# Evaluation of Subsurface Exploration Programs

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**Abstract:** This paper presents a decision support system for the evaluation of geologic exploration programs in underground construction. This system can be used to quantify the economic value of different subsurface investigation alternatives, and it provides owners and designers with a solid basis for making the associated technical and financial decisions. The description of the system includes the methodology for encompassing all the existing geologic information about a site in a consistent geologic-prediction model that can be used for design, and construction, planning and estimation. It illustrates how to account for the context and reliability of this information, how to predict its effect on design and construction decisions, and how to arrive at a monetary measure of its value. Finally, it describes the methodology for using simulation to arrive at an estimate of the expected value and the standard deviation of the value of sampled geologic information. The evaluation of a pilot tunnel as an exploration alternative for the water discharge tunnel of the Seabrook Power station is presented as an example application.

## Introduction

Geologic uncertainty is the primary source of risk in underground construction, often leading to the assumption of the worst possible ground conditions and, thus, to inflated costs. Significant savings are possible by reducing design and construction conservatism, and by selecting tunnel excavation and support based on the expected geologic conditions to be encountered during construction.

Geologic exploration is the most effective risk reduction strategy available to owners, during the preconstruction phase, for reducing the effects of geologic uncertainty on project cost. Often, however, it is not obvious what the optimal level of investment in exploration should be, or how these funds should be used to acquire additional geologic information. As a result, the amounts allocated to exploration are typically less than what they should be.

This paper describes a decision support system for the evaluation of geologic exploration programs in underground construction, which can be used to quantify the economic value of different subsurface investigation alternatives. The purpose of this system is to provide owners and designers with a solid framework for making the associated technical and economic decisions.

## System Overview

A decision support system is a computer-based system that facilitates decision making in an interactive mode through man-machine interaction. Well-known examples are simulation systems, such as SIMAN, STELLA, GPSS, etc. Decision support systems should be distinguished from optimization sys-

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tems. The latter are used to produce "optimal" decisions directly, based on a set of input data that describe the objective and the constraints of the problem. They are limited to problems for which a solvable formulation does exist, and their effectiveness depends on how well the objective and the constraints can capture all the relevant factors that influence the optimality of the solution. In contrast, decision support systems exploit the decision-maker's ability to use human judgment and experience to manually guide the search, to employ heuristics, to explore new alternatives, to perform sensitivity analysis, to look for improvements to existing solutions, etc. Hence, decision support systems are typically large, multifaceted programs that are applied to the most difficult and complex problems.

The proposed system includes four major models (technical terms are explained in subsequent sections of this paper) whose function can be summarized as follows:

1. The geologic prediction model is based on the premise that, within homogeneous regions, the spatial variability of geotechnical parameters, such as rock type, joint density, etc., can be described by discrete-state continuous-space Markov processes. The parameters of these processes are based on expert knowledge about geologic formations and general site observations. Location-specific information reflecting the findings of already undertaken exploration programs is used to update the resulting Markovian processes, based on the reliability of the methods used. The output of the geologic prediction model is a probabilistic geologic parameter vector profile, which incorporates all the subjective and objective information available.

2. The design-construction model uses the concept of design-construction ground classes to aggregate the probabilistic geologic vector profiles of the geologic prediction model into ground class profiles. The underlying concept is that many combinations of geologic parameter states require the same combination of design-construction methods. The resulting ground class profile describes the ground class state probabilities as a function of location along the project axis. The choice of design-construction methods is based on the concept of the "threshold probability," which uses a variation of hypothesis testing to capture the conservatism traditionally associated with decision-making under uncertainty in underground construction.

3. The cost estimating model uses the sequence of design-construction methods chosen using the preceding model. The probabilistic cost model uses a second-order approximation to provide an estimate of the mean and variance of the project cost. These estimates associate a given level of geologic information with a dollar value on the cost of the work, and are the final output of the system's first stage.

4. The exploration evaluation model estimates the mean and variance of the project cost under the assumption that a proposed exploration program is indeed undertaken. This model integrates the three preceding models and uses simulation to generate and evaluate sets of future observations from the proposed program. These become the input for updating the geologic prediction model based on the reliability of the exploration methods to be employed. The resulting profiles of geologic parameter vectors are transformed into ground-class profiles, which in turn are used to predict the expected sequence of design-construction methods and the associated project cost. Finally, the cost results from repeated simulations of future observation sets are used to estimate the distribution and

the first two conditional moments of the project cost associated with the proposed exploration program.

The models described above have been implemented as a computer-based decision support system (EVGE) that can be used for comparing the effectiveness of alternative exploration programs of different costs, spatial configuration, and reliability. This system allows the efficient use of funds to reduce geologic uncertainty and its cost-inflating impact on underground construction. The models can also be used in stand-alone decision support systems for the design, construction planning and estimating of underground facilities. An example application of this system is presented at the end of this paper.

## 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, it is necessary to account for the spatial variability of these parameters along the tunnel alignment. This is the purpose of the geologic prediction model, the output of which is a probabilistic description of the geologic parameters of interest.

The geologic prediction model presented in this paper is based on the discrete-state, continuous-space Markov process. Its basic assumptions can be summarized as follows (Ioannou 1984; Chan 1981):

1. It is possible to define a set of geologic parameters (such as rock type, joint density, faulting, joint appearance, degree of weathering, permeability, etc.) which—for all practical design and construction purposes—provide a complete description of a project's geologic conditions. Each of these parameters is associated with an enumerable set of feasible values (states). Any number of feasible states can be assigned to each parameter to approximate continuous variables (such as joint density) to any degree of accuracy.
2. In the absence of location-specific information (e.g., information from boreholes) linking certain parameter states to particular locations, each of the parameters describing the geology undergoes state transitions along the tunnel alignment, according to the laws of the discrete-state, continuous-space Markov process. The distribution parameters defining the Markov process for each geologic parameter are estimated based on general geologic information.
3. Location-specific observations on parameter states obtained from exploration programs are used to update the geologic parameter state predictions of the underlying 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):

1. Tunnel profiles generated by the model are compatible with general expectations on the actual profile.
2. The model makes full use of all available information, be it general or location-specific.





J. Constr. Eng. Manage., 1989, 115(3): 339-356

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

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

5. The model is complete. All relevant geologic parameters and the entire ranges of their possible states can be included. Furthermore, it is 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 a Markov process. A Markov process is a random process with single-step memory, described by two sets of parameters: The transition probabilities $P_{ij}$ and the transition intensity coefficients $c_i$. The transition probabilities $P_{ij}$ express the probability of entering state $j$ when a transition is made out of state $i$. The transition intensity coefficients $c_i$ 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, $c_i = 1/$(average extent of state $i$).

The estimation of the parameters $P_{ij}$ and $c_i$ can be accomplished by either statistical procedures or direct subjective assessment. The applicability of statistical methods is obviously dependent on the form and amount of available data. For example, if geological maps of the project area are available, then the parameters $c_i$ can be estimated by computing the inverse of the average extent of each state, and $P_{ij}$ can be estimated by drawing a set of lines parallel to the tunnel alignment—spaced far apart to avoid a strong dependence between them—and computing the frequency of geologic parameter state transitions. 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 (Ioannou 1984; Chan 1981; Ashley et al. 1981; Spetzler 1972). However, it must be pointed out that an attractive feature of the 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 be readily used for estimating the initial parameters of the Markov process.

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. This is usually in the form of observations from exploration programs, such as borehole drilling. Depending on the exploration method used and the geologic parameter being examined, these observations may be deterministic in nature, or they may lead to probabilistic assessments. In the latter case, one may use direct subjective encoding 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 (reliability) matrix associated with the observation method and the prior parameter state probabilities of the Markov process to compute the posterior parameter state probabilities using Bayes theorem. The





J. Constr. Eng. Manage., 1989, 115(3): 339-356

limiting state probabilities of the initial Markov process serve as the vague prior.

Apart from philosophical issues, the main difference between the two approaches is that the first requires the use of an expert geologist every time a new observation is made available, whereas the second can be programmed into a computer procedure and thus be automated.

In the model for the evaluation of future exploration programs, it is necessary to update the parameter state probabilities based on a large number of simulated observations. As result, the geologic prediction model for the evaluation system uses the likelihood method because the direct encoding approach is practically infeasible. This method updates the parameter state profiles and the interval transition probabilities by applying Bayes theorem to the corresponding prior probabilities of the Markov processes using the reliability matrices associated with the available observations to produce updated geologic parameter profiles that reflect all the available information. A detailed discussion of the mathematical formulation for this model is presented elsewhere (Ioannou 1987, 1984; Chan 1981).

## 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 geology information.
2. The conservatism traditionally exhibited by the engineer and the contractor, which primarily depends on their risk exposure and risk aversion.

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

Ground classes have been used extensively in tunneling to describe the ground characteristics pertinent to the design and construction of underground structures (Einstein et al. 1983; Chan 1981; Ioannou 1984; Kim 1984; Vick 1974). The definition of ground classes is based on the following underlying concepts:

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 modeling accuracy.
2. There exists a finite set of design-construction methods (excavation and support combinations) $CM_i$ ($i = 1, \ldots, g$) that may be used in a particular project. Of these, at least one ($CM_g$) is adequate for the construction of every possible set of geologic conditions that may be encountered within the extent of the project. 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 $CM_2, \ldots, CM_g$, whereas $CM_g$ cannot be substituted by any other method.
3. A ground class $gc_i$ ($i = 1, \ldots, g$) 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 and feasible 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 possibly be adopted. This 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. Thus, at each point along the tunnel, there exists a joint state probability for each vector. If the parameters are assumed to be independent, then this is simply given by the product of the individual parameter state probabilities. 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 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 decisions and the resulting consequences on project cost. The problem, however, is that it is virtually impossible to predict the decision-making behavior of the designer 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 the following:

1. How the consequences of the geologic risk are shared between the project participants (owner, designer, contractor). This 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.
2. The relative magnitude of the risk consequences, which depend on the type, size, and location of the project.
3. The designer's and contractor's attitudes towards risk, which depend on factors such as firm size, reputation, work backlog, availability of other projects, the desirability of the project at hand, general economic conditions, market penetration strategies, etc.

A prescriptive model would require that the owner 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 approach is for the owner to make use of a design-construction expert and adopt a model that describes rather than prescribes how designers and contractors make decisions. The descriptive model presented below incorporates the findings of previous research on this subject (Qaddumi 1981; Ioannou 1980, 1984, 1988a, 1988b) and is based on the concept of hypothesis testing.

From the definition of ground classes it is apparent that, in general, there is some non-zero probability for any ground class $gc_i$ to exist at any location





J. Constr. Eng. Manage., 1989, 115(3): 339-356

along the alignment of a project. Using the ground class numbering convention above, and assuming that $g$ ground classes (corresponding to $g$ design-construction methods) have been defined, $gc_1$ represents the most favorable geologic conditions that may be encountered, whereas $gc_g$ 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 $CM_g$. Since it would be inefficient to use method $CM_g$ 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 $H_0$ that method $CM_i$ is indeed adequate. The alternate hypothesis $H_1$ is that method $CM_i$ is inadequate and that a more conservative method, $CM_j$ ($j > i$), 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 to 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 $CM_i$ is adequate when, in reality, a more conservative method should be used. The probability of a type II error, commonly known as $\beta$, is defined to be the threshold probability.

As a result, the above decision rule should be modified to reflect the importance of the type II error. The resulting rule can be stated as follows:

- 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 $\beta$.

The application of the threshold probability rule can be illustrated by considering as an example the complement of the cumulative ground class profile shown in a figure at the end of this paper. Each curve in the cumulative ground class profile corresponds to a particular ground class $gc_i$ ($i = 1, \ldots, 5$) and represents the probability that the true ground class at each particular location along the alignment of the tunnel is worse than ground class $gc_i$. For example, at location $t = 2{,}500$ ft there is a 0.78 probability that the true ground conditions are worse than $gc_3$, which equals the sum of the state probabilities for classes $gc_4$ and $gc_5$ at that location. By definition, this figure also gives the probabilities that the methods $CM_i$($i = 1, \ldots, 5$) are inadequate. For example, the probability that $CM_3$ is inadequate at location $t$ is also 0.78. A horizontal line drawn at the level of the threshold probability gives the least conservative acceptable sequence of design-construction methods as defined by the points of intersection of the threshold probability line and the ground class curves, as indicated in the figure. This sequence represents the expected design and construction decisions as a function of the threshold probability.

The determination of the threshold probability is not a trivial or intuitive task. For this reason, the implemented system does not require the *a priori* input of this parameter. Instead, color graphics are used to portray the computed ground class profile to allow 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 graphical form. The objective of this interaction is to allow the user to specify a threshold probability that reflects his own experience and attitude toward risk. The ability to experiment and to guide the model is a fundamental requirement for the general acceptance of the system by practicing engineers. This is the main feature that distinguishes a decision-support system from an optimization model.

It must be emphasized, however, that 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 modeled directly. Doing so would require the conditional prediction of the contractor's behavior given the designer's decisions, a task which cannot be easily quantified and for which there are no objective data.

The threshold probability rule is a simple but effective procedure that, for the purposes of developing a decision support system for the evaluation of exploration, enjoys certain advantages over other more "formal" decision models. An example of a more formal approach is stochastic dynamic programming (Howard 1960; Kim 1984). These advantages can be summarized as follows:

1. It eliminates the necessity to predict design decisions without considering the designer's reaction to contractual and financial liability. This is done by allocating this task to the most appropriate party (i.e., 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 expected cost minimization as the only possible criterion to be used by designers or owners for evaluating exploration alternatives. Optimization 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. It also reflects 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.

## 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:

$$C = a + \sum_{i=1}^{g} b_i \delta_i + \sum_{i=1}^{g} \sum_{j=1}^{g} c_{ij} f_{ij} + \sum_{i=1}^{g} \sum_{k=1}^{m_i} \left( d_{ik} + \frac{e_{ik}}{r_{ik}} \right) w_{ik} \quad (1)$$

where $a$ = fixed cost, independent of the construction methods used; $b_i$ = fixed cost uniquely associated with the use of $CM_i$; $\delta_i$ = binary (0,1) variable indicating whether $CM_i$ is used at least once; $g$ = the number of construction methods $CM_i$ considered; $m_i$ = the number of segments in which $CM_i$ is used; $c_{ij}$ = 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 unit length 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 $k$; and $w_{ik}$ = the extent (length) of the $k^{th}$ segment in which $CM_i$ is used.

The policy-dependent variables corresponding to the specified threshold probability and the current (posterior) ground class profile are $\delta_i$, $f_{ij}$, and $w_{ik}$. The rest of the necessary input, i.e., the cost and performance parameters presented above, can be 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 subjective encoding of the mode $m$, and the 5 and 95 percentiles $p_5$ and $p_{95}$.

The cost, 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.

## Evaluation of Exploration Programs

The preceding models illustrate the basic methodology for estimating the expected value and 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.

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 at 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 three parameters, each having four observation states, and the proposed exploration program





J. Constr. Eng. Manage., 1989, 115(3): 339-356

consists of sinking 15 boreholes, then the number of combinations that must be considered is $3 \times 4^{15} = 3{,}221{,}225{,}472$. 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 exploration methods to be employed.
- The specification of which exploration 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 by using the reliability matrices associated with the methods employed by the proposed exploration program. The geologic parameter profiles used for this purpose are the ones prepared by the original application of the geologic prediction model, which already reflect the findings of previous actual exploration. These profiles 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).
- Produce an estimate of the corresponding expected value and variance of the project cost.

By simulating a number 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 number of simulations depends on the required accuracy of the estimates, which is typically determined by specifying the desired width of confidence intervals around the estimate.

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 acceptable alternatives.

## Example Application

The preceding models have been integrated into the computerized decision support system EVGE (Expected Value of Geologic Exploration). EVGE runs on a DEC VAX 11-780 with a color graphics terminal that interprets REGIS commands, or an IBM AT with an EGA display. It is available upon request from the author.

This section presents a simple application of this system to illustrate the data input requirements and the form of the corresponding system output. The example presented here is the discharge water tunnel project of the Seabrook Power Station (Ioannou 1984, 1987, 1988a). The actual Seabrook Power Station discharge tunnel is over 15,000 ft (4,572 m) long. This example considers only the western portion from boreholes ADT-1 ($t$ = 0 ft) to ADT-42 [$t$ = 7,662 ft (2,335 m)] as shown in the estimated Rock Type Profile, Fig. 1 (Chan 1981). The exploration program being considered is a pilot tunnel running the full length of this portion. A detailed description of the project's regional geology can be found elsewhere (Rand 1974).

Four geologic parameters $X_i$ are used to describe the tunnel characteristics: $X_1$ = Rock Type; $X_2$ = Joint Density ($RQD$); $X_3$ = Degree of Weathering; and $X_4$ = Availability of Water. The number of discrete states $n_i$ and their definitions for each geologic parameter are shown in Table 1.

Table 2 shows the transition intensity coefficients $c_i$ and the transition probabilities $P_{ij}$ for each geologic parameter. These parameters were directly encoded using a geologist's expert judgment and were based on available general information. Table 2, for example, indicates that the geologist's estimate for the probability that a diorite segment ($X_1$ = 3) is followed by a

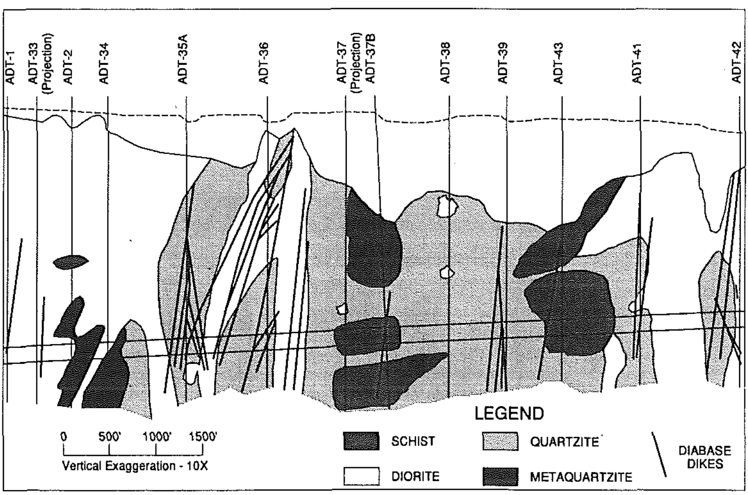


**FIG. 1. Rock Type Profile, Seabrook Power Station Discharge Tunnel**

**TABLE 1. Geologic Parameter and State Definition**

| GEOLOGIC PARAMETERS ($N$ = 4) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Rock Type $X_1$ | | Joint Density ($RQD$) $X_2$ | | Degree of Weathering $X_3$ | | Water Availability $X_4$ | |
| $i$ (1) | State (2) | $i$ (3) | State (4) | $i$ (5) | State (6) | $i$ (7) | State (8) |
| 1 | Schist | 1 | 75–100% | 1 | Not severe | 1 | Low |
| 2 | Metaquartzite | 2 | 25–75% | 2 | Severe | 2 | Medium |
| 3 | Diorite | 3 | 0–25% | | | 3 | High |
| 4 | Quartzite | | | | | | |
| $n_1 = 4$ | | $n_2 = 3$ | | $n_3 = 2$ | | $n_4 = 3$ | |

metaquartzite segment ($X_1$ = 2) is $P_{32}$ = 0.20, and that the average extent of a diorite segment is estimated to be $1/c_3 = 1/0.00262 = 382$ ft (116 m).

Although no frequency data were available for estimating the necessary Markov process parameters for this project, there were 13 point observations obtained from boreholes along the tunnel axis. The observations $Y_i(t_b)$ for each geologic parameter $X_i$ and their locations $t_b$ are shown in Table 3. For the purposes of this example, the definitions of the observation states are identical to the definitions of the geologic parameter states (Table 1). For example, Table 3 shows that the borehole observations at location $t$ = 1945 ft (593 m) indicated that the rock was quartzite [$Y_1(1945) = 4$], moderately jointed with $RQD$ = 25–75% [$Y_2(1945) = 2$], not severely weathered ($Y_3(1945) = 1$), with high availability of water ($Y_4(1945) = 3$).

The estimated likelihood (reliability) matrices $L_{ij}(t_b)$ for the borehole observations have been assumed independent of location $t_b$ and are shown in Table 4. From this table, for example, it can be seen that the probabilities that a borehole core sample would indicate low, moderate or high joint density, given that the true joint density is moderate, are $P[Y_2 = 1|X_2 = 2] = 0.05$, $P[Y_2 = 2|X_2 = 2] = 0.85$, $P[Y_2 = 3|X_2 = 2] = 0.10$, respectively.

These data constitute the basic input to the geologic prediction model. The resulting probabilistic profiles for the geologic parameters Rock Type ($X_1$) and Joint Density ($X_2$) are shown in Figs. 2 and 3. The profiles for the other

**TABLE 2. Interval Transition Probabilities $P_{ij}$ and Interval Transition Coefficients $c_i$**

| | ROCK TYPE $X_1$ | | | | | JOINT DENSITY ($RQD$) $X_2$ | | | | DEGREE OF WEATHERING $X_3$ | | | WATER AVAILABILITY $X_4$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $P_{ij}$ | | | | | $P_{ij}$ | | | | $P_{ij}$ | | | $P_{ij}$ | | | |
| $i$ (1) | $j$ = 1 (2) | 2 (3) | 3 (4) | 4 (5) | $c_i$[a] (6) | 1 (7) | 2 (8) | 3 (9) | $c_i$[a] (10) | 1 (11) | 2 (12) | $c_i$[a] (13) | 1 (14) | 2 (15) | 3 (16) | $c_i$[a] (17) |
| 1 | 0.00 | 0.02 | 0.23 | 0.75 | 138 | 0.00 | 0.93 | 0.07 | 233 | 0.00 | 1.0 | 45 | 0.00 | 0.55 | 0.45 | 82 |
| 2 | 0.02 | 0.00 | 0.50 | 0.48 | 822 | 0.83 | 0.00 | 0.17 | 394 | 1.0 | 0.00 | 162 | 0.90 | 0.00 | 0.10 | 633 |
| 3 | 0.02 | 0.20 | 0.00 | 0.78 | 262 | 0.50 | 0.50 | 0.00 | 188 | | | | 0.90 | 0.10 | 0.00 | 170 |
| 4 | 0.23 | 0.17 | 0.60 | 0.00 | 250 | | | | | | | | | | | |

[a]Units: $10^{-5}$ ft$^{-1}$.

Note: 3.28 ft = 1 m.

TABLE 3. Borehole Locations and Observed States

| $b$ (1) | Borehole (2) | $t_b$ (ft) (3) | Observed States $Y_1(t_b)$ (4) | $Y_2(t_b)$ (5) | $Y_3(t_b)$ (6) | $Y_4(t_b)$ (7) |
|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 3 | 2 | 1 | 1 |
| 2 | 33 | 341 | 3 | 1 | 1 | 1 |
| 3 | 2 | 717 | 3 | 1 | 1 | 1 |
| 4 | 34 | 1,239 | 2 | 2 | 1 | 3 |
| 5 | 35A | 1,945 | 4 | 2 | 1 | 3 |
| 6 | 36 | 2,788 | 4 | 3 | 2 | 1 |
| 7 | 37 | 3,566 | 1 | 2 | 2 | 3 |
| 8 | 37B | 4,010 | 1 | 3 | 2 | 3 |
| 9 | 38 | 4,659 | 4 | 3 | 2 | 1 |
| 10 | 39 | 5,256 | 4 | 1 | 1 | 2 |
| 11 | 43 | 5,785 | 1 | 1 | 1 | 1 |
| 12 | 41 | 6,604 | 3 | 1 | 1 | 1 |
| 13 | 42 | 7,662 | 4 | 1 | 1 | 1 |

Note: 3.28 ft = 1 m.

two geologic parameters ($X_3$ and $X_4$) are similar. Each of these profiles shows the updated state probabilities for the associated geologic parameter as a function of location $t$ along the tunnel axis. Fig. 2, for example, shows that the updated Rock Type state probabilities at location $t$ = 2,400 ft (732 m), for the states schist, metaquartzite, diorite and quartzite are $P[X_1 = 1] = 0.097$, $P[X_1 = 2] = 0.043$, $P[X_1 = 3] = 0.251$, and $P[X_1 = 4] = 0.609$, respectively.

Five tunnel excavation-support alternatives, $CM_i$, have been identified as suitable for the construction of this project. These alternatives have been ordered according to their cost and technical feasibility as shown in Table 5. This table also shows the definitions of the corresponding five ground classes $gc_i$. Each row lists a set of states for each geologic parameter $[X_1,X_2,X_3,X_4]$. The possible combinations of geologic parameter states $[x_1,x_2,x_3,x_4]$ in each row define geologic vectors $\mathbf{x}$ that belong to the corresponding ground class. For example, ground class $gc_2$ is defined by the two vectors [4, 1, 1, 1] and [4, 1, 1, 2]. The number of possible geologic vec-

TABLE 4. Estimates for Likelihood (Reliability) Matrices

| | $L_{ij} = P(Y_k = j \mid X_k = i)$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Rock Type ($k$ = 1) | | | | Joint Density ($RQD$) ($k$ = 2) | | | Degree of Weathering ($k$ = 3) | | Water Availability ($k$ = 4) | | |
| $i$ (1) | $j$ = 1 (2) | 2 (3) | 3 (4) | 4 (5) | $j$ = 1 (6) | 2 (7) | 3 (8) | $j$ = 1 (9) | 2 (10) | $j$ = 1 (11) | 2 (12) | 3 (13) |
| 1 | 0.85 | 0.05 | 0.05 | 0.05 | 0.90 | 0.05 | 0.05 | 0.95 | 0.05 | 0.95 | 0.05 | 0.00 |
| 2 | 0.05 | 0.85 | 0.05 | 0.05 | 0.05 | 0.85 | 0.10 | 0.05 | 0.95 | 0.05 | 0.90 | 0.05 |
| 3 | 0.05 | 0.05 | 0.85 | 0.05 | 0.00 | 0.05 | 0.95 | | | 0.00 | 0.05 | 0.95 |
| 4 | 0.05 | 0.05 | 0.05 | 0.85 | | | | | | | | |

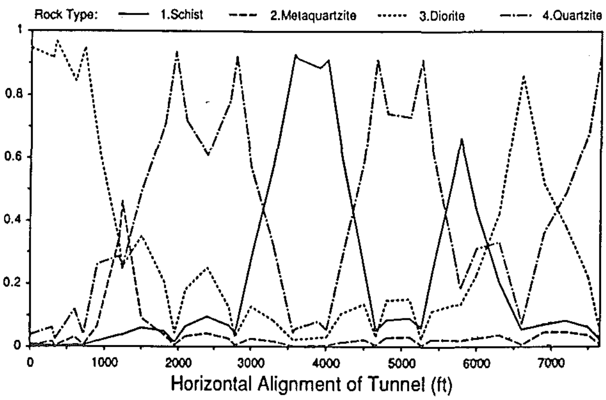


**FIG. 2. Probabilistic Geologic Parameter Profile—Rock Type**

tors $\mathbf{x}$ for this example is $4 \times 3 \times 2 \times 3 = 72$, six of which belong to $gc_1$, two belong to $gc_2$, eight belong to $gc_3$, 20 belong to $gc_4$, and 36 belong to $gc_5$.

The ground class profile for the Seabrook tunnel is shown in Fig. 4. This profile shows the ground class state probabilities as a function of location along the tunnel axis. Fig. 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 using color graphics on the computer screen. This allows the user to check the validity of the geologic prediction produced by the system against his own subjective expectations. The user can also experiment with different levels of threshold probability by evaluating the resulting sequence of design-construction methods shown on the screen.

The unit costs and production parameters used for estimating the cost of the project are shown in Table 6 (Salazar 1983). Columns 2 and 3 in Table

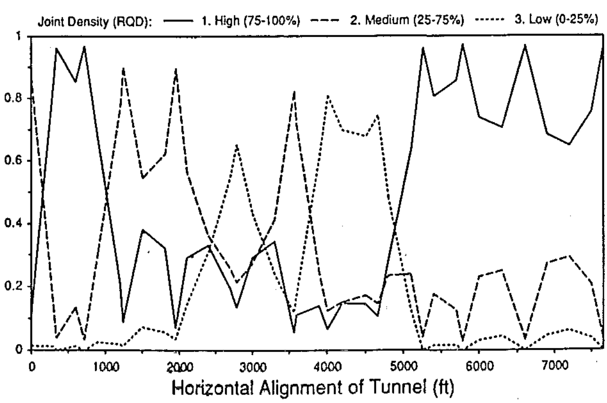


**FIG. 3. Probabilistic Geologic Parameter Profile—Joint Density (RQD)**



J. Constr. Eng. Manage., 1989, 115(3): 339-356

**TABLE 5. Excavation-Support Methods and Ground Classes**

| $i$ (1) | Excavation-support method $CM_i$ (2) | Ground class $GC$ (3) | Geologic parameter states $X_1$ (4) | $X_2$ (5) | $X_3$ (6) | $X_4$ (7) |
|---|---|---|---|---|---|---|
| 1 | Full face drill and blast<br>No support | $gc_1$ | 1, 2, 3 | 1 | 1 | 1, 2 |
| 2 | Full face drill and blast<br>Conventional steel sets<br>Amount of support: medium | $gc_2$ | 4 | 1 | 1 | 1, 2 |
| 3 | Heading and bench drill and blast<br>Conventional steel sets<br>Amount of support: medium | $gc_3$ | 1, 2, 3, 4 | 2 | 1 | 1, 2 |
| 4 | Heading and bench drill and blast<br>Conventional steel sets<br>Amount of support: large | $gc_4$ | 1, 2, 3, 4<br>1, 2, 3, 4 | 1, 2, 3<br>3 | 1<br>1 | 3<br>1, 2 |
| 5 | Multiple drift drill and blast<br>Conventional steel sets<br>Amount of support: large | $gc_5$ | 1, 2, 3, 4 | 1, 2, 3 | 2 | 1, 2, 3 |

7 show the resulting estimates for the expected value and the standard deviation of the project cost as a function of the threshold probability level.

For the purposes of this example it was assumed that the pilot tunnel being evaluated as an exploration alternative provides observations with perfect reliability. The continuous observations provided by the pilot tunnel were discretized and assumed to occur every 300 ft (91.44 m). The resulting estimates for the expected value and the standard deviation of project cost using 100 simulated sets of the pilot tunnel observations are shown in columns 4 and 5 in Table 7.

From the point of view of an expected monetary value, the pilot tunnel is an acceptable exploration alternative if the cost of its construction is less than the difference between the expected value of the work with and without the pilot tunnel. For example, at a threshold probability level of 0.10, the

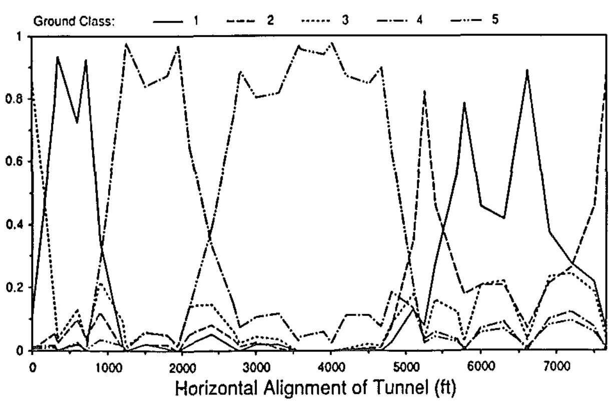


**FIG. 4. Probabilistic Ground Class Profile**

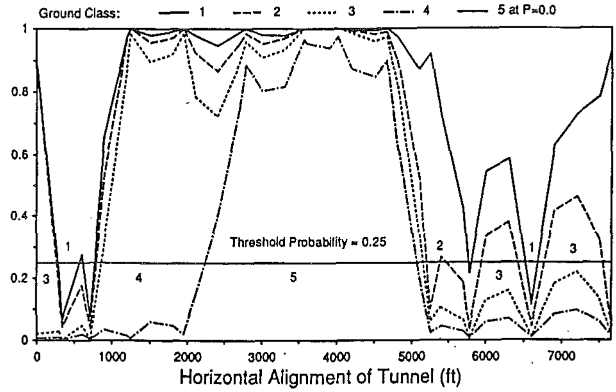


**FIG. 5. Complement of Cumulative Ground Class Profile**

pilot tunnel should cost less than $3,846,050. As expected, the value of the information provided by the pilot tunnel decreases as we increase the acceptable threshold probability level because of the implied reduction in design and construction conservatism. 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

**TABLE 6. Unit Costs and Advance Rates (Salazar 1983)**

| Excavation support method (1) | Fixed costs ($) (2) | Materials and supplies ($/ft) (3) | Labor and equipment ($/hr) (4) | Variable OH ($/mo) (5) | Change method ($/shf) (6) | Advance Rate [ft/(8 hr shf)] | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | $p_5$ (7) | $m$ (8) | $p_{95}$ (9) |
| $CM_1$ | 1,265,800 | 112.79 | 632.49 | 81,100 | 2,600 | 18 | 16 | 13 |
| $CM_2$ | 1,265,800 | 219.24 | 632.49 | 81,100 | 2,600 | 10 | 8 | 7 |
| $CM_3$ | 1,610,900 | 307.21 | 745.52 | 81,900 | 2,600 | 9 | 7 | 5 |
| $CM_4$ | 1,630,400 | 811.15 | 745.52 | 81,900 | 2,600 | 7 | 5 | 4 |
| $CM_5$ | 1,936,900 | 1,186.23 | 793.52 | 85,200 | 2,600 | 4 | 3 | 2 |

**TABLE 7. Expected Value and Standard Deviation of Project Cost**

| Threshold probability (1) | No Pilot Tunnel | | Pilot Tunnel | |
|---|---|---|---|---|
| | $E(C)$ (2) | $\sigma_C$ (3) | $E(C)$ (4) | $\sigma_c$ (5) |
| 0.01 | 34,999,210 | 4,985,429 | 22,377,460 | 2,615,011 |
| 0.05 | 30,369,990 | 3,669,945 | 22,127,050 | 2,566,577 |
| 0.10 | 25,660,090 | 2,368,057 | 21,814,040 | 2,507,584 |
| 0.15 | 24,497,840 | 2,269,068 | 21,501,030 | 2,450,595 |
| 0.20 | 22,881,770 | 2,171,479 | 21,188,010 | 2,395,816 |
| 0.25 | 21,947,380 | 2,033,009 | 20,875,010 | 2,343,133 |



J. Constr. Eng. Manage., 1989, 115(3): 339-356

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.

## Conclusion

The development of the models described in this paper, and their integration into the decision support system EVGE, allow, for the first time, the rational evaluation of subsurface exploration programs. The proposed system provides owners and designers of underground construction projects with the capability to quantify the benefits of exploration and, thus, with a solid basis for making the associated technical and economic decisions. This capability should promote the advantageous utilization of subsurface investigation as an effective means of reducing the defensive strategies of design conservatism and excessive construction contingencies typically employed by designers and contractors in the U.S. 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.

## Acknowledgments

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