threshold probability rule enjoys certain advantages over other more "formal" decision models (for example, stochastic dynamic programming (Howard,1960; Kim, 1984)):

1. It eliminates the necessity to predict the designer's decisions without considering the latter's reaction to contractual and financial liability by allocating this task to the most appropriate party (the designer).

2. It models the conditionality between design and construction decisions, which cannot be predicted a priori without considering the specific characteristics of the project, both technical and contractual.

3. It permits the development of a system that does not force the designer or the owner into evaluating exploration by assuming that design and construction decisions are simply based on expected cost minimization. Formal models (like stochastic dynamic programming) cannot readily account for the defensive strategies associated with underground design

and construction. In contrast, the threshold probability rule can be used to evaluate exploration according to the personal preferences of the entities involved, taking into account the adopted risk sharing approach as implemented in both the design and construction contracts - the behavioral effects of which cannot be predicted by other means.

4 The Cost Model.

The objective of the cost model is to produce an estimate of the project cost given the sequence of design-construction methods predicted by the threshold probability rule. This is accomplished by a second order approximation which computes the mean and variance of the following cost function:

$$C = a + \sum_{i=1}^{n} b_i + \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} f_{ij} + \sum_{i=1}^{n} \sum_{k=1}^{m_i} d_{ik} w_{ik} + \sum_{i=1}^{n} \sum_{k=1}^{m_i} \frac{e_{ik}}{r_{ik}} w_{ik}$$

Where:

n : the number of construction methods CM_i considered.

m_i : the number of segments in which CM_i is used.

w_{ik} : the extent of the k^{th} segment in which CM_i is used.

a : fixed cost, independent of the construction methods used.

b_i : fixed cost uniquely associated with the use of CM_i.

c_{ij} : cost of change from CM_i to CM_j.

f_{ij} : the number of times CM_j follows CM_i.

d_{ik} : the cost per foot of using CM_i in segment k.

e_{ik} : the time dependent cost of using CM_i in segment k.

r_{ik} : the advance rate when using CM_i in segment k.

The policy-dependent variables corresponding to the specified threshold probability and the current (posterior) ground class profile are f_{ij} and w_{ik}. The rest of the necessary input, i.e. the cost and performance parameters presented above, can be easily provided by the designer with little additional effort since most of the required unit costs are also necessary for preparing the engineer's estimate. In addition to the expected value of these variables, however, the designer must also specify the variance of their distribution. This can be accomplished through statistical analysis of existing data or direct encoding of the mode, and the 5 and 95 percentiles using subjective judgment.

The cost model along with the geologic prediction and design-construction models represent the basic components of the estimating system that links the amount of available geologic information to the final cost of a project.

5 The Evaluation of Exploration Programs.

The models presented above illustrate the basic methodology for estimating the expected value and the variance of project cost as a function of the already available geologic information. This section describes how the same basic models can be integrated into a simulation system for evaluating future exploration programs.

In order to evaluate a future exploration program the evaluation model uses Monte Carlo simulation to create a sufficient number of sets of "artificial" observations, where each set represents a possible outcome of the proposed exploration. Each set of simulated observations consists of one observation for each geologic parameter and for each location where exploration will be conducted. The alternative to simulation is to use event trees and the traditional decision analysis methodology for the evaluation of sampled information. This approach, however, requires the complete enumeration of all possible combinations of observation states, for all parameters and for all observation locations. For example, if the geologic model includes 3 parameters, each having 4 observation states, and the proposed exploration program consists of sinking 15 boreholes, then the number of combinations that must be considered is $3*4^{15}=3,221,225,472$. It is obvious from the magnitude of this number that direct enumeration is not a viable alternative even for seemingly simple cases. Simulation is the only methodology that can be successfully employed.

The necessary input to the evaluation model consists of:

- A list of locations along the project alignment where observations will be made,

- The reliability matrices of the methods to be employed, and

- The specification of which method will be used at each location and for each geologic parameter.

This input is used to generate artificial observations at each location by performing Monte Carlo sampling on the inverse cumulative observation state probability profiles. These profiles are easily generated by applying the Total Probability Theorem to the updated geologic parameter profiles produced by the geologic prediction model and the reliability matrices associated with the methods employed by the proposed exploration program. The geologic parameter profiles used for this purpose, are already updated to reflect the findings of previous ("actual") exploration; they also constitute the "prior" which must be updated for each set of simulated observations using the geologic prediction model.

For each set of simulated observations the three previous models are repeated in order to:

- Update the parameter geologic profile and the ground class profile,

- Determine a new sequence of design-construction methods (using the already established threshold probability), and

- Produce an estimate of the corresponding expected value and variance of the project cost.

By simulating a number[3] of observation sets enough data points can be generated to produce a reliable estimate of the expected value and variance of the project cost under the assumption that the proposed exploration program is indeed undertaken.

The cost estimates provided by the simulation model are then used to compute the expected value of sampled information (EVSI) of the exploration program. If the owner is a risk-neutral decision maker, then the EVSI is equal to the difference between the expected cost of the work with and without the proposed exploration minus the cost of conducting the investigation. If the decision maker is risk averse, then the model results can be used for constructing a simple decision tree showing the owner's two alternatives: to adopt, or to reject the proposed exploration program. Since the terminal monetary outcomes of either decision can be readily computed using the described models (at least in a mean-variance form) it is quite easy to apply the concepts of Utility Theory and compute the EVSI taking into account the owner's attitude towards risk.

Given this analysis an exploration program is considered acceptable if it has a positive EVSI; furthermore, it is considered optimal if it has the highest EVSI among all

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3. The number of simulations depends on the required accuracy of the estimates, which is typically quantified by specifying the desired width of confidence intervals around the estimate.

acceptable alternatives.

6 An Example Application.

The previous models for the evaluation of subsurface exploration have been implemented as a computerized decision support system called EVGE (Expected Value of Geologic Exploration). This system runs on a DEC VAX 11-780 using a DEC GIGI color graphics terminal.

This section presents an example application of this system for the discharge water tunnel project of the Seabrook Power Station, NH (Ioannou 1984; Rand, 1974; GEI, 1974). The actual discharge tunnel is over 15,000 ft. long. Only the western portion from boreholes ADT-1 (t=0 ft.) to ADT-42 (t=7662 ft.) are used in this example (Figure 2). The exploration program being considered is a pilot tunnel running the full length of this portion.

Four geologic parameters are used to describe the tunnel characteristics: Rock Type, Joint Density (RQD), Degree of Weathering and Availability of Water. An estimated profile for rock type for this project is shown in Figure 3. A detailed description of the regional geology can be found elsewhere (Rand, 1974). The definition of states for these parameters are shown in Table 1. On the basis of available information the transition intensity coefficients and the transition probabilities for each parameter were directly encoded using a geologist's expert judgment (Table 2).

Although no frequency data were available for estimating the necessary Markov process parameters for this project, there were several point observations obtained from boreholes along the tunnel axis. The observed parameter states and the reliability of these observations are shown in Tables 3 and 4. Based on the above data the geologic prediction model produced the parameter profiles shown in Table 5.

Five design-construction alternatives were identified as suitable for the construction of this project (Table 6). Table 7 shows the definitions of the corresponding five ground classes in terms of the geologic parameter states. The resulting ground class profiles computed from the output of the geologic prediction model are shown in Figure 4. Figure 5 shows the complement of the corresponding cumulative ground class profile and an example application of the threshold probability rule.

During an actual session with the system these profiles are shown in color graphics on the GIGI terminal. This permits the designer to check the validity of the geologic prediction produced by the system using his own subjective expectations; furthermore, he can also experiment with different levels of the threshold probability by comparing the resulting sequence of design-construction methods shown on the screen against his own judgment.

The unit costs and production parameters used for estimating the cost of the project are shown in Table 8. Table 9 shows the resulting cost estimates for different levels of the threshold probability.

For the purposes of this example the pilot tunnel being evaluated as an exploration alternative was assumed to provide observations with perfect reliability. Furthermore, the continuous observations provided by the pilot tunnel were discretized and assumed to occur every 300 ft. The resulting estimates of project cost using 100 simulated sets of the pilot tunnel observations are shown in Table 9.

The difference between the expected value of the work with and without the pilot tunnel represents the upper limit for the cost of constructing the pilot tunnel, if it is to be an acceptable alternative. As expected, the value of the pilot tunnel decreases as the acceptable threshold probability increases (and hence the conservatism in design and construction decreases). This is an illustration of the fact that the effectiveness of risk sharing and risk reduction are closely interrelated. If most of the risks are borne by the designer and the contractor, the resulting conservatism might make the construction of a pilot tunnel an acceptable investment. On the other hand, if the owner assumes a significant portion of the risk, the resulting decrease in conservatism could very well make the pilot tunnel unattractive due to its high cost.

7 Conclusion.

The development of the models described in this paper and their integration in a decision support system (EVGE) allow - for the first time - the rational evaluation of subsurface exploration programs. The proposed system provides the owner entities of underground projects with the capability to quantify the benefits of exploration by reducing the defensive strategies of design conservatism and excessive construction contingencies typically employed by designers and contractors in the US. Even though this system cannot be used to identify the globally optimal exploration alternative, it represents a major improvement over current practice and its further development and use should eventually help decrease the high cost of underground construction in this country.

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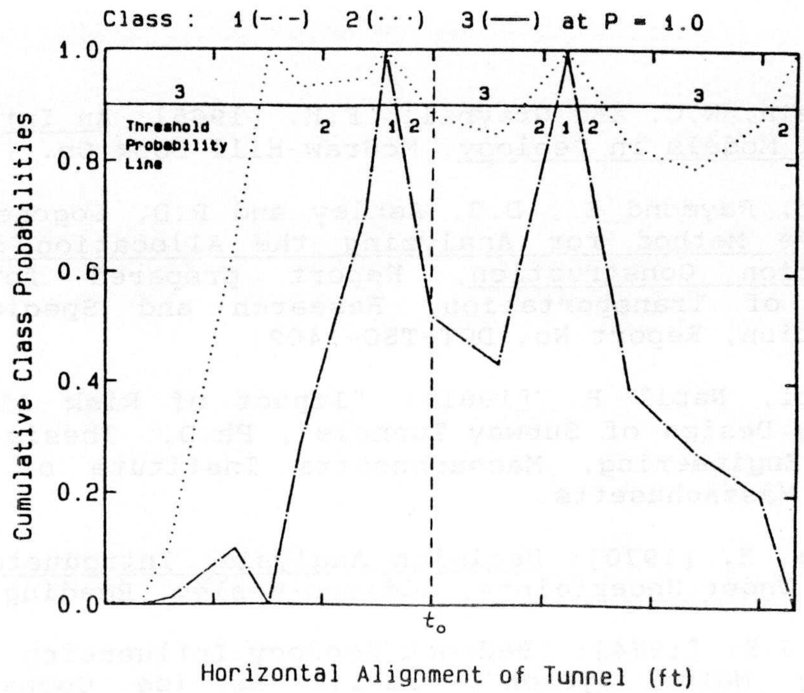

Figure 1: The Cumulative Form of the Ground Class Profile
And the Application of the Threshold Probability.

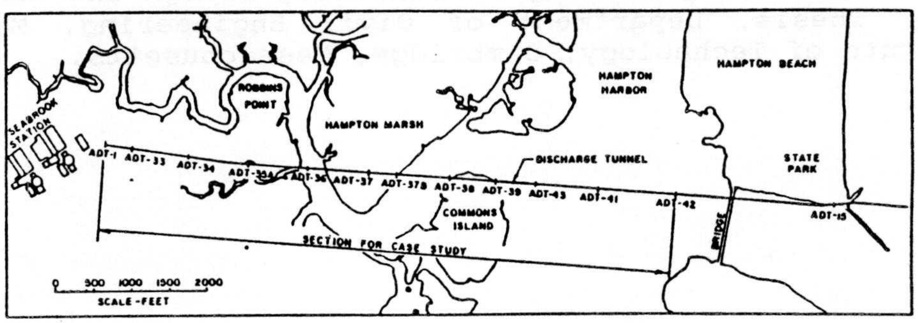

Figure 2: Seabrook Power Station Discharge Water Tunnel.

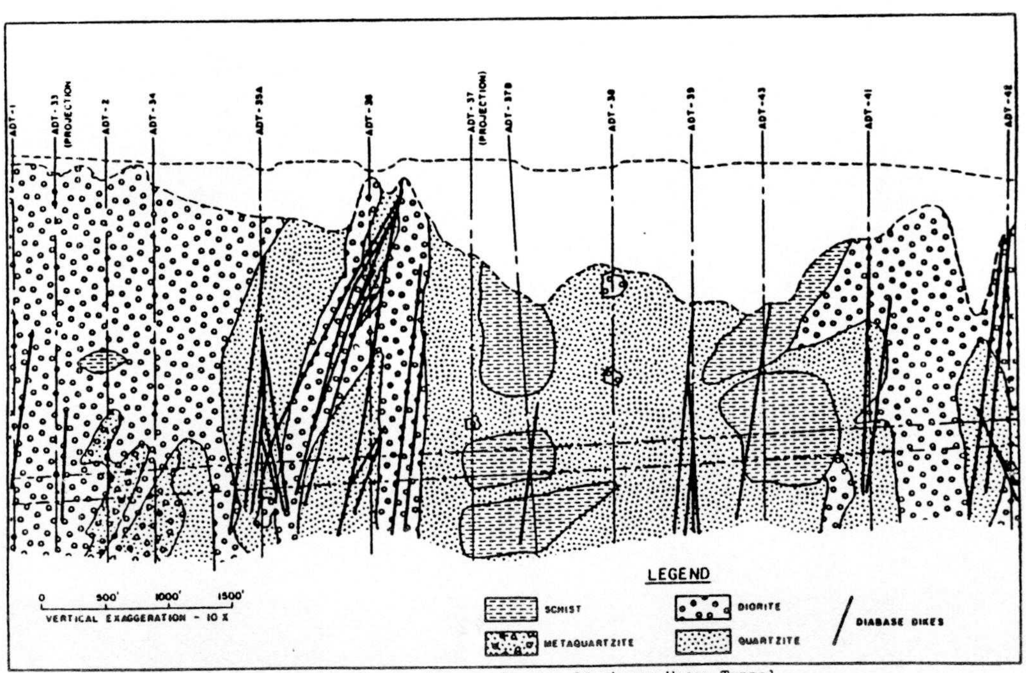

Figure 3 : Seabrook Power Station Discharge Water Tunnel.
Estimated Rock Type Profile (Chan, 1981).

(a) Rock Type (R)

r	Definition
1	Schist
2	Metaquartzite
3	Diorite
4	Quartzite

(b) RQD (D)

d	Definition
1	High 75-100%
2	Medium 25-75%
3	Low 0-25%

(c) Degree of Weathering (E)

e	Definition
1	Not Severe
2	Severe

(d) Availability of Water (W)

w	Definition
1	Low
2	Medium
3	High

Table I: Definition of Parameter States.

i \ j =	1	2	3	4	c_{Ri}
1	.00	.02	.23	.75	.00138
2	.02	.00	.50	.48	.00822
3	.02	.20	.00	.78	.00262
4	.23	.17	.60	.00	.00250

Table 2 : Transition Probabilities (first 4 columns) and Transition Intensity Coefficients for R.

Bore-hole	t (feet)	State Observed R	D	E	W
1	0	3	2	1	1
33	341	3	1	1	1
2	717	3	1	1	1
34	1239	2	2	1	3
35A	1945	4	2	1	3
36	2788	4	3	2	1
37	3566	1	2	2	3
37B	4010	1	3	2	3
38	4659	4	3	2	1
39	5256	4	1	1	2
43	5785	1	1	1	1
41	6604	3	1	1	1
42	7662	4	1	1	1

Table 3 : States Observed at Each Location.

s_R \ b_R =	1	2	3	4
1	.85	.05	.05	.05
2	.05	.85	.05	.05
3	.05	.05	.85	.05
4	.05	.05	.05	.85

s_D \ b_D =	1	2	3
1	.90	.05	.05
2	.05	.85	.10
3	.00	.05	.95

s_E \ b_E =	1	2
1	.95	.05
2	.05	.95

s_W \ b_W =	1	2	3
1	.95	.05	.00
2	.05	.90	.05
3	.00	.05	.95

Table 4 : Likelihood (Reliability) Matrices.

PROBABILITY PROFILE OF X1 (ROCK TYPE)

IP	RL	1	2	3	4
1	0.0000E+00	0.000	0.000	1.000	0.000
2	0.3000E+03	0.001	0.013	0.948	0.038
3	0.3410E+03	0.000	0.000	1.000	0.000
.	.	.	.	.	.
37	0.7500E+04	0.045	0.036	0.204	0.715
38	0.7662E+04	0.000	0.000	0.000	1.000

PROBABILITY PROFILE OF X2 (JOINT DENSITY)

IP	RL	1	2	3
1	0.0000E+00	0.000	1.000	0.000
2	0.3000E+03	0.874	0.114	0.012
3	0.3410E+03	1.000	0.000	0.000
.	.	.	.	.
37	0.7500E+04	0.772	0.191	0.038
38	0.7662E+04	1.000	0.000	0.000

PROBABILITY PROFILE OF X3 (DEGREE OF WEATHERING)

IP	RL	1	2
1	0.0000E+00	1.000	0.000
2	0.3000E+03	0.993	0.007
3	0.3410E+03	1.000	0.000
.	.	.	.
37	0.7500E+04	0.950	0.050
38	0.7662E+04	1.000	0.000

PROBABILITY PROFILE OF X4 (AVAILABILITY OF WATER)

IP	RL	1	2	3
1	0.0000E+00	1.000	0.000	0.000
2	0.3000E+03	0.984	0.010	0.006
3	0.3410E+03	1.000	0.000	0.000
.	.	.	.	.
37	0.7500E+04	0.910	0.045	0.044
38	0.7662E+04	1.000	0.000	0.000

Table 5: Geologic Parameter Profiles.

CM	EXCAVATION-SUPPORT METHOD
1	Full face drill and blast. No support.
2	Full face drill and blast. Conventional steel sets. Amount of support: medium.
3	Heading and bench drill and blast. Conventional steel sets. Amount of support: medium.
4	Heading and bench drill and blast. Conventional steel sets. Amount of support: large.
5	Multiple drift drill and blast. Conventional steel sets. Amount of support: large.

Table 6 : Generalized Construction Methods Corresponding to Defined Ground Classes.

G	r	d	e	w
1:	1,2,3	1	1	1,2
2:	4	1	1	1,2
3:	1,2,3,4	2	1	2
	1,2,3,4	2	1	1
4:	1,2,3,4	3	1	3
	1,2,3,4	2	1	3
	1,2,3,4	1	1	3
	1,2,3,4	3	1	2
	1,2,3,4	3	1	1
5:	1,2,3,4	3	2	1,2,3
	1,2,3,4	2	2	1,2,3
	1,2,3,4	1	2	1,2,3

Table 7 : Ground Class Classification Table.

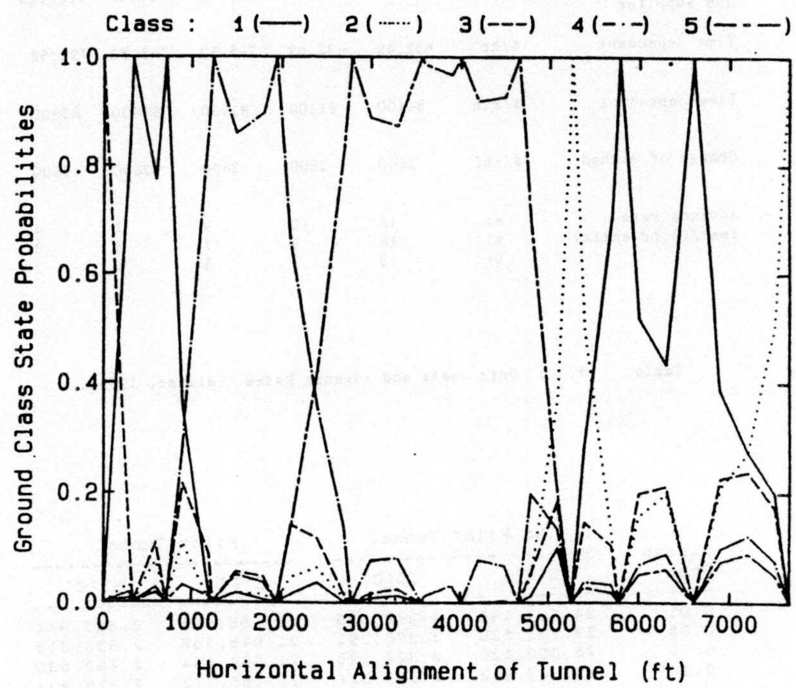

Figure 4: Ground Class Profile (All Classes)

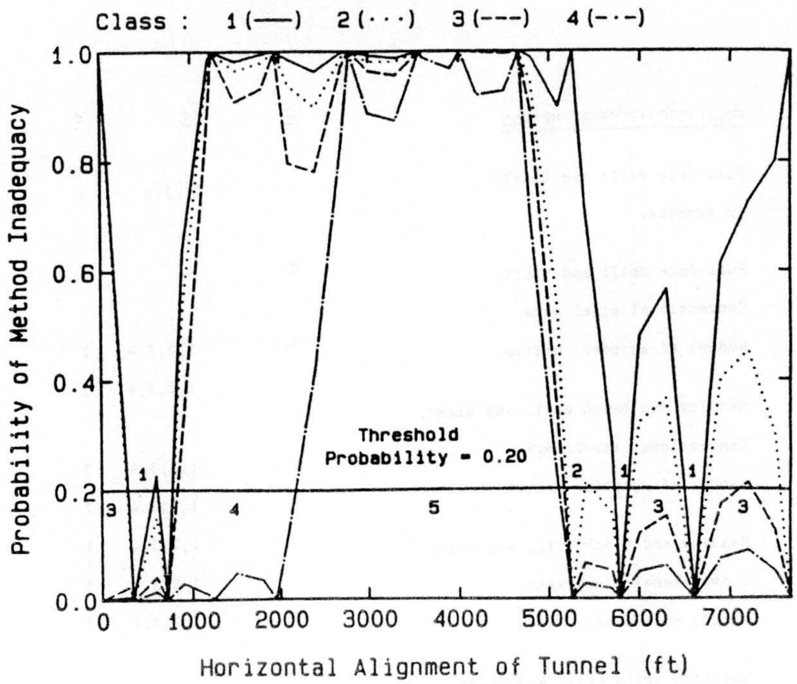

Figure 5: Probability of Design-Construction Method Inadequacy.

		CM1	CM2	CM3	CM4	CM5
Fixed Costs	$	1265800	1265800	1610900	1630400	1936900
Permanent Materials and Supplies	$/ft	112.79	219.24	307.21	811.15	1186.23
Time dependent	$/hr	632.49	632.49	745.52	745.52	793.52
Time dependent	$/mth	81100	81100	81900	81900	85200
Change of method	$/shf	2600	2600	2600	2600	2600
Advance rate feet/(8 hr shift)	a:	18	10	9	7	4
	m:	16	8	7	5	3
	b:	13	7	5	4	2

Table 8 : Unit Costs and Advance Rates (Salazar, 1983).

Thresh. Prob.	No Pilot Tunnel E[C]	SD[C]	Pilot Tunnel E[C]	SD[C]
0.01	34,467,148	4,848,535	22,155,656	2,583,944
0.05	29,231,520	3,376,091	21,945,368	2,538,318
0.10	25,003,520	2,322,125	21,682,494	2,482,630
0.20	22,347,852	2,145,024	21,156,772	2,375,934

Table 9: The Expected Value and the Standard Deviation Of Project Cost As a Function of the Threshold Probability.