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UPDATING GEOLOGICAL CONDITIONS USING BAYES THEOREM AND MARKOV CHAIN

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ABSTRACT

Due to cost constraints, geological conditions are investigated using boreholes. However, this means conditions are never known exactly, particularly for deep and long tunnels, because uncertainties exist between neighboring boreholes. Simulation can deal with underlying uncertainty, and offers benefits to project planners in the development of better alternatives and optimization. This research developed a simulation model using Bayes theorem and Markov chain, aiming to continuously update geological conditions of one-meter sections for tunnel construction, given the geological condition of the previous one-meter section is observed as construction progresses. An actual tunneling project is used as a case study to demonstrate the applicability of the developed methodology. The impacts are analyzed and discussed in detail. The simulation results show that continuous updates during construction can significantly improve prediction of project performance by eliminating uncertainty in the original assumption. The model can be expanded to predict results of future geologic exploration programs.

1 INTRODUCTION

Tunneling is characterized by high degrees of uncertainty, more so than many other areas of civil engineering (Haas and Einstein 2002). Geologic uncertainty is the primary source of risk in underground tunnel construction, often leading to the assumption of the worst possible ground conditions, and therefore, to inflated costs (Ioannou 1987). Thus, great savings are possible by adapting design and construction methods to the conditions actually encountered during excavation (Einstein 2004). However, the geological conditions can never be known exactly in actual projects, particularly for deep and long tunnels, since preconstruction information may be very sparse. Even if geological conditions are investigated by means of drilling several distributed boreholes, considerable uncertainties still exist in the determination of geological conditions between the neighboring boreholes. This aspect of uncertainty in the geological conditions of a tunneling project may influence major project decisions, such as selection of excavation methods, advance rate of the tunnel boring machine (TBM) operation, as well as the decision to perform additional exploration (Haas and Einstein 2002). The challenge is therefore to formalize the decision process under uncertainty.

Simulation is a powerful decision support technique for construction management, and is an efficient tool to deal with uncertainty to some extent, and can offer many benefits to a tunnel project planner in the development of better alternatives and optimization (AbouRizk and Mohamed 2000). To make the simulation effective, the input information of the developed models must be accurate and precise. Input into these models from industry experts, when these models are prepared to resemble actual construction processes, is generally subjective and represents a best estimate in the form of a deterministic value or a statistical distribution (Chung, Mohamed and AbouRizk 2006). A successful approach to enhance the estimates is simply to obtain actual data as a project commences construction and to utilize this data to enhance the base distributions used in the simulation model.

Bayes updating techniques can provide a systematic approach to combine subjective data and observed data in order to produce a balanced estimation. Basically, Bayes updating techniques allow explicit modeling of changes over time, and therefore, can model the evolution of the probabilistic dependencies within a complex system. These techniques can considerably improve the quality of the subjective input data even with only a small number of data sets collected in the early stages of a project's lifecycle. Project designers can then easily update the prediction when additional information or evidence is available (Špačková and Straub, 2013; Zhang, Wu, Skibniewski, Zhong and Lu 2014). However, to model and demonstrate the real world in terms of predictions is a stochastic process, since the process may start in one state and then move successively from one state to another in a random manner. In order to address the stochastic nature of the real world, Markov chain, named after Andrey Markov, can be used to model a random process that undergoes transition from one state to another on a state space (Gilks 2005). It possesses a property that is usually characterized as memoryless, indicating that the next state depends only on the current state and not on the sequence of events that precede it. More specifically, the Bayes technique uses external observation to update the system outcome, while the Markov chain uses internal transitions to update the system outcome over time. With both the external and internal updating mechanisms taken into account in the simulation model, improved simulation outcomes can be expected. This paper investigates the possibility of merging Bayes technique and Markov chain to facilitate updating geological conditions over time in tunnel construction.

This research develops a simulation model consisting of Bayes technique and Markov chain, in which the geological condition of one-meter sections in the tunnel construction can be updated in a continuous manner, given the geological conditions of the previous one-meter section is observed over time. An actual tunneling project (details skewed for confidentiality) is used as a case study to demonstrate the applicability of the developed methodology. The impacts of given evidence, geological fluctuations, and additional geological investigations on the updating of the geological conditions are analyzed and discussed in this research. The use of these updating techniques shows that the quality of projection for the simulation model can be considerably improved.

2 OBJECTIVE OF THE STUDY

Process interaction simulation has been in use for many years in the analysis of complex dynamic systems. The simulation community has a number of well-established methods to apply a simulation-based approach in solving problems: Discrete Event Simulation (DES), Continuous Simulation, System Dynamics (SD), and Agent-Based Modeling. The use of each of these methods depends on the complexity of the system being analyzed and the level of abstraction desired. Simphony is a DES system that was originally developed by Hajjar and AbouRizk (2000). It has evolved over the past 15 years and is currently being extended and maintained by Dr. AbouRizk's research team at the Hole School of Construction Engineering at the University of Alberta. To simplify the use of Simphony, a variety of special templates have been developed within the Simphony Modeling Environment in the past years. The Simphony tunneling template is one successful special template that has been applied in the construction industry. See details of the Simphony tunneling template in AbouRizk et al. (2014).

In the current Simphony tunneling template, the rate at which the TBM advances is stochastic and depends on the type of soil being excavated. As a result, the conditions of the soil to be excavated at the tunneling face play a significant role in the performance of the TBM, as well as the production. In fact, the distribution of the geological conditions is fixed for simplicity during the simulation process

(Ruwanpura, AbouRizk, Er and Fernando 2001). However, the geologic conditions are never known exactly, since the preconstruction information may be very sparse (H. H. Einstein, Indermitte, Sinfield, Descoeudres and Dudt 1999; Haas and Einstein 2002). Due to the underlying uncertainties in the determination of geologic conditions, the production simulation of tunnel projects cannot accurately predict the actual performance in real practice. The objective of this research is to formally represent the uncertainty to reveal the actual distribution of geologic conditions, and further formalize the decision process.

The objectives are as follows:

(i) Model the random evolution of the probabilistic dependencies on the distribution of geologic conditions;

(ii) Update the prediction of geologic conditions over time when the observed information is available.

3 METHODOLOGY

Generally, any updating process will use new information to improve a prediction. Every probabilistic input is a prediction of an individual parameter that one tries to improve during the updating process. This will consequently also improve the output of the simulator, leading to the reduction of uncertainty. A framework has been developed as shown in Figure 1, which consists of two steps, outlined in 3.1 and 3.2

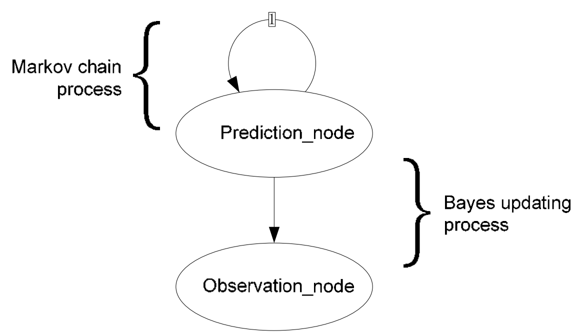

Figure 1: A general simulation framework.

3.1 Step 1: Bayes Updating Process

It is assumed that a prediction has already been made and that new information has become available since this initial prediction was made. The updating process then leads to an updated prediction. The appropriate mathematical model for updating probabilistic input is Bayes theorem. Bayes theorem is able to model the evolution of the probabilistic dependencies within a random system, and allows users to easily update the prediction when additional information is available.

In general terms, the posterior prediction is a function of the prior prediction and the new information. New information can be obtained by performing any kind of test, such as drilling an exploratory borehole. However, most tests are not perfect. Bayes theorem relates the posterior probability $P''(Z = z_i | X = x_i)$ to the prior probability $P'(Z = z_i)$ and new information $P(X = x_i | Z = z_i)$, as shown in Equation 1

$$P''(Z = z_i | X = x_i) = N * P'(Z = z_i) * P(X = x_i | Z = z_i) \tag{1}$$

where, $P''(Z = z_i | X = x_i)$ stands for the posterior probability z_i, given that the outcome of the test X is x_i; $P'(Z = z_i)$ stands for the prior probability of z_i; and $P(X = x_i | Z = z_i)$ stands for the probability of the outcome being x_i if the true state of Z is z_i.

3.2 Step 2: Markov Chain Process

The Markov process is a stochastic process that involves both a random variable and a "time" parameter that monotonically increases during the process. The Markov process is characterized by a single-step memory. To determine the next step, all previous steps except for the most recent one are neglected. This is a restrictive condition, but the most recent step is usually the most important one in determining the next step. By using a single-step memory, parameter states behind the tunnel face depend only on the parameter state at the tunnel face.

A discrete-time Markov chain is a mathematical system that simulates transitions from one state to another in the real world. It is a random process usually characterized as memoryless, indicating that the next state depends only on the current state and not on the sequence of events that precede it. Based on the Markov chain process, as illustrated in Equation 2, the DBN model is a probability distribution function on the sequence of T hidden-state variables $X = \{x_0, \ldots, x_{T-1}\}$ and the sequence of T observables $Y = \{y_0, \ldots, y_{T-1}\}$ that has the following factorization, which satisfies the requirements for DBN that state x_t depends only on state x_{t-1}.

$$Pr(X_{1:T} | Y_{1:T}) = \prod_{t=1}^{T-1} Pr(x_t | x_{t-1}) \times \prod_{t=0}^{T-1} Pr(y_t | x_t) \times Pr(x_0) \tag{2}$$

where, $Pr(x_t|x_{t-1})$ is the state transition probability density function, $Pr(y_t|x_t)$ is the observation probability density function, and $Pr(x_0)$ is the initial state distribution.

4 CASE STUDY

A tunnel case is used to verify the feasibility of the proposed methodology. The length of a concrete liner segment is usually one meter. In order to perform the production rate of a specific one-meter tunnel section, the whole tunnel route is also separated into a number of one-meter sections. Thus, a one-meter section can be considered a separate unit during the excavation process.

4.1 Background

The construction of tunnel projects is very sensitive to geological conditions due to complex tunnel-soil interaction. Several particular geological features may increase the hazardous nature of construction. In order to determine the underground geological profile, six boreholes were drilled to depths of approximately 35 and 40 meters below ground surface (mBGS). Standard penetration tests (SPT) were performed at regular intervals in the boreholes and SPT soil samples were collected and visually classified in the field according to the Modified Unified Classification System for soils. Shelby tube samples were also collected at select intervals based on the soil conditions encountered in the boreholes. Natural moisture contents were determined for all of the samples collected from the boreholes. Figure 2 illustrates of the result of the geological investigation of cross sections for the project.

Tunnels have been installed successfully in till deposits in the Edmonton area. However, within the till deposits, there is the potential to encounter obstructions, such as boulders or hard layers of rafted bedrock. Rafted clay shale and sandstone was encountered in one borehole at 24 mBGS and hard drilling was encountered in another borehole at 27 mBGS. It is possible for the diameter of the obstructions to exceed that of the tunnel and this should be accounted for during design of tunnel construction methodology and equipment. Two options for the invert level of the proposed tunnel are proposed, as shown in Table 1. It is anticipated that the Empress Formation will negatively impact the tunnel construction, and therefore Option 1 is considered more favorable and adopted in this case.

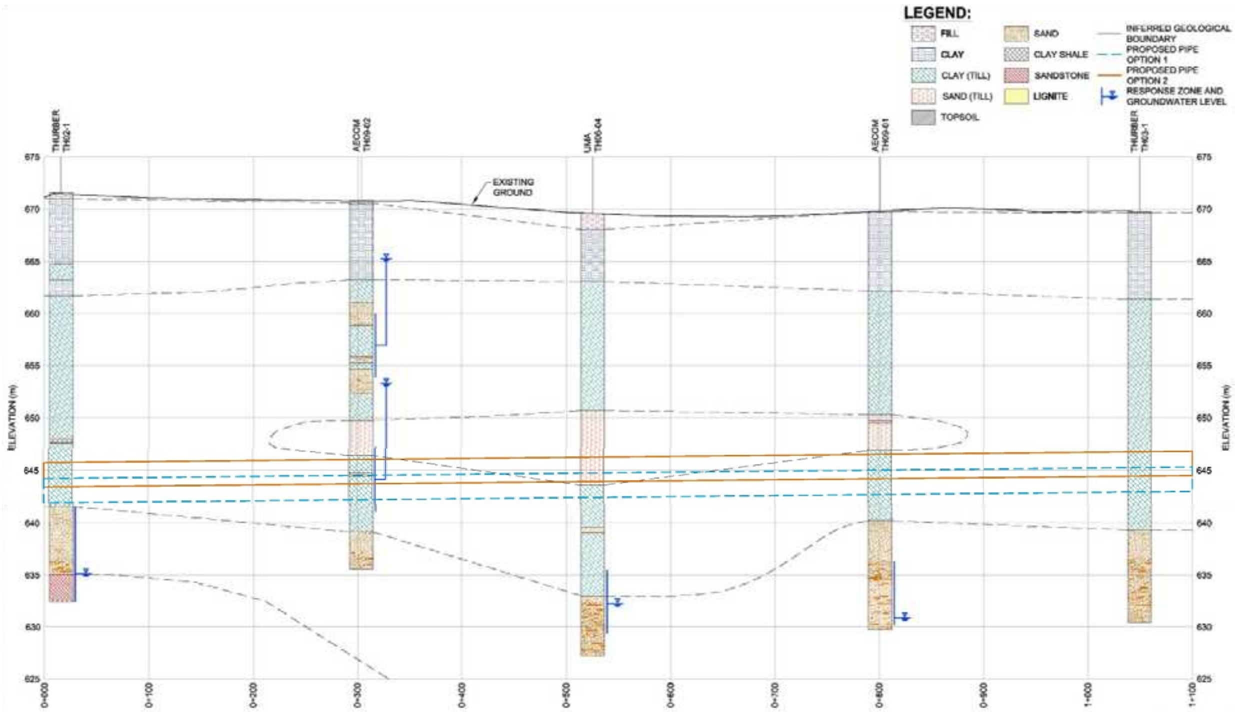

Figure 2: Geological investigation of cross section for the project.

Table 1: Comparison of the proposed options.

Option 1	Option 2
• Located primarily within clay-rich till deposits • Located within 0.2 m of Empress Formation • Lignite/Lacustrine deposit is near obvert level of tunnel	• Located within clay and sand-rich till deposits • Located within 1.8 m of Empress Formation • Lignite/Lacustrine deposit is in central portion of tunnel

4.2 Model Construction

Geological conditions play a significant role in TBM performance in underground tunnel projects. Engineers, typically geotechnical engineers, classify soils according to their engineering properties as they relate to use for foundation support or building material. Modern engineering classification systems are designed to allow an easy transition from field observations to basic predictions of soil engineering properties and behaviors. The most common engineering classification system for soils in North America is the Unified Soil Classification System (USCS). The USCS has three major classification groups: (i) highly organic soils (referred to as "peat"), (ii) fine-grained soils (e.g. silts and clays); and (iii) coarse-grained soils (e.g. sands and gravels). Also, in accordance with the research work by Einstein. et al. (1999), the geologic condition in this research is classified into three separate types, namely “little,” “medium” and “intense,” representing the three specific soil types in USCS, respectively.

The objective of this research is to update the geological conditions through given observations over time. In order to determine the geological conditions in a detailed and precise manner, the long cross tunnel section can be divided into short sections, such as one-meter sections that are almost equal to the width of a segment. Figure 3 illustrates the segments at the construction site. We assume that each one-meter section only has one specific soil type, rather than a combination of different soil types. For simplicity, the construction layout of the cross section is abstracted into a rectangle with 1192 one-meter sections, as shown in Figure 4. The dotted box as shown in the left part of Figure 4 represents the section that has been excavated at T=0. The solid boxes, as shown in the right part of Figure 4, represent the sections that will be excavated at T=1~1191, respectively. The observed geologic conditions at the last time slice can provide new information for updating the geologic conditions of the next section.

Figure 3: Segments for the project: (a) segments at the site; and (b) segments in the tunnel.

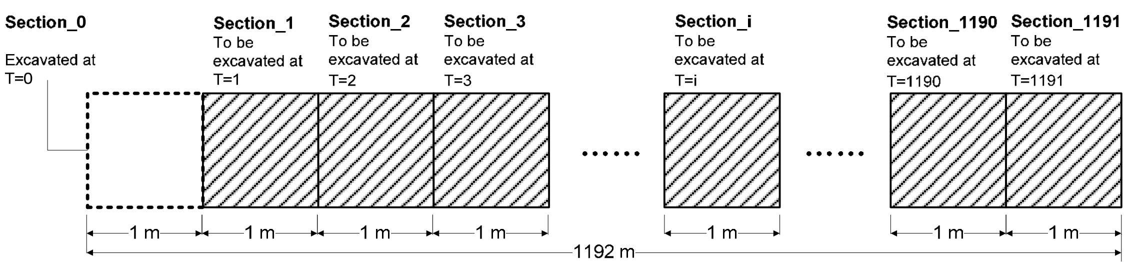

Figure 4: Layout of 1192 nine-meter sections on construction site for the project.

In order to consider the interactions between neighboring one-meter sections over time during the continuous excavation process, the updating chain for the prediction of soil conditions based on the Markov chain and Bayes theorem is established, as shown in Figure 5. The established model consists of a series of submodels (see Figure 1). More specifically, the virtual arrow lines that connect neighboring submodels indicate that the posterior probability distribution of the *i*th section at T=t_i can provide soft evidence information on the observation of the *i*th section at T=t_i-1 in case no observation information is available. In regard to the *i*th specific submodel (1≤*i*≤1091), there are two nodes, predition_*i* and observation_*i*, that are involved in the updating process. Specifically, the node of the prediction_*i* stores the predicted probability distribution, while the observation_*i* stores the observed information at the previous time slice. In this study, the geological conditions are classified into three separate types, namely "little," "medium" and "intense," indicating each node has three states.

According to the geological condition profile for the project (see Figure 2), the whole tunnel is mainly located in the layer of the clay (till) and sand in option 1. To some extent, the surrounding soil tends to stay in the type of "medium" throughout the whole cross section, associated with slight fluctuations. Thus, the conditional and transitional probability distributions between Bayes nodes keep consistent in each submodel. Table 2 illustrates the conditional probability table (CPT) between prediction_*i* and observation_*i*. Table 3 illustrates the transition probability table (TPT) of prediction_*i*. Table 4 illustrates the prior probability distribution of prediction_*i* at time T=*i*.

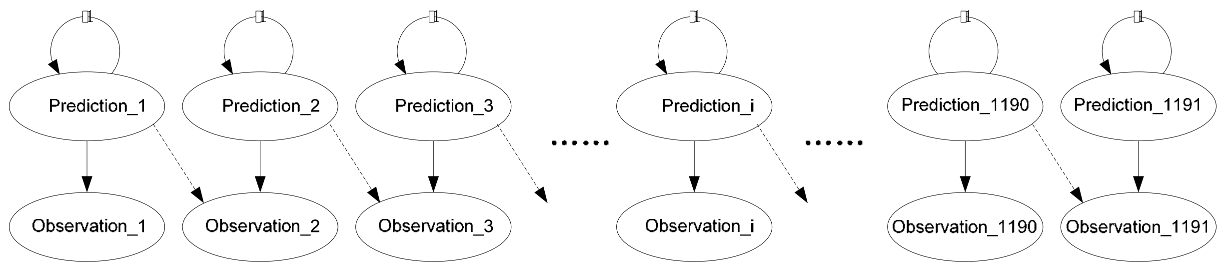

Figure 5: Updating chain for the prediction of soil conditions.

Table 2: Conditional probability table (CPT) between prediction_*i* and observation_*i*.

Observation_*i* states	Prediction_*i* states		
	Little	Medium	Intense
Little	0.7	0.15	0.1
Medium	0.2	0.7	0.2
Intense	0.1	0.15	0.7

Table 3: Transition probability table (TPT) of prediction_*i*.

Prediction_*i* states (T=*t*)	Prediction_*i* states (T=*t*-1)		
	Little	Medium	Intense
Little	0.8	0.1	0.05
Medium	0.15	0.8	0.15
Intense	0.05	0.1	0.8

Table 4: Prior probability distribution of prediction_*i*.

Prediction_*i* states	Prior probability
Little	0.1
Medium	0.8
Intense	0.1

4.3 Analysis of Results

As shown in Figure 2, the geologic conditions are investigated by means of a few distributed boreholes, due to cost constrains, and thus, the geologic conditions are never known exactly, particularly for deep and long tunnels. Great uncertainties exist in the determination of geological conditions between the neighboring boreholes. Simulation provides an efficient tool to deal with the underlying uncertainty. In the proposed methodology, when the observed information at the current time slice is available, the posterior probability distribution at subsequent time slices will be updated. Using this updating technique, engineers on working sites can be provided with more insight on geological conditions ahead of the excavation face. In order to verify the applicability of the proposed approach, the impacts of given evidence, geological fluctuations, and additional geological investigations, are tested in 12 different scenarios. Table 5 illustrates descriptions of those 12 scenarios.

Table 5: Descriptions of different scenarios.

No.	Description
Scenario 1	No given evidence is provided at T=0
Scenario 2	The type “little” is observed for section_0 at T=0
Scenario 3	The type “medium” is observed for section_0 at T=0
Scenario 4	The type “intense” is observed for section_0 at T=0
Scenario 5	The type “medium” is observed at T=0~5, and the type “little” is observed at T=6~8
Scenario 6	The type “medium” is observed at T=0~5, and the type “intense” is observed at T=6~8
Scenario 7	The type “medium” is observed at T=0~5, the type “little” is observed at T=6~8, and the type “little” is observed at T=18~20
Scenario 8	The type “medium” is observed at T=0~5, the type “little” is observed at T=6~8, and the type “medium” is observed at T=18~20
Scenario 9	The type “medium” is observed at T=0~5, the type “little” is observed at T=6~8, and the type “intense” is observed at T=18~20
Scenario 10	The type “medium” is observed at T=0~5, the type “intense” is observed at T=6~8, and the type “little” is observed at T=18~20
Scenario 11	The type “medium” is observed at T=0~5, the type “intense” is observed at T=6~8, and the type “medium” is observed at T=18~20
Scenario 12	The type “medium” is observed at T=0~5, the type “intense” is observed at T=6~8, and the type “intense” is observed at T=18~20

4.3.1 Impact of Given Evidence

Evidence at the current time slice should have an impact on the posterior probability distribution of the predicted node. In order to test the degree of the impact, an experiment with four different scenarios is conducted, and results of the posterior probability distribution of the predicted node over time in case of different evidence at T=0 are presented in Figure 6. Here, in Scenario 1, no given evidence is provided at T=0; in Scenario 2, the type “little” is observed for section_0 at T=0; in Scenario 3, the type “medium” is observed for section_0 at T=0; and in Scenario 4, the type “intense” is observed for section_0 at T=0. The first 30 one-meter sections (see Figure 4) are chosen to show the impact of different evidence on the posterior probability distribution.

As shown in Figure 6, the results indicate that the posterior probabilities vary a lot with respect to different observations at T=0. Obviously, the posterior probability distribution is very sensitive to the observed evidence, indicating the established model is valid to some extent. On the other hand, the impact of given evidence at one specific time slice drops gradually in the subsequent time slices, and tends to be very slight after almost ten time slices. In a sense, this updating technique acts like a flashlight in the darkness which can shed a bright light on the path ahead; however, the range is limited. Therefore, a series of continuous observations are very meaningful in reducing the underlying uncertainties on the sections to be excavated ahead in a more sustainable manner.

4.3.2 Impact of Geological Fluctuations

As shown in Figure 2, most of the tunnel is located in the clay (till) and sand layer with respect to option 1. Thus, the prior probability regarding the type “medium” is set to be 0.8, and those of “little” and “intense” are both set to be 0.1 among all the prediction nodes in the updating chain (see Table 4). However, the occurrence of geological fluctuations is very common in actual construction practice due to uncertainties underlying a complex underground environment. In order to analyze the impact of geological fluctuations on the posterior probability distribution of the predicted node over time, an experiment with two different scenarios is carried out. Figure 7 illustrates results of the posterior probability distribution of the predicted node over time in Scenarios 5 and 6. Here, in Scenario 5, the type "medium" is observed at T=0~5, and the type "little" is observed at T=6~8; and in Scenario 6, the type "medium" is observed at T=0~5, and the type "intense" is observed at T=6~8. The first 30 one-meter sections (see Figure 4) are also chosen to show the impact of geological fluctuations on the probability updating.

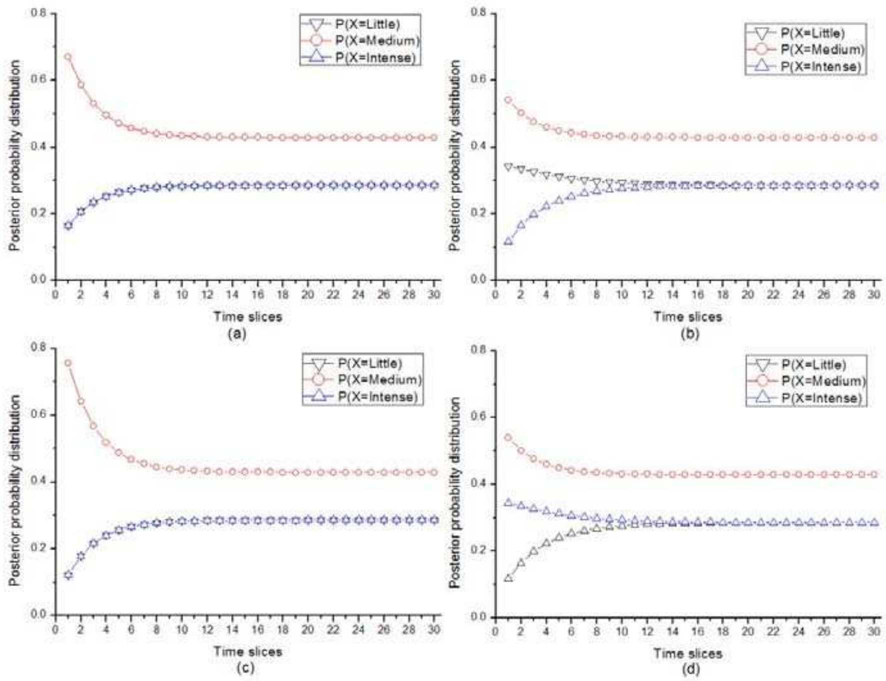

Figure 6: Results of the posterior probability distribution of the predicted node over time in case of different evidence at T=0: (a) Scenario 1; (b) Scenario 2; (c) Scenario 3; and (d) Scenario 4.

As shown in Figure 7, the results indicate that the observation of the geological fluctuation can lead to a sudden fluctuation on the posterior probability distribution. Specifically, in Scenario 5, the type "little" experiences a rapid rise and fall at T=6~12 in the case of a geological fluctuation from the type "medium" to "little." In Scenario 6, the type "intense" experiences a rapid rise and fall at T=6~12 in the case of a geological fluctuation from the type "medium" to "intense." However, in both scenarios, the influence of the geological fluctuations on probability updating can be generally extended to the subsequent 16 time slices, and tends to be very slight after that.

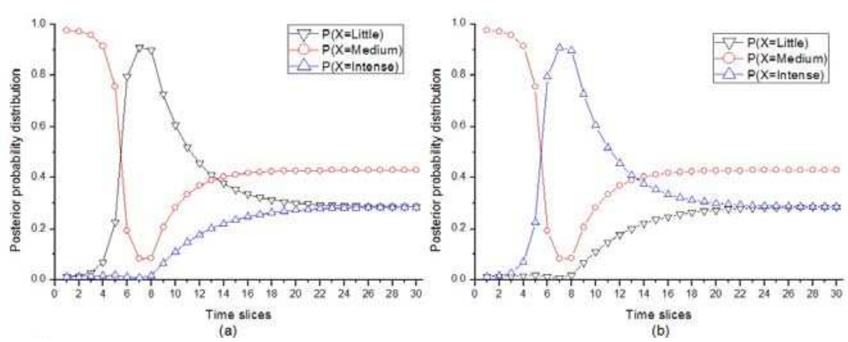

Figure 7: Results of the posterior probability distribution of the predicted node over time in the case of a geological fluctuation: (a) Scenario 5; and (b) Scenario 6.

4.3.3 Impact of Additional Geological Investigations

In actual tunnel construction practice, when undiscovered geological conditions are observed, such as sudden geological fluctuation, additional geological investigations should be carried out in order to determine how long the newly observed condition will last. In order to analyze the impact of additional geological investigations on the posterior probability distribution of the predicted node over time, an experiment with six different scenarios is carried out. Figure 8 illustrates results of the posterior probability distribution of the predicted node over time in Scenarios 7 to 12. Here, in Scenario 7, the type "medium" is observed at T=0~5, the type "little" is observed at T=6~8, and the type "little" is observed at T=18~20; in Scenario 8, the type "medium" is observed at T=0~5, the type "little" is observed at T=6~8, and the type "medium" is observed at T=18~20; in Scenario 9, the type "medium" is observed at T=0~5, the type "little" is observed at T=6~8, and the type "intense" is observed at T=18~20; in Scenario 10, the type "medium" is observed at T=0~5, the type "intense" is observed at T=6~8, and the type "little" is observed at T=18~20; in Scenario 11, the type "medium" is observed at T=0~5, the type "intense" is observed at T=6~8, and the type "medium" is observed at T=18~20; and in Scenario 12, the type "medium" is observed at T=0~5, the type "intense" is observed at T=6~8, and the type "intense" is observed at T=18~20. The first 30 one-meter sections (see Figure 4) are also chosen to show the impact of additional geological investigations on the probability updating.

As shown in Figure 8, the results indicate that the observation in additional geological investigations can provide new evidence for probability updating in the zone from the currently excavated section to the additionally investigated section, as well as the zone ahead of the additionally investigated section. Specifically, in the zone from the currently excavated section to the additionally investigated section, a "U" shape (see Figure 8 (a) and (f)) develops in the case of geological conditions of the above sections remaining consistent, and an "X" shape (see Figure 8 (b) ~ (e)) develops if otherwise. In the zone ahead of the additionally investigated section, the posterior probability of the observed soil type in the additionally investigated section drops gradually in the subsequent time slices, and this influence disappears after some time slices.

5 CONCLUSIONS

The geologic prediction model is a means for explicitly structuring the information customarily used by engineers and geologists in assessing the geological conditions of a tunneling project. The objectives of the developed simulation model in this research are (i) model the random evolution of the probabilistic dependencies on the distribution of geological conditions; (ii) develop a geological description that reflects the uncertainty of the information on which it is based; and (iii) update the prediction of geological conditions over time when the observed information is available.

The developed model, consisting of Bayes technique and Markov chain, achieves these objectives to a satisfactory degree. The geological conditions of one-meter sections in the tunnel construction can be updated in a continuous manner, given the geological conditions of the previous one-meter section is observed as the construction progresses. A real project was used to verify the applicability of the developed simulation model. The simulation results show that the continuous updates during construction can significantly improve the prediction of the project performance by eliminating the uncertainty contained in the original assumption. The model's updating procedure can be easily expanded to predict the results of future geologic exploration programs, as well as the project productivity and quality, as a function of the reliability of the observation methods employed.

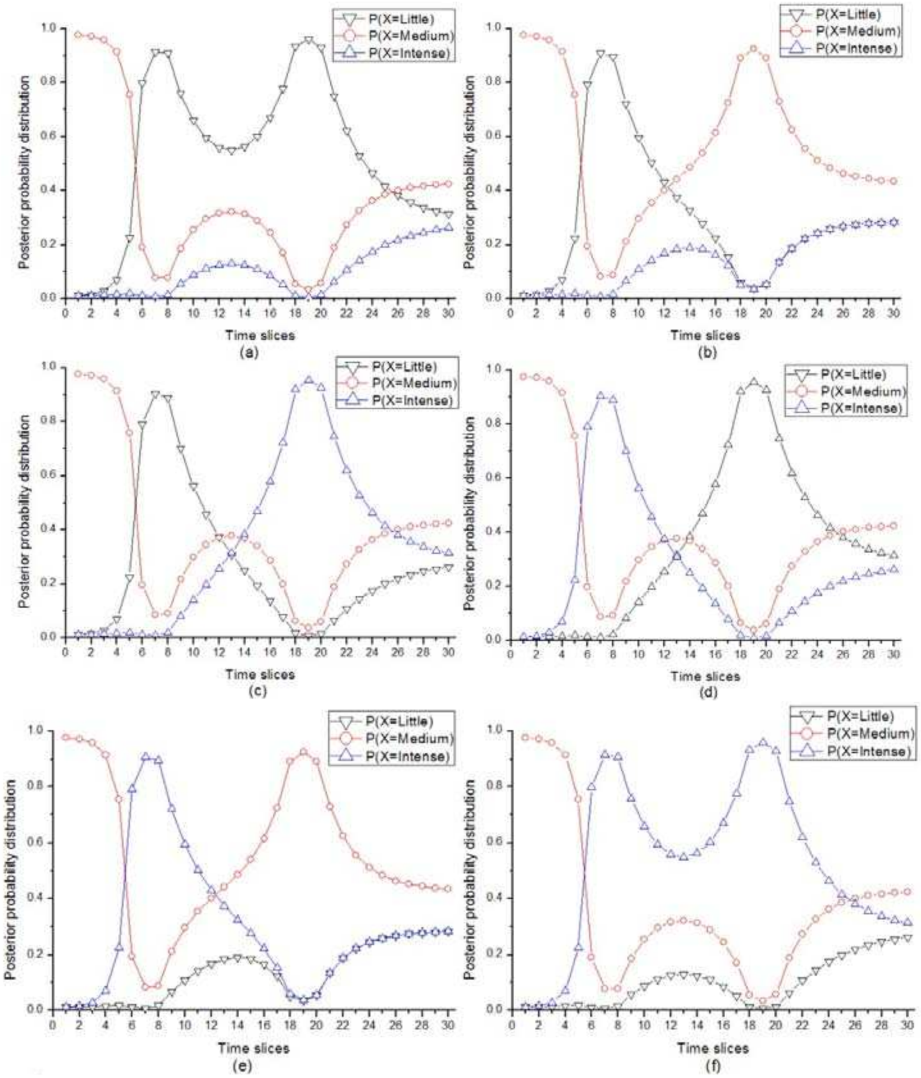

Figure 8: Results of the posterior probability distribution of the predicted node over time in the case of additional geological investigations: (a) Scenario 7; (b) Scenario 8; (c) Scenario 9; (d) Scenario 10; (e) Scenario 11; and (f) Scenario 12.

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