UNIVERSITY OF ALBERTA

SIMULATION-BASED PRODUCTIVITY MODELING FOR TUNNEL CONSTRUCTION OPERATIONS

BY

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A thesis to the Faculty of Graduate Studies in partial fulfillment of the requirements for the degree of **DOCTOR OF PHILOSOPHY**

in

Construction Engineering and Management

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

EDMONTON, ALBERTA

Fall 2007

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Your file Votre référence
ISBN: 978-0-494-32941-2
Our file Notre référence
ISBN: 978-0-494-32941-2

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ABSTRACT

Due to many unforeseen factors for tunnel construction projects, the precise estimate of the tunnel productivity is a challenging task for the tunnel project planners. The current industry practice of the tunnel productivity estimate based on experts' opinions may lead to the erroneous schedule prediction. The use of simulation techniques can provide many benefits. Construction project planners can effectively plan the schedule and cost by examining multiple simulation scenarios instead of conducting costly experimentation in the field.

This thesis presents the development and implementation of a simulation-based productivity model for utility tunnel construction operations. The tunnel productivity model is an effective approach for identifying the effects of uncertainty factors and predicting the productivity under various project circumstances. The modeling concept is utilized to identify the soil characteristics for various soil conditions. The thesis is composed of three major areas of research.

The first part is Bayesian updating application into simulation in the tunneling project to update an original schedule and estimate major input parameters for a tunnel simulation model. The second part is the development of a simulation-based tunnel productivity model to accurately predict tunnel productivity by quantifying the effects of uncertainty factors. The third part is the inference of soil transitions along the tunnel path from the use of the developed productivity model. The proposed framework can be effectively utilized for identifying the soil characteristics for various soil conditions and improving the prediction of Tunnel Boring Machine (TBM) penetration rates and productivity for tunnel construction operations.

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The following symbols are used in this thesis.

θ = Random variable for the parameter of a distribution;

k = Normalizing constant $k = \left[\int_{-\infty}^{\infty} L(\theta) f'(\theta) d\theta\right]^{-1}$

$L(\theta)$ = Likelihood of observing the experimental outcome assuming a given θ.

$\bar{x}$ = Mean of Likelihood Function

σ^2 = Variance of Likelihood Function

n = Number of Sample Data

μ' = Mean of Prior Distribution

$(\sigma')^2$ = Variance of Prior Distribution

μ''_μ = Mean of Posterior Distribution

σ''_μ = Standard Deviation of Posterior Distribution

$p(\theta)$ = Prior distribution

$p(y|\theta)$ = Sampling distribution

$p(\theta|y)$ = Posterior density

CHAPTER 1: INTRODUCTION

1.1 Introduction

In order to understand how the operations of real world system work, a set of assumptions should be made usually in the form of mathematical or logical relations. However, due to the complexity of most real world systems, realistic models can not be simply evaluated with an analytical approach and these models should be solved by means of simulation. In a simulation, a computer is utilized to numerically evaluate the model as a representation of a system for estimating the true characteristics of the model. Simulation has been widely accepted and utilized to solve the operations of complex systems in various areas. There are numerous advantages of simulation. Simulation allows one to easily evaluate the performance of an existing system under specific conditions and provides a quick evaluation of alternative proposed system design for a better decision-making (Law and Kelton 2000).

Construction simulation also offers many benefits in analyzing various construction operations. Construction project planners can effectively plan the schedule and cost by examining multiple simulation scenarios instead of conducting costly experimentation in the field. Although the use of computer simulation has been an appealing method for academia, its application to real construction projects has been limited to only a few large contractors who can afford to employ dedicated simulation professionals (Hajjar 1999). One of main reasons for its minimal application to real construction projects is that many industry personnel believe simulation models are expensive and time-consuming to develop. There is also some skepticism from many who are not familiar with simulation, and are suspicious of the simulation results. However, these drawbacks can be overcome by demonstrating the practical benefits of simulation.

In order to provide greater confidence in a simulation result, a model must first be a valid representation of the actual system and the quality of the input provided by its users must be precise. While models can be prepared to largely resemble actual construction processes, arbitrary distributions such as uniform and triangular distribution based on industry experts' opinions are commonly utilized as input to the simulation due to lack of numeric data for various construction activity durations. Although this input may represent the best initial estimate, subjective and inaccurate estimates generally translate into inaccurate simulation results and consequently produce erroneous schedule and cost predictions.

This research utilizes a special purpose simulation for actual tunnel construction operations and produces a tunnel productivity model based on the simulation results. Bayesian techniques are first applied to a simulation model of an actual tunnel project, the North Edmonton Sanitary Trunk (NEST) to update an original schedule planned prior to construction as the project progresses. With the obtained feedback on progress, causes for delays, production loss, production increase, and other relevant information, the uncertainty factors and their impacts on the tunnel productivity are thoroughly identified from the simulation experiment and a tunnel productivity model is developed in a structured and comprehensive manner. The soil transitions along the tunnel path are modeled using the developed tunnel productivity model.

1.2 Research Objectives

The overall objective of this research is to improve the prediction of project performance with the application of Bayesian techniques into simulation for tunnel construction operations, and to develop a simulation-based tunnel productivity model with effects of the critical factors, and to implement the modeling concept to make inferences of soil transitions along the tunnel path based on the predicted TBM penetration rates. To achieve these objectives, the following sub-objectives and steps were identified.

1. Implement the special purpose simulation template and Bayesian input modeling approach for the schedule updating of an actual tunneling project.
2. Utilize a sampling-based Bayesian inference for estimation of major input parameters for a tunnel simulation template from a fully instrumented and continuously monitored actual project.
3. Develop a simulation-based tunnel productivity model to identify the effects of the critical factors on the productivity and predict the realistic and accurate project performance.
4. Implement a tunnel productivity modeling concept to predict the TBM penetration rates for different soil types and make inferences of soil transitions along the tunnel path.
5. Validate the obtained results by comparing with the actual sample for TBM penetration rates collected during the construction and relating to the productivity patterns in various soil conditions.

1.3 Research Summary

For this research, one of the tunneling projects completed by the City of Edmonton Public Works Department, NEST was selected as a major case study. The project was fully instrumented and continuously monitored to obtain continuous feedback on progress, causes for delay, production loss, production increase, and other relevant information. For the data collection, a summer co-op student was involved in the project and recorded actual site conditions during construction. For the collection of TBM penetration rates, a wheel anchored to the conveyor traveling on the segmental liner behind the TBM was connected to a data recorder which monitored the advancement of the wheel.

A special purpose simulation template for tunneling developed under *Simphony* was utilized for this research. The tunneling template in *Simphony* is a special purpose simulation tool for design and analysis of tunnel construction methods. The simulation tool was developed under the successful collaborative research work between the City of Edmonton Asset Management and Public Works Department and the NSERC/Alberta Construction Industry Research Chair in Construction Engineering and Management (Ruwanpura 2001). It should be noted that the author was not involved with developing the current tunneling template. It was utilized for modeling this research due to the author's expertise with it and the flexibility and extensibility it provides. Since it has been successfully used and validated to plan and control for numerous tunneling projects carried out by the City of Edmonton Public Works Department (Ruwanpura et al, 2001), it was decided that major efforts for this research were made on enhancing input modeling approaches and embellishing modeling of unforeseen events for tunnel simulation instead of developing a new template.

Based on the established objectives, the research was conducted in three phases. During the first phase, Bayesian input modeling approach was implemented to update an original schedule planned prior to construction as the project progressed. A regression analysis based on the data extracted from the project progress report was first conducted to identify the factors affecting the productivity. A sampling-based Bayesian inference method was then utilized for estimation of major input parameters for a tunnel simulation template.

During the second phase, six different geological zones from the NEST project were first determined based on the actual soil types and TBM penetration rates sample, and the simulation experiment was then conducted with major input parameters such as TBM penetration rates, survey, and rock drilling activities. After simulation and input models were validated with the actual results, a tunnel productivity model using a multiple regression technique was developed to systematically identify the effects of uncertainty factors and accurately predict the productivity under various project circumstances related to the geological uncertainty and machine performance.

During the third phase, based on the tunnel productivity model, the TBM penetration rates were predicted for eleven soil segments, which were divided by the major soil types. The analytical approach using the tunnel productivity model not only provided an accurate prediction of TBM penetration rates for soil segments containing limited or even no sample data but also provided a logical method to make an inference of soil transitions along the entire tunnel path. The predicted TBM rates from the analytical approach were first compared with actual sample. The soil transition models along the entire tunnel path were then validated with the patterns identified from the plots of actual productivity.

1.4 Thesis Organization

Chapter 2 presents a summary of the state-of-the-art in computer simulation, its applications in tunneling, the overall tunnel construction process used for modeling, an overview of the *Simphony* tunneling template, and Edmonton geology.

Chapter 3 provides an overview of the case study–NEST project and explains data collection procedures. It includes data analysis based on the project progress report focusing on developing a regression model to evaluate the factors on the productivity.

The overview of the Bayesian updating techniques is discussed in Chapter 4. Bayesian input modeling procedures to update the distributions of input parameters for a tunnel simulation model are explained in this chapter along with a case study of an actual tunnel construction project of NEST.

Chapter 5 presents a sampling-based Bayesian inference method for estimating the input parameters for the simulation model. It focuses on the major input parameters such as TBM penetration rates for different soil types and soil transitions, probability of rock encountering by the TBM, and survey activities. A case study is conducted for validating the input models described in this chapter.

Chapter 6 proposes a simulation-based tunnel productivity model with a multiple regression technique based on the data sets generated from simulation experiment. The established tunnel productivity model is validated with simulation experiments and actual results.

Based on the developed tunnel productivity model, a methodology to predict the TBM penetration rates and make an inference of the soil transitions along the tunnel path is presented in Chapter 7. The predicted TBM rates are compared with actual sample and the soil transition model is validated by comparing with the actual productivity patterns. Chapter 8 presents the final discussion describing the findings, conclusions, contributions, limitations, and recommendations for further research.

CHAPTER 2: BACKGROUND

2.1 Introduction

The City of Edmonton has increasingly utilized the tunnel construction method since its first use of hand tunneling in early 1950's. The use of tunneling boring machine (TBM) expands their ability to excavate as large as 6.8 meters diameter tunnels. *Simphony* is a simulation environment for developing special purpose simulation tools for construction domains (Hajjar and AbouRizk 2002). A special purpose simulation template for tunneling under *Simphony* was developed collaboratively with the City of Edmonton Asset Management and Public Works Department under NSERC/Alberta Construction Industry Research Program in Construction Engineering and Management. The objective of the simulation tool was to establish the possible productivity of the tunnel and to develop an estimate and construction plan (Ruwanpura 2001).

This chapter is organized as follows: Section 2.2 presents a summary of the state-of-the-art in computer simulation and its applications in tunneling. Section 2.3 briefly describes the overall tunnel construction process. The overview of the *Simphony* tunneling template is discussed in Section 2.4. Section 2.5 briefly explains the Edmonton geology, which can be classified into 11 different soil types.

2.2 Construction Simulations and Applications

2.2.1 Simulation Modeling in Construction

In recent years, the rapid development of computer technologies enables simulation to become one of the most widely used operation-research and management-science techniques. Simulation allows its user to evaluate a model numerically for estimating the desired true characteristics of the model (Law and Kelton 2000). Halpin (1977) initiated the application of simulation in construction research with his invention of a system called CYCLONE (CYCLic Operation NEtwork). CYCLONE became the basis for a wide range of construction simulation research efforts and motivated the developments of some other derivatives such as INSIGHT (Paulson et al. 1978), UM-CYCLONE (Ioannou 1989a), RESQUE (Chang and Carr 1987), and STROBOSCOPE (Martinez and Ioannou 1994). Although there are obvious benefits from those simulation tools, the use of computer simulation has been limited only to academia. In order to improve the appeal of computer simulation that fulfills the need of industry practitioners for planning various construction projects, the development of a more comprehensive approach is required (Hajjar and AbouRizk 2002).

A computer system called *Simphony* for building general and special purpose simulation (SPS) tools was developed under the Natural Science and Engineering Research Council (NSERC) / Alberta Construction Industry Research Chair Program in Construction Engineering and Management. Simphony based on the unified modeling methodology greatly simplified and shortened the development of new SPS tools in the form of modeling element templates (Hajjar and AbouRizk 2002). Simphony fulfills the complete needs of the construction simulation practitioners as a comprehensive approach: with its object oriented application framework using graphical, hierarchical, modular, and integrated modeling techniques, any simulation template can be easily built in a structured approach (Ruwanpura 2001).

2.2.2 Tunnel Simulation Tools and Applications

Because tunnel construction is relatively repetitive, simulating the process of tunnel advancement can offer many benefits to the engineers, planners, and constructors to plan and control the project efficiently. Ruwanpura (2001) describes the design, development, and application of a special purpose simulation tool for actual tunnel construction operations performed by the City of Edmonton Public Works Department. The special purpose simulation template under *Simphony* was very useful in predicting the productivity of tunneling and evaluating the cost and duration from various tunneling options. The cost planning module in the tunnel template provided estimators and planners with the opportunities to produce more realistic project schedule and cost estimate.

Tunneling projects are commonly considered high-risk projects. Unknown soil conditions are major contributors to uncertainty since soil samples taken from vertical boreholes usually spaced about 300-500 m apart show only the soils present in the discrete borehole locations. Ruwanpura et al. (2004) presented analytical and simulation methods to predict soil profiles between boreholes. An analytical model for soil prediction was created using existing borehole data and was then incorporated with a simulation model using special purpose simulation concepts and advanced geotechnical characterization techniques.

Estimating tunneling time and cost performance is a challenging task for contractors due to the complexity of tunneling operations and the variety of associated uncertainties. Likhitruangsilp and Ioannou (2003) presented a stochastic methodology for evaluating tunneling performance by using discrete-event simulation. The probabilistic scheduling networks for different tunneling alternatives were analyzed using discrete-event simulation performed in *ProbSched*, a graphical probabilistic scheduling program implemented as an add-in to the STROBOSCOPE simulation system. The simulation results provide probability distributions of tunnel advance rates and tunneling unit costs for all possible alternatives to determine optimal excavation and support policies for the project.

Haas and Einstein (2002) applied Bayesian techniques to their developed tool, "Decision Aids for Tunneling (DAT)." They updated the mean length of the geologic and geotechnical parameters using Bayesian techniques and successfully showed that this update considerably reduced uncertainty in estimates of construction cost and schedule. In their work, however, approximate data were assumed for demonstration purposes. Furthermore, the construction simulation of the case study uses a macro-level relationship between the ground classes in the tunnel profile and project cost/time.

2.3 Literature Review

2.3.1 Literature on Modeling Geological Uncertainty

Uncertainty of Geological condition is one of major factors often leading to design and construction conservatism and thus inflating project costs. Various researchers have conducted studies to model the geological conditions using a combination of many concepts such as Markov chains, statistical techniques, and simulation. Ioannou (1987, 1988a, 1988b) presented an extensive study to reduce uncertainty in underground construction. As part of his study, Ioannou (1987) presented a general model for the probabilistic prediction of tunnel geology with a set of geologic parameters such as rock type, joint density, and degree of weathering, which follows a continuous-space, discrete-state Markov process.

Ioannou (1988b) presented the contractor's view concerning the usefulness of constructing a pilot tunnel as part of the site investigation program to offer guidelines for evaluating its benefits. This research demonstrated that pilot tunnels are generally most useful in large projects with limited surface access with unfavorable geologic conditions. He claimed that the construction of a pilot tunnel can reduce bid contingencies up to 20% of the project cost.

Site investigation can reduce geologic uncertainty and thus decrease costs by reducing the contingency amounts included in bids. Ioannou (1988a) presented research findings that provide a better understanding of how subsurface exploration and improved contractual risk sharing can decrease the cost of underground projects. Major issues discussed in this paper were the methodology used by tunneling contractors to estimate geologic profiles given a set of available geologic information, the geologic classification methods used to associate the expected profile with acceptable construction alternatives, the spatial prediction of ground classes, and the extents over which different excavation and support methods will be necessary.

Ioannou (1989) presented a decision support system for the evaluation of geologic exploration programs in underground construction to quantify the economic value of different subsurface investigation alternatives and to provide owners and designers with a solid basis for making associated technical and financial decisions. It described the methodology for using simulation to obtain an estimate of the expected value and the standard deviation of the value of sampled geologic information.

Geotechnical design requires the interpretation of ground conditions from site investigation information. As an approach of a computer system to produce an interpretation of the ground conditions, Toll (1995) described a knowledge-based (expert) system to assist a geotechnical specialist with the processing of raw site investigation data to arrive at interpreted design parameters and a model of the ground condition. Oliphant et al. (1996) described the operation of a knowledge-based system (KBS) to improve the inadequate site investigation practice. The developed system called ASSIST (Advisory System for Site InveSTigations) comprising three linked sub-systems of preliminary site investigation, data acquisition, and main site investigation was presented in this paper.

Touran (1997) demonstrated that the states of work and nonwork for the tunnel boring machine from the actual tunnel project in Boston can be modeled with a Markov chain. In this paper, a general probabilistic approach was proposed to develop the cumulative distribution function (CDF) of the total length that can be tunneled in a given time frame. Developed simulation models verified the results of the analytical model and simulated the distribution for the time necessary to tunnel a certain length of the tunnel.

Optimal decisions for tunneling plans should be made in order to minimize time and cost while addressing important factors such as geologic uncertainty and variability, uncertainty in tunneling productivity, and contractor's risk sensitivity. Likhitruangsilp and Ioannou (2004) proposed a computerized risk-sensitive decision support system quantifying and incorporating all important tunneling risks. The system can be utilized to determine dynamic optimal tunneling plans and risk-adjusted costs as functions of a contractor's risk sensitivity.

Site exploration programs (e.g., borehole tests) are commonly used to mitigate geologic uncertainty associated with underground projects. Likhitruangsilp and Ioannou (2005) presented a methodology to evaluate the economic value of sequential subsurface exploration programs by using stochastic dynamic programming. They demonstrated the application of Bayes' theorem to analyze effects of exploration results on geologic prediction. Preposterior analysis was performed to evaluate the economic value of the site exploration program based on the concept of value of information.

Abdallah (2005) explored the utilization of exploratory tunnels as a project management tool for estimating the cost and duration of the tunnel construction project. Based on data collected from the Kaponig 2.75 kilometers exploratory tunnel, a part of a double-track high-speed railway development in Austria, the risks associated with design details for the final tunnel enlargement were evaluated. A deterministic model based on Monte-Carlo simulation was developed to predict potential outcomes of the total project in terms of cost and duration and their associated probabilities.

Predicting productivity is the key for success in tunneling projects. Hegab et al. (2006) presented statistical models that represent the soil penetration rate of microtunneling machines with collected data from 35 microtunneling projects. The selected model parameters included shear force of the cutter head, jacking force, diameter, jacking length, and the driving (tunneling) time through different soils. Penetration time of microtunneling project can be accurately predicted from the developed mathematical models, which can help contractors to estimate the required time for a microtunneling drive.

Exploration planning is a process of decision making under uncertainty. Karam et al. (2007) presented an approach for assessing the effect of additional exploration before actually committing to exploration, through a process of so-called virtual exploration. They developed a software package, the Decision Aids for Tunnel Exploration (DATE). It allows one to asses the consequences of collecting new information through virtual exploration prior to actually performing (or not) the exploration. The input parameters are the geologic state descriptions and their prior probabilities, the construction cost matrix, and the exploration reliability matrix. The outcomes are decision trees for the cases of no, perfect, and imperfect exploration, from with the expected value of perfect information (EVPI) and expected value of sample information (EVSI) are computed.

2.3.2 Literature on Diggability and Machine Performance

In tunneling, the performance of the TBM may be controlled by the diggability characteristics of soils being excavated. The diggability is strongly related to the geology and is influenced by geotechnical parameters such as shear strength, density, and water content, etc. The presence of hard rocks can make digging difficult. Equipments and geometric parameters such as the operator's practice and skill, tooth design, and digging trajectory (depth and size of TBM penetration) may also affect the TBM performance.

In oil sand mining, Patnayak and Tannant (2005) conducted a shovel performance monitoring study related to oil sand diggability. For the purpose of assessing ground diggability, the study utilized current and voltage data from hoist, crowd, and swing motors of P&H 4100 series electric cable shovels.

By monitoring the performance of shovels in various digging environment, it is possible to develop relationships between the key shovel performance indicators and diggability of the ground. The digging cycle time varies with the diggability of the oil sands. For a given shovel in similar operating condition (digging trajectory and operator), the digging time would be longer in a difficult digging condition, compared to an easy digging condition. Therefore, the length of digging time could be used as a simple performance indicator for ground diggability characteristics (Patnayak and Tannant, 2005).

For their study, digital video recording of different operating electric cable shovels were taken and corresponding shovel performance data were collected. They examined the video records to identify the start and stop times of specific shovel activities, especially the dig cycle. Figure 2-1 shows an example of shovel activities identified from the video observation. This figure demonstrates that a consistent pattern of signal responses from the hoist motor matches the start of each dig cycle identified from the video record.

Identification of shovel activities from the shovel performance data were based on the interpretation of motor voltage and current. Positive (+) and negative (-) voltages represent direction of the motor. For the hoist motor, a positive voltage means the dipper is moving upward and a negative voltage means the dipper is moving downward. For the crowd motor, a positive voltage implies crowd arm extension and a negative voltage implies crowd arm retraction. For the swing motor, the sign of voltage depends on position of the truck with respect to the shovel (Patnayak and Tannant, 2005).

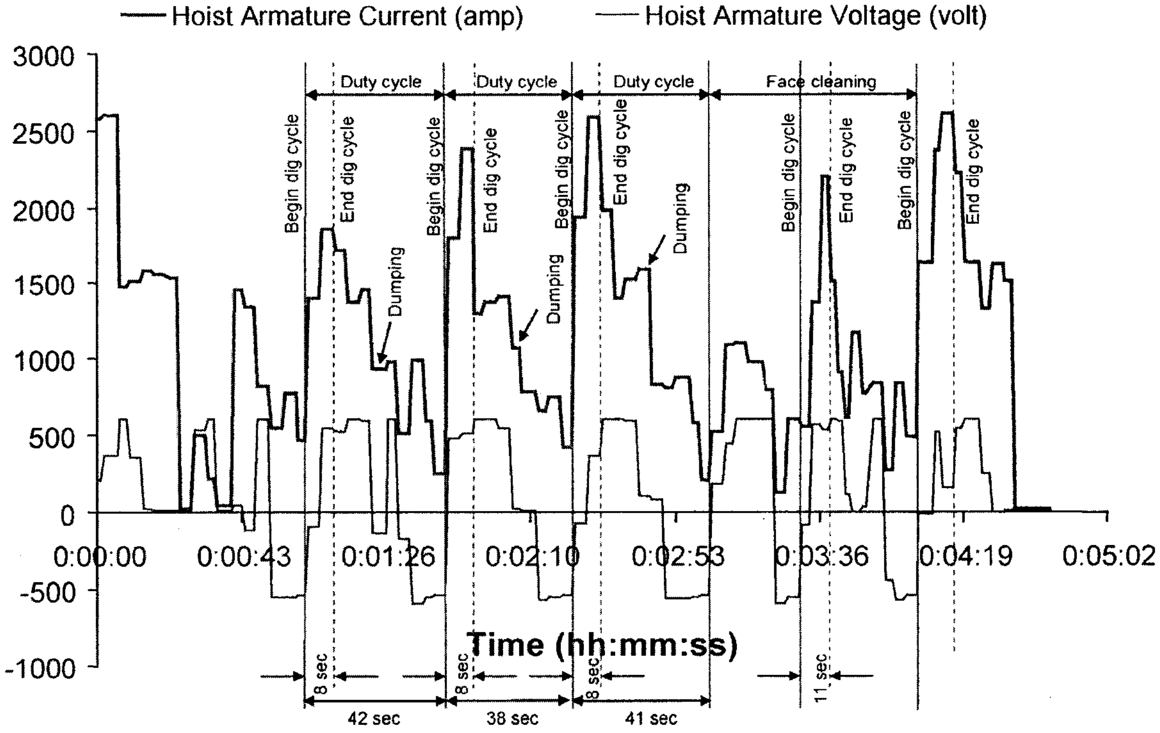

Figure 2-1: Hoist Motor Reponses and Shovel Activities identified from Video Observation (Patnayak and Tannant, 2005)

Armature current of hoist and crowd motors also change from positive to negative and vice versa. For instance, at the beginning of hoisting, both armature voltages and currents are positive. When the dipper approaches the boom point but is still going up, the operators reverse the joy stick in the downward direction to stop the upward hoisting motion. At this point, the hoist armature voltage remains positive but the hoist armature current becomes negative to cancel out the hoisting, usually referred to as plugging.

They found that hoist and crowd motor responses can be utilized to identify different shovel activities, especially the dig cycle. Some key shovel performance indicators examined are the dig cycle time, digging energy, and digging power. By averaging the hoist power over a number of dig cycles, the average hoist power is less sensitive to digging trajectory and could be useful parameter for assessing ground diggability characteristics. Analysis of performance indicators showed that the shovel performance can be significantly influenced by the operator. The study revealed that freezing temperature can have a minor and localized influence on shovel performance (Patnayak and Tannant, 2005).

2.3.3 Literature on Input Modeling for Construction Operations

Accurate estimates of numerical characteristics of the input processes are mainly required for planning and analyzing the operations in an engineering project. Whether the project management system is based on a network model such the critical path method (CPM) and program evaluation and review technique (PERT), and simulation models, the validity of the system's outputs is strongly related to the quality of the estimates of the input characteristics (AbouRizk et al. 1991).

AbouRizk et al. (1991) presented a visual interactive procedure for fitting beta distributions to activity times in a simulation model when sample data are scarce for statistical analysis of the model's input process. The fitting procedure included efficient methods for computing the shape parameters of the beta distribution mostly matching the specified characteristics and was implemented in a computer-based system called VIBES (visual interactive beta estimation system).

AbouRizk et al. (1994) presented numerical techniques that can be utilized to fit beta distributions to sample data for construction operations. In this paper, it was found that the least-square minimization method provided better quality fits in general, compared to other two approaches, moment matching and maximum likelihood. The adopted fitting procedures were successfully implemented in BetaFit, an interactive microcomputer-based software package.

Maio et al. (2000) analyzed the project data in California using BestFit software to obtain the parameters of the theoretical distribution functions that best described the field data set. The research confirmed that the use of a chi-square fitting procedure is subjective regarding the choice of the number of class intervals. The paper discussed the issue relating to the reliability of goodness-of-fits tests when dealing with large data sets.

In the classical PERT, the mean and variances are approximated based on a three time estimate reflecting the pessimistic, optimistic, and the most likely values of the duration. Moder and Rodger (1968) argued that the exact optimistic and pessimistic values are hard to define. They suggested the 5% and 95% thresholds of the range using 3.2 instead of 6 for the variance estimation in the denominator. Troutt (1989) suggested using the median instead of mode for the PERT mean calculation stating that the use of median produces a good estimate of the mean regardless of the probability distribution assumed. Cottrell (1999) proposed a simplified version of the PERT by implementing the normal distribution, rather than beta, in order to reduce the number of estimates required for activity durations from three (pessimistic, optimistic, and the most likely) to two (the most likely and pessimistic).

Lu and AbouRizk (2000) presented the derivation of a PERT simulation model, which incorporates the discrete event modeling approach and a simplified critical activity identification method in an attempt to overcome the limitations and improve the computing efficiency of classical CPM/PERT analysis. The developed model demonstrated remarkable enhancement in analyzing the risk of project schedule overrun and determination of activity criticality.

Lu (2002) presented an artificial neural network (ANN)-based approach for PERT simulation in terms of input modeling to estimate the true properties of the beta distributions from statistical sampling of actual data combined with subjective information. The developed ANN-based input modeling methods demonstrated an efficient and accurate methodology to fit the distribution for activity duration in construction through a sample application.

Salem et al. (2003) presented an approach for estimating life-cycle costs and evaluating infrastructure rehabilitation and construction alternatives, derived from probability theory and simulation application. The developed risk-based life-cycle cost model considered the time to failure of each pavement rehabilitation/construction alternative and provides additional knowledge about the uncertainty levels that accompany the estimated life-cycle costs. Infrastructure service life (time to failure) is modeled by following a formal input data modeling procedure including fitting statistical distributions to pavement-failure data within each pavement group, testing the goodness of fit, and determining the distribution parameters.

Shaheen et al. (2005) proposed a framework for integrating fuzzy expert systems with discrete event simulation for enhancing the input modeling process in discrete event simulation. The proposed integration was designed to provide real-time prediction of the activity output by capturing and modeling the changes in the factors affecting the activity output whenever the simulation time advances.

Ranging estimating is a simple method of simulating a project estimate by breaking the project into work packages and approximating the variables in each package using statistical distributions. Shaheen et al. (2007) proposed an alternative approach to ranging estimating that is grounded in fuzzy set theory. They presented a methodology for extracting fuzzy numbers from experts and processing the information in fuzzy range estimating analysis.

2.4 Tunnel Construction Process

A shielded TBM has been typically utilized for excavation of long tunnels while the tunneling by manpower resources or hand tunneling is more suitable for shorter tunnels. For hand tunneling, an excavation crew using jackhammers, drills, and shovels is deployed at the tunnel face to excavate various tunnels ranging from 0.91 to 3.20 meters in diameters.

Tunnel projects are composed of three major processes: excavation, dirt removal, and tunnel support. The tunnel construction typically starts with the excavation and liner support of a vertical shaft to a depth corresponding to the invert level of the tunnel excavation. The following tunnel activities include:

1. Excavation and support of the undercut area (an enlargement at the bottom of the shaft used for staging material handling and dirt removal operations),
2. Excavation of the tunnel and tail tunnel,
3. Disposal of dirt from the tunnel face,
4. Hoisting the dirt to the ground level,
5. Lining the tunnel,

6. Extending the services and rail track,
7. Excavation and support of the removal shaft (if a TBM is used).

There are two different types of TBM: open-face and closed-face shield machines. Open-faced machines are commonly used in competent soils with reasonable stability while closed-face machines are more suitable for conditions of runny soils such as silt or sand. One of the most important properties of TBMs is their excavation rate, which is mainly influenced and determined by the soil conditions and the TBM horsepower. The stroke length is another important property because it determines how often the TBM needs to be reset.

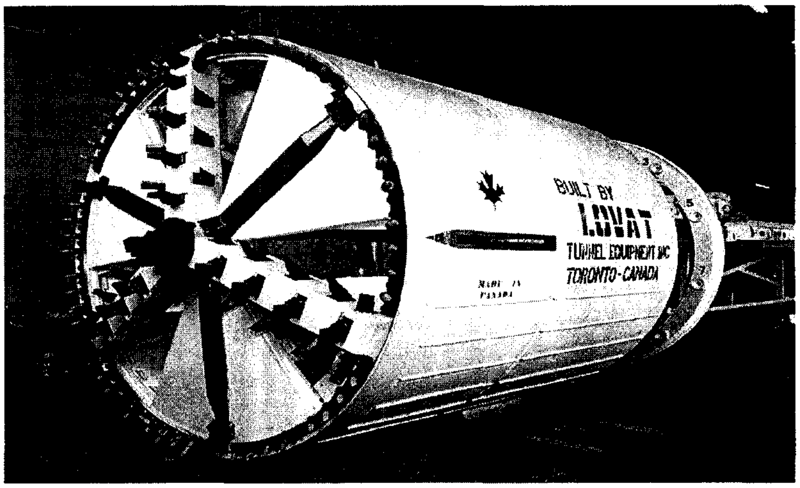

Figure 2-2: Tunnel Boring Machine (TBM)

After excavation, the dirt is hauled horizontally using trains and/or belt conveyors and disposed from the tunnel to the shaft, where is lifted to the surface. The working shaft is used to remove the spoil and to transport construction materials and personnel. The dirt can be hoisted with a skip, a clamshell bucket, a crane, a gantry, or a derrick hoist.

The tunnel support systems mainly consist of either (1) rib-and-lagging or (2) pre-cast concrete segments. The rib-and-lagging demonstrates high performance in various ground conditions. During installation, lagging is wedged circumferentially between rib and soil. The rib-and-lagging support system acts as the primary lining system. Cast-in-place concrete is placed as a secondary layer after tunnel excavation. Pre-cast concrete segment lining system can be used as the alternative to rib-and-lagging. Pre-cast liners act as both the primary and final lining. Each segment designed as a compact structural unit requires the least amount of handling during erection. The full ring typically consisting of four identical segments is partially installed inside the shield of the TBM, and the ring is expanded tightly against the soil as it leaves the shield. Metal spacers are inserted in the gap created by the ring expansion to maintain its structural integrity. The gap is subsequently filled with concrete, and the joints are patched with cement mortar (Ruwanpura 2001).

Figure 2-3: Segmental Liners being lowered into tunnel

2.5 Overview of *Simphony* Tunneling Template

The tunneling template developed in *Simphony* is a special purpose simulation tool for design and analysis of tunnel construction methods. Ruwanpura (2001) described the following major reasons for using simulation for tunnel construction operations.

(1) Project Planning: Simulation enables the project planners to plan the sequence of work activities, evaluate the method of operation, select the suitable resources for the given project, and analyze the production of the system prior to actual construction.

(2) Identifying bottlenecks in tunnel operations: Early identification of potential problems in a typical tunnel construction operation helps the planners to decide on corrective measures before actual construction commences.

(3) Examining productivity improvements and optimizing resource utilization: Simulation allows the planners and engineers to observe productivity and resource utilization levels and conduct additional experiments to improve the efficiency of the system.

(4) Offering a quick comparison of alternative scenarios: Simulation offers a quick comparison for alternate scenarios and allows the planners to make a better decision before the project.

The tunneling template consists of sixteen modeling elements through which tunnel activities in various stages can be defined. Each modeling element may include input parameters, outputs, and statistics. These tunnel elements can be divided into three major categories under the *tunnel parent* element: the *shaft undercut*, *soil segment*, and *removal shaft* element. Figure 2-4 illustrates the structure of the tunneling template. The *tunnel parent* element is the main hierarchical element of the template including major input factors globally required for each modeling element. Global outputs and statistics generated from various other elements are reported to this element.

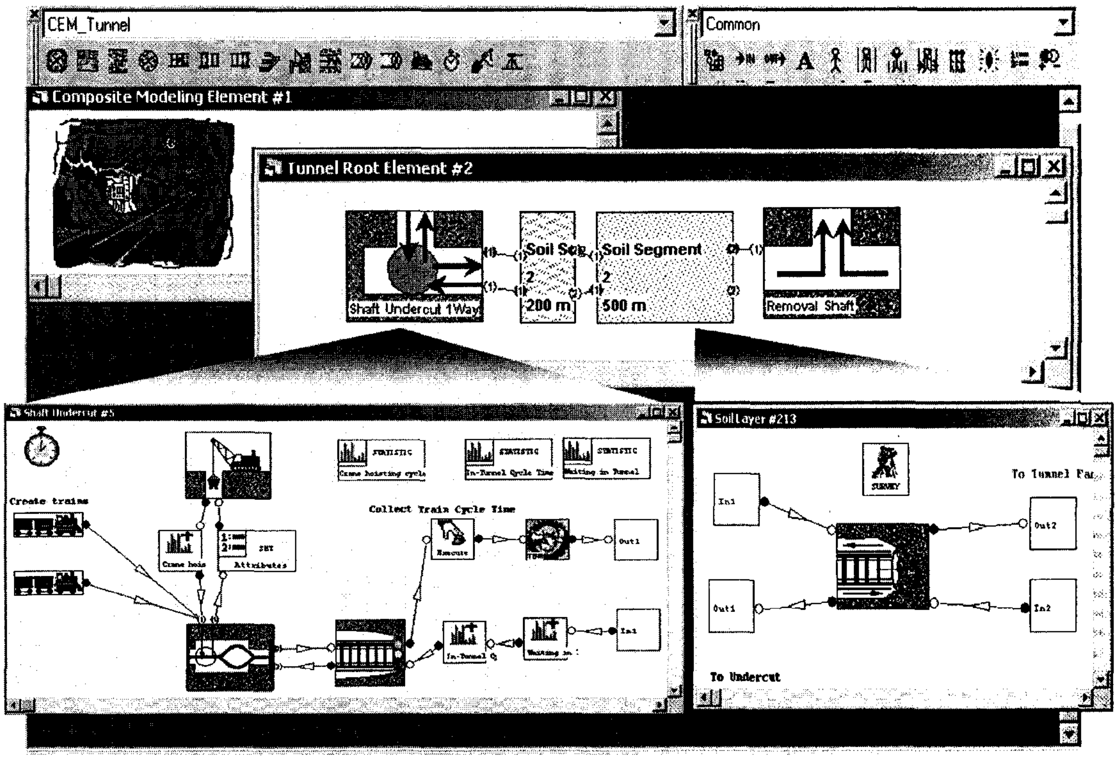

Figure 2-4: Tunneling Template Structure

The soil segments are used to model the changes in soil conditions and tunnel geometry. Users can add many soil segments to the model depending on the soil properties. For instance, if the tunnel to be bored is 300 m long in clay soil and there are

50 m of bedrock in the tunnel to be bored starting at the 100th m of the tunnel, the user can add three soil segments: the first segment (clay) with a length of 100 m, second segment (bedrock) with a length of 50 m, and third segment (clay) with a length of 150 m. Each soil segment has an element for modeling the TBM excavation and lining processes in addition to an element for modeling surveying activities. Users enter basic input data such as the tunnel length, soil type, and TBM penetration rate of each section.

The *shaft undercut* element contains the following modeling elements: *train, track layout, TBM, dirt removal system*, and *shift control*. The user can specify the shift length, mobilization time at each shift length, and lunch break time on the *shift control* element. The *train* element has input parameters related to trains and muck cars including number of trains and muck cars, muck car capacity, and train speed. The input parameters for *TBM* element contain boring diameter, TBM resetting time, and liner installation time.

2.6 Edmonton Geology

The geology of Edmonton can be classified into 11 different soil types. The geologic terminology used in the drill log and the stratigraphic section descriptions is briefly explained (McPherson and Kathal 1972).

1. Bedrock: The Edmonton Formation, composed of interbedded bentonitic shales and sandstone with numerous coal seams, underlies most of the area.
2. Bedrock (ice-shoved): Block of bedrock material underlain by glacial deposits is common in the area. They have been moved by glacier ice and are referred to as ice-shoved bedrock.

3. Disturbed Saskatchewan gravels and sands: Saskatchewan gravels and sands that have been distributed by glacier ice.
4. Saskatchewan gravels and sands: Quartzose sediments varying from fine sand to coarse gravel, fluviatile in origin and deposited prior to glaciation in the area.
5. Glacial till: Unsorted unstrafied sediment deposited by a glacier, composed of clay, silt, and sand with pebbles and boulders; lenses of outwash sand, gravel, or disturbed bedrock are common.
6. Glacial sand and gravel: Mainly sand and gravel deposited by glacial melt water.
7. Lacustro-till: Glaciolacustrine sediments melted with pebbles and till-like layers deposited by mudflows, ice rafting, or both, into a glacial lake.
8. Glaciolacustrine deposits: Bedded sands, silts, and clays deposited in a large preglacial lake called Glacial Lake Edmonton
9. Glaciolacustrine deposits: Mainly fine sand and silt deposited in a large delta in Glacial Lake Edmonton.
10. Aeolian deposits: Sand, medium- to fine-grained in sheet or dune form, thin to 50 feet thick.
11. Alluvium: Recent river terrace and floodplain deposits consisting of clay, silt, and gravel.

However, according to Montgomery and Eisenstein (1995), these soils conditions can be divided into four major categories for tunneling purposes:

1. Bedrock (type 1 and 2 above),
2. Glacial till (mainly type 5 above),

3. Saskatchewan sands and gravels (type 3 and 4 above) and sand lenses (type 6 above),
4. Lake Edmonton Clay (type 7, 8, 9, 10, and 11 above).

CHAPTER 3: DATA COLLECTION AND ANALYSIS FOR TUNNEL CONSTRUCTION OPERATION [1]

3.1 Introduction

Tunnel constructions are composed of three major processes: excavation, dirt removal, and tunnel support. The success of a tunneling project mainly depends on the performance of equipment and experienced personnel, many unforeseen factors - namely geological conditions - can affect project outcomes. For instance, tunnel boring machine (TBM) penetration rates are significantly affected by the hardness of soil layer being excavated, the type of soil, the presence of water and sand, and other unforeseeable conditions such as encountering rocks. Thus, the good quality data obtained from actual tunneling projects can offer many benefits for identifying the relation of various factors with the overall tunnel productivity.

This chapter presents the data collection procedures and data analysis for an actual tunnel project: North Edmonton Sanitary Trunk (NEST). The project was fully instrumented and continuously monitored to obtain continuous feedback on progress, causes for delay, production loss, production increase, and other relevant information. For the collection of TBM penetration rates, a wheel anchored to the conveyor traveling on the segmental liner behind the TBM was connected to a data recorder which monitored the advancement of the wheel. Based on the obtained data points, the TBM

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[1] This chapter mainly contains extracts from the paper "Bayesian Updating Application into Simulation in the North Edmonton Sanitary Trunk Tunnel Project" published in the Journal of Construction Engineering and Management, ASCE, 132(8), 882-894

penetration rates are first calculated and analyzed. Then, a regression analysis based on the actual project data is utilized to identify the factors affecting the productivity. This chapter is organized as follows: Section 3.2 describes the overview of the case study – NEST project. Data collection procedures are explained in detail in Section 3.3. Section 3.4 discusses data analysis for the NEST project focusing on developing the regression model to evaluate how the factors influenced the productivity. The conclusions are presented in Section 3.5.

3.2 Overview of the Case Study – NEST Project

North Edmonton Sanitary Trunk (NEST) was developed as part of a plan to increase the capacity of the existing sewage system and allow continued growth in North Edmonton. The case study focuses on the first section of NEST (NC1), which was proposed as the first stage construction of NEST as shown in Figure 3-1.

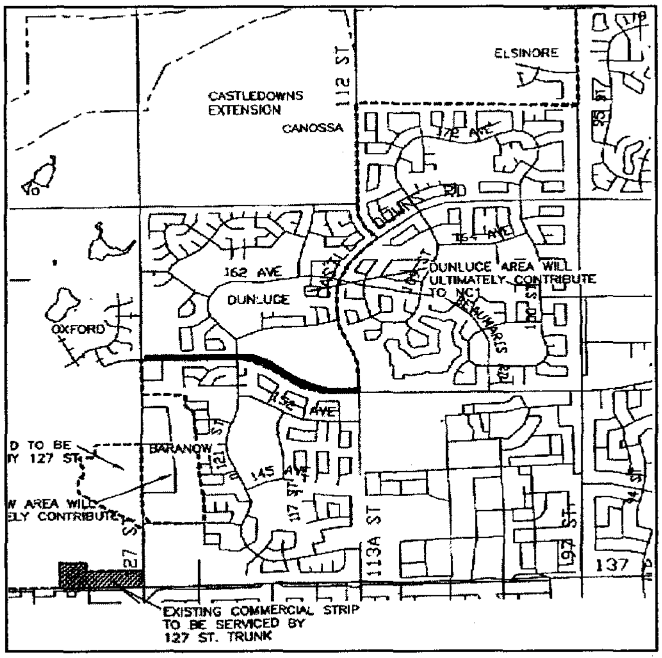

Figure 3-1: NC1 Service Area of NEST

The proposed NC1 section will serve as a temporary outlet, which will be used for storage during the wet weather flow and for conveyance during the dry weather flow. During the dry weather conditions, the discharge from the NC1 section of NEST will be conveyed through the available capacity in the City of Edmonton's sanitary system. The NC1 section of NEST is a 1538-meter tunnel having a 2.94-meter finished diameter lined with pre-cast concrete segments (NEST Design Report 2002). Figure 3-2 illustrates the tunnel cross section of NEST. LOVAT M 126 TBM was used for the tunnel excavation. The major soil type for this project was clay till making up about fifty-six percent of the total tunnel length. Throughout the entire tunnel length, rock boulders were frequently encountered and a considerable amount of time was spent on drilling and splitting these rocks.

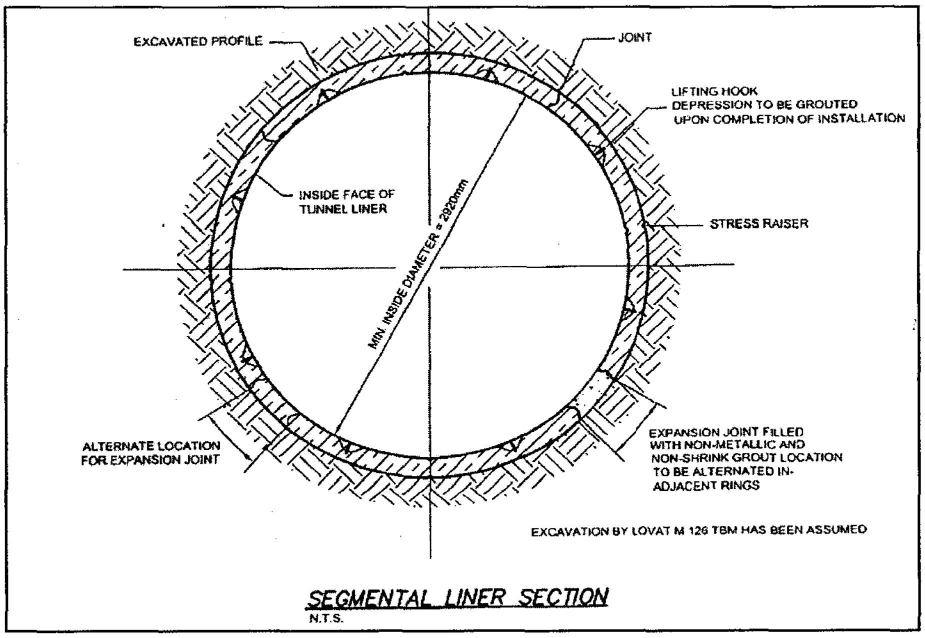

Figure 3-2: Tunnel Cross Section

3.3 Data Collection Procedures

During the construction of this project, actual project data such as soil types and TBM penetration rates were recorded. For the collection of TBM penetration rates, a wheel anchored to the conveyor traveling on the segmental liner behind the TBM was connected to a data recorder which monitored the advancement of the wheel with a rate of 0.002278 m/pulse.

Since the data obtained from the data recorder had many outliers and inadequate data points, considerable effort was expended to identify and remove the outlier points. The daily production from the data logger was compared with the actual recorded daily production from the progress report. If significant deviations (more than 1 m/shift) were detected between the two record sets, the logger data for the entire day was deleted. After this data cleaning process, the correlation coefficient between these two data sets was computed and the obtained correlation factor (0.942) was shown to be statistically significant at the 0.01 level (2-tailed). Based on this statistical result, the cleaned logger data consisting of 140,772 data points were believed to be reliable and were used in further analysis.

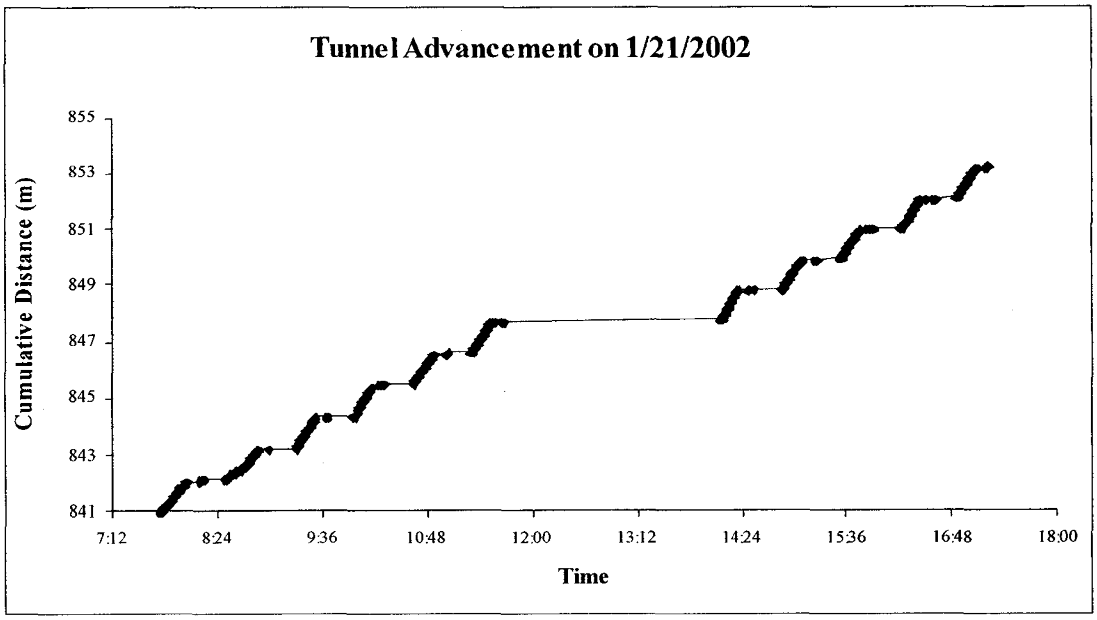

Figure 3-3: Tunnel Advancement on January 21, 2002

Figure 3-3 shows a sample of the recorded data, which plots the advancing distance on the time of day. The inclined portions of the plot indicate the times when the TBM was advancing, whereas the flat portions indicate the times when the TBM was not advancing due to segmental linings being installed, TBM maintenance/breakdown, surveying times, rock drilling, or another disruption. For instance, this chart shows that the TBM advanced at least eleven meters and eleven-meter-long segmental linings were installed on January 21, 2002. The simple visual inspection also indicates that one major disruption occurred between 12:00 PM and 14:00 PM. According to the project progress report, it was primarily due to the surveying time required for the surveying crews to realign the curve.

Based on the plots in Figure 3-3, the TBM penetration rate for the advancing distance of each meter was calculated with a slope for the advancing distance on the time.

Since the flat portions were the times when TBM was not actually advancing, these times were excluded for the calculation of TBM penetration rates. The average TBM penetration rate for the advancing distance of eleven meters on January 21, 2002 was 4.427 m/h with a standard deviation of 0.730.

3.4 Data Analysis

3.4.1 TBM Penetration Rates

The TBM penetration rate is defined as the rate at which the TBM advances (m/hr). The sample for TBM penetration rates consists of 521 data points and the histogram shows the frequencies and distribution of data as shown in Figure 3-4. The average TBM penetration rate was 5.04 m/hr with a standard deviation of 1.27. The highest rate achieved was 9.01 m/hr while the lowest rate recorded was 1.85 m/hr.

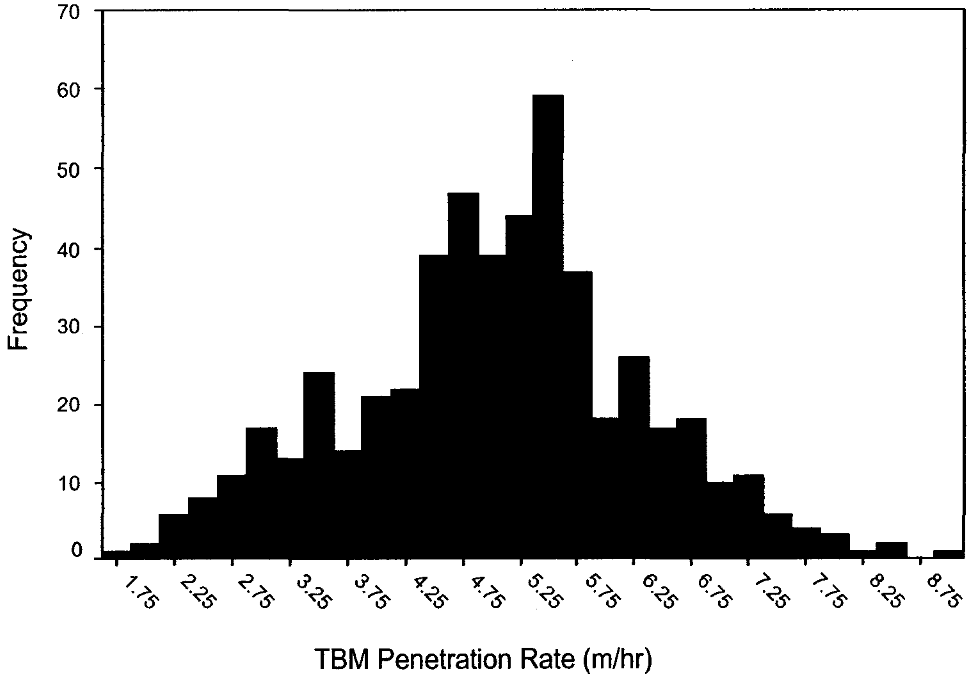

Figure 3-4: Histogram for TBM Penetration Rates

3.4.2 Production per Shift

According to the project progress report, the daily production recording started on July 23, 2001 and ended on February 8, 2002. The total number of working days and accumulated shifts were 139 days and 163 shifts respectively. There were two shifts per day for 24 working days starting on October 1, 2001 and ending on November 2, 2001. The average production was 8.87 m per shift with a standard deviation of 3.42. Among the total 163 shifts, the highest production rate of 15 m per shift was achieved for four shifts while a zero production rate was recorded for six shifts.

3.4.3 Factors Affecting Production

A review of the project progress report indicated that there are some factors which affect the overall tunneling production including rock drilling, TBM breakdown, muck car breakdown, surveying time, pulling cables, and TBM teeth replacement among others. The summary of statistics on these activities is shown in Table 3-1. These statistics include the total number of occurrences, total hours, and descriptive statistics such as mean, minimum, and maximum occurrence time of each activity.

One category, “Other,” was defined to include some activities that could not strictly conform to the categories set out in Table 3-1, such as pouring shaft, undercut, and patching blocks. These activities were also believed to significantly influence the overall productivity. For sixteen cases identified in that category, very low production rates were mainly recorded on these shifts and no tunneling production was recorded on six shifts.

Table 3-1: Summary of Statistics for Factors affecting Production

	Rock Drilling (hr)	TBM Breakdown (hr)	Muck Car Breakdown (hr)	Survey (hr)	Pulling Cable (hr)	TBM Teeth Change (hr)
Frequency	32	12	4	30	5	7
Total Hour	105.00	27.00	11.75	57.45	13.00	9.92
Mean (Hr)	3.28	2.25	2.94	1.92	2.60	1.42
Min. (Hr)	0.50	0.50	0.75	0.25	0.50	0.67
Max. (Hr)	10.00	7.00	6.00	4.00	4.00	3.00

3.4.4 Productivity Analysis Using Regression Technique

A multiple regression analysis was conducted using SPSS to evaluate how the factors influenced productivity. The independent variables were twelve factors identified in the previous section and different soil types, while the dependent variable was the production per shift (m/shift).

The record of the actual soil conditions that the TBM went through shows six different soil types. The descriptions and compositions of each soil type are shown in Table 3-2. Since it was believed that the TBM penetration rates were mostly affected by the soil types, different soil types were selected to be included in independent variables instead of the TBM penetration rates. Five dummy variables for the six different soil types were included as independent variables. One of the major soil types, soil type 5, making up fifty-six percent of the total tunnel length, was chosen as a reference variable and excluded in this regression model.

The linear combination of these factors was significantly related to the production per shift, $\underline{F}(12, 138) = 19.64$, $\underline{p} < .001$, indicating that the explained variance by the regression equation is large compared to the unexplained variance. The sample multiple regression coefficient was 0.79, indicating that 63% of the variance of the production per shift in the sample can be accounted for by the linear combination of factors. Table 3-3 shows coefficients for each factor and the statistical results of the regression model.

Table 3-2: Descriptions and Compositions of Each Soil Type

Soil Types	Soils	Percent of Project
Type 2	Clay shale	3.9 %
Type 5	Clay till	55.5 %
Type 6	Glacial sand	3.1 %
Type 8	Sandy clay	12.0 %
Type 9	Clay silt	10.7 %
Type 5 & 9	Combination of clay till and silt	14.7 %

Table 3-3: Summary of Regression Outputs

Predictors	Unstandardized Coefficients	Std. Error	t	Sig.
Rock Drilling (hrs)	-0.983	0.115	-8.543	< 0.001
TBM Breakdown (hrs)	-1.123	0.243	-4.617	< 0.001
Muck Car Breakdown (hrs)	-0.850	0.326	-2.604	0.010
Survey (hrs)	-0.329	0.233	-1.413	0.160
Pulling Cable (hrs)	-1.118	0.352	-3.173	0.002
TBM Teeth Change (hrs)	0.008	0.552	0.144	0.886
Other (Yes/No)	-6.759	0.614	-11.018	< 0.001
Soil 2	-0.536	0.898	-0.597	0.552
Soil 6	3.457	1.190	2.906	0.004
Soil 8	0.999	0.618	1.617	0.108
Soil 9	-0.767	0.584	-1.314	0.191
Soil 5 & 9	2.277	0.571	3.987	< 0.001

Coefficients for each factor can be explained as the increase in production if each independent variable is increased by one unit while all other independent variables are held constant. For instance, when the rock drilling time increases by one hour and other variables are held constant, productivity decreases by 0.983 m. For the factors affecting production, all independent variables except for "Survey" and "TBM Teeth Change" were statistically significant, which indicates that these factors had significant impacts on productivity loss. Since the unit for the variable "Other" is *yes* or *no* instead of hours, it should be explained in a different way. That is, when one of these activities defined as "Other" occurs, a productivity loss of 6.759 m is expected.

For the six different soil types, only soil types 6 and 5 & 9 are statistically significant. The average production in soil types 6 and 5 & 9 are 3.457 m and 2.277 m, respectively, higher than the production on soil type 5.

In order to analyze the relative importance of those factors affecting the production loss, the unstandardized coefficients were multiplied by the total hours for each statistically significant factor from the regression model. These calculations show the production loss incurred for each factor. The percentage of each category was calculated as shown in Figure 3-5. "Other" (41%) was recognized as the most significant factor affecting production loss and was followed by "Rock Drilling" (39%), "TBM Breakdown" (11%), "Pulling Cables" (5%), and "Muck Car Breakdown" (4%). The two major leading factors, "Other" and "Rock Drilling," comprise about 80% of the entire production loss.

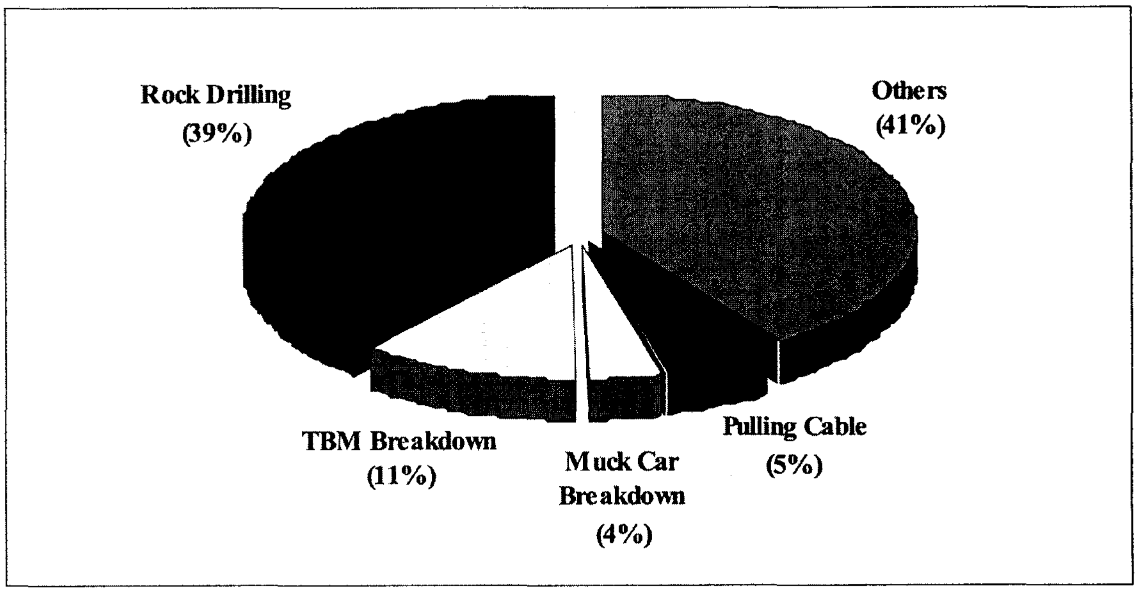

Figure 3-5: Comparison of Factors Affecting Production Loss

3.5 Conclusions

This chapter presented the data collection procedure and data analysis for an actual tunnel project: North Edmonton Sanitary Trunk (NEST). The project was fully instrumented and continuously monitored to obtain continuous feedback on progress, causes for delay, production loss, production increase, and other relevant information.

During this project, a wheel anchored to the conveyor traveling on the segmental liner behind the TBM was connected to a data recorder which monitored the advancement of the wheel. Since the data obtained from the data recorder had many outliers and inadequate data points, considerable effort was expended to identify and remove the outlier points. After the data cleaning process, 140,772 data points were obtained. Based on the cleaned logger data, the TBM penetration rates were first calculated and analyzed. The obtained sample for TBM penetration rates are believed to be reliable and are also used in further analysis.

A Regression analysis based on the actual project data was then conducted to identify the factors affecting the productivity. The results show that factors such as rock drilling and TBM breakdown significantly affect productivity. It should also be noted that some activities such as pouring the shaft, constructing the undercut, and patching blocks considerably affect the tunnel production since tunneling operations cannot normally proceed during these activities.

CHAPTER 4: BAYESIAN UPDATING APPLICATION FOR SCHEDULE UPDATES IN THE NEST PROJECT [2]

4.1 Introduction

Due to the repetitive characteristic of tunnel construction, simulation can offer many benefits to a project planner. Project planners can effectively plan the schedule and cost by examining multiple simulation scenarios instead of conducting costly experimentation in the field. For simulation to be effective the model must first be accurate and valid and the quality of the input provided by its user must be precise. While models can be prepared with a great degree of resemblance to the actual construction processes, input to these models from industry experts is generally subjective, representing a best estimate in the form of a deterministic value or a statistical distribution (such as a "three times" estimate to characterize a triangular or beta distribution). Inaccuracies in those estimates generally translate into inaccurate simulation results and consequently erroneous schedule and cost predictions.

A successful approach to enhance these estimates is simply to obtain actual data as the project commences construction and to utilize this data to enhance the base distributions used in the simulation model. A statistically valid strategy for this exercise is the use of Bayesian updating techniques.

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[2] This chapter mainly contains extracts from the paper "Bayesian Updating Application into Simulation in the North Edmonton Sanitary Trunk Tunnel Project" published in the Journal of Construction Engineering and Management, ASCE, 132(8), 882-894

Bayesian updating techniques provide a systematic approach to combine subjective data and observed data, producing a balanced estimation. 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; much better simulation outcomes can therefore be expected.

This chapter describes how Bayesian updating techniques can be applied to a simulation model of an actual tunneling project: the North Edmonton Sanitary Trunk (NEST). The objective is to establish whether models created during the planning stage of the project with its contractor can be improved upon by receiving actual progress data in such a manner as would improve decision making and present a more appropriate project control. It should be noted that the techniques described in this chapter are best suited to updating the original schedule planned prior to construction as the project progresses.

This chapter is organized as follows: Section 4.2 describes the overview of the Bayesian updating techniques. Pre-construction simulation analysis for the case study of the NEST is explained in Section 4.3. Section 4.4 discusses Bayesian updating process to update the distributions of input parameters for a tunnel simulation model of the NEST. The conclusions are then presented in Section 4.5.

4.2 Overview of Bayesian Updating Techniques

If the value of an input parameter to a simulation model is assumed to be continuous with an underlying probability density function (PDF), the prior assumptions made about the parameter can be formally updated using Bayes' theorem when factual results become available. After the prior distribution $f'(\theta)$ is revised in light of the actual results, the posterior distribution $f''(\theta)$ is expressed as follows (Ang and Tang, 1975):

$$f''(\theta) = kL(\theta)f'(\theta) \tag{1}$$

where θ = the random variable for the parameter of a distribution;

k is a normalizing constant $k = \left[\int_{-\infty}^{\infty} L(\theta)f'(\theta)d\theta\right]^{-1}$; and

$L(\theta)$ = the likelihood of observing the experimental outcome assuming a given θ.

The initial distribution assumption for the parameters is thus updated using observed data. In this way, judgments and observational data can be systematically combined since the posterior distribution is obtained from the combination of both the prior distribution and the likelihood function.

The posterior distribution of a parameter can be derived with considerable mathematical simplicity if the prior distribution of the parameter is appropriately selected in terms of its underlying random variable. That is, if a prior distribution is a conjugate of the distribution of the underlying random variable, a posterior distribution can be conveniently obtained as the same mathematical form as the prior (Ang and Tang 1975). Table 4-1 shows the updating process for normal distribution as an example of the conjugate distributions.

Table 4-1: Updating Process for Normal Distribution (Ang and Tang 1975)

Prior and Posterior Distributions of Parameter	Posterior Statistics
Normal $f_M(\mu) = \frac{1}{\sqrt{2\pi}\sigma_\mu} \exp\left[-\frac{1}{2}\left(\frac{\mu-\mu_\mu}{\sigma_\mu}\right)^2\right]$	$\mu_\mu'' = \frac{\bar{x}(\sigma')^2 + \mu'(\sigma^2/n)}{(\sigma')^2 + (\sigma^2/n)}$ $\sigma_\mu'' = \sqrt{\frac{(\sigma')^2(\sigma^2/n)}{(\sigma')^2 + (\sigma^2/n)}}$

Where $\bar{x}$: Mean of Likelihood Function

σ^2 : Variance of Likelihood Function

n : Number of Sample Data

μ' : Mean of Prior Distribution

$(\sigma')^2$: Variance of Prior Distribution

μ_μ'' : Mean of Posterior Distribution

σ_μ'' : Standard Deviation of Posterior Distribution

If more sample data are collected after the first update, updating can be done successively. For a normal distribution, for example, the prior distribution at the second updating stage is composed of the parameters μ'' and σ'', obtained from the first updating stage. That is, the parameters for the posterior distribution obtained from the previous stage become those for the prior distribution at the next updating stage. Based on the updating techniques described in this section, the assumption of a subjective input in a simulation model made during the planning phase due to a lack of data can be improved once sets of actual data become available as the project progresses.

4.3 Pre-Construction Simulation Analysis

4.3.1 Special Purpose Simulation Template for Tunneling in *Simphony*

A simulation model was created in collaboration with the project superintendent and project manager from the tunneling division at the City of Edmonton to establish the possible productivity of the tunnel and to develop an estimate and construction plan. A special purpose simulation template for tunneling developed under *Simphony* was utilized. *Simphony* is a simulation environment for developing special purpose simulation tools for construction domains (Hajjar and AbouRizk 2002). It has been used for modeling this case study due to the author's expertise with it and the flexibility and extensibility it provides.

The tunneling template developed in *Simphony* consists of sixteen modeling elements through which tunneling activities in various stages can be defined. A base model for the NC1 section of NEST consists of an undercut, soil segments, and a removal shaft. The undercut is a one-way undercut and contains the following elements: two trains, a hoisting element, a TBM, a track layout, and a shift controller.

The soil segments are used to model the changes in soil conditions and tunnel geometry. Every soil segment has an element for modeling the TBM excavation and lining processes in addition to an element for modeling surveying activities. Users need to enter basic input data such as the length, soil type, and the TBM penetration rate of each section.

For simulation analysis at the pre-construction stage, some input data were obtained from assumptions based on the superintendent's expert opinion. These subjective inputs can generally be used as a starting point. In the next section, the actual distributions based on sample data colleted during construction are compared with those used for the original simulation model. Other model parameters that remained unchanged are described in Table 4-2.

Table 4-2: Model parameters unchanged during the update process

Element	Simulation Parameter	Value
Trains	Empty speed (km/hr)	5
	Loaded speed (km/hr)	5
	Number of muck cars	3
	Number of material cars	1
	Muck car capacity (m^3)	4.2
TBM	Excavation Diameter (m)	3.2
	Resetting time (min)	Uniform (2,4)
	Liners installation time (min)	Triangular (15,18,25)
Hoisting	Muck car cycle	Uniform (4.00,7.00)
	Material car cycle	Uniform (7.00,10.00)
Shift control	Start time	800
	Mobilization time (min)	Uniform (10,15)
	Coffee break at	1000
	Coffee break time (min)	Uniform (25,35)
	Lunch break at	1200
	Lunch break time (min)	Uniform (40,50)
	Finish time	1700

4.3.2 Comparisons of Distributions based on Assumption vs. Actual Sample

Statistical distributions of major input parameters were fitted based on sample data using commercial distribution fitting software (BestFit). Distributions were fitted for a set of parameters that include: TBM penetration rates, time between TBM breakdowns, time to repair the TBM, and survey time. These parameters, which were available from the data collection process or the project progress report, were believed to play important roles in the simulation modeling and affect the overall productivity.

Table 4-3: Comparisons of Distributions for Each Parameter

Parameter	Original Distributions	Actual Distributions
TBM Penetration Rate (m/hour)	Uniform (2, 4)	Normal (5.04, 1.27)
Time between Breakdown for TBM (min)	Exponential (3000)	Exponential (7335)
Time to Repair TBM (min)	Uniform (60, 300)	Triangular (30, 50, 420)
Survey Time (min)	Uniform (120, 180)	Triangular (15, 95, 240)

The distributions fit based on the sample data (referred to as actual distributions) were compared to those used for the original simulation model developed at the pre-construction stage (original distributions), as shown in Table 4-3. The comparison of these two distributions of each parameter shows some discrepancies. For instance, the distributions for "Time to Repair TBM" were compared, as shown in Figure 4-1. Calculated means and variances of each parameter were also compared as shown in Table 4-4. For the TBM penetration rate, the original model assumed a uniform distribution with a mean of 3 m/hour while the actual distribution was normally distributed with a mean of 5.04 m/hour. For both "Time to Repair the TBM" and "Survey Time," triangular distributions with lower means were better fit than uniform distributions assumed for the original model. These results require further analysis of how the different distributions affect the overall simulated tunnel productivity. Also, as the tunneling construction proceeds and sample data are collected, analysis must be undertaken to determine how input updating can be effectively utilized to improve accuracy of simulation output.

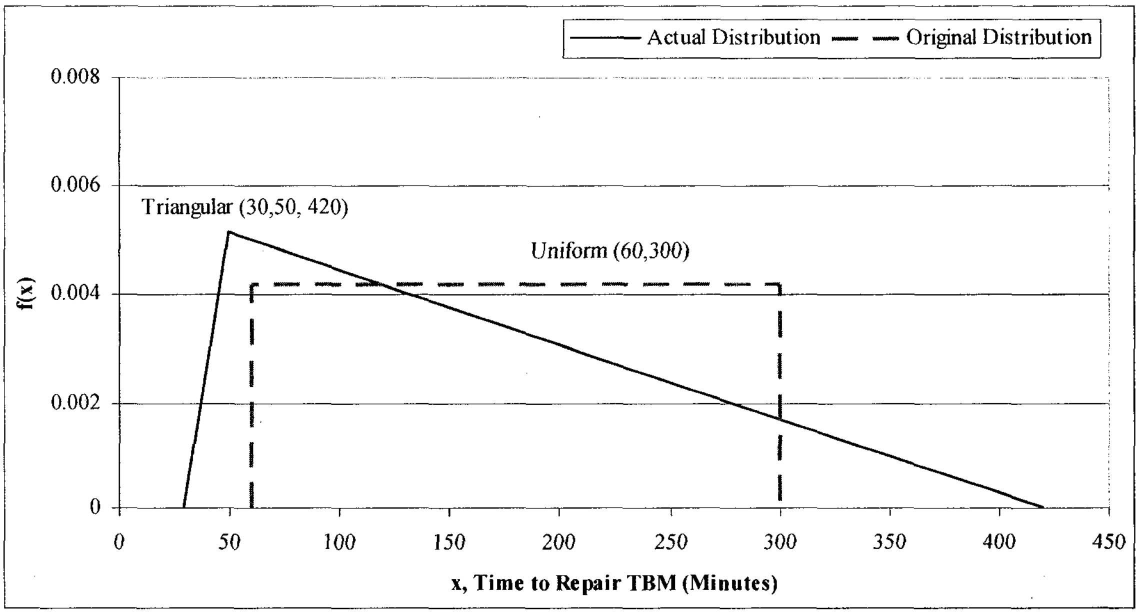


Figure 4-1: Comparisons of Distributions for Time to Repair TBM

Table 4-4: Comparisons of Means and Variances for Each Parameter

Parameter		Original Distributions	Actual Distributions
TBM Penetration Rate (m/hour)	Distribution	Uniform	Normal
	Mean	3.00	5.04
	Variance	0.33	1.61
Time between Breakdown for TBM (min)	Distribution	Exponential	Exponential
	Mean	3000	7335
	Variance	3000^2	7335^2
Time to Repair TBM (min)	Distribution	Uniform	Triangular
	Mean	180	166.67
	Variance	4800	8038.89
Survey Time (min)	Distribution	Uniform	Triangular
	Mean	150	116.67
	Variance	300	2168.06

4.3.3 Simulation Results at the Pre-Construction Stage

In original simulation studies, a base simulation model was built from certain assumptions including TBM breakdowns and surveying activity delays. The production rate obtained from this model was 7.77 m/shift, while the actual production of this project was 8.87 m/shift. The obtained simulation result was close to the actual performance as an initial projection and successfully served as a guideline for the schedule and cost estimate. However, the initial simulation model assumed low TBM penetration rates, as discussed in the previous section, and did not include certain delays such as rock drilling. These results suggest that the obtained simulation outputs were estimated somewhat conservatively due to inaccurate simulation inputs and that there is a need to update simulation input parameters as the project progresses.

4.4 Bayesian Updating Process of Model Inputs

In order to update the input parameters for simulation, a systematic approach is required to combine original assumptions with actual sample data. Bayesian techniques can be a useful methodology for updating these parameters. The information to be updated can be either objective data based on the sample or subjective judgments taken from the experts' opinions.

One of the major input parameters, "TBM Penetration Rates," was selected to show how these techniques can be applied to simulation. Two soil segment elements in the simulation model were selected to use for the different time frames. One segment is used for the sections completed on a specific day during the construction process while the other is used for the remaining sections. For instance, on November 15, 2001, the first soil segment represents the completed 963-meter-long section while the second segment represents the remaining 483-meter-long section, as shown in Figure 4-2. The actual information can be used as the first modeling segment while the updated information based on Bayesian techniques can be used as the second modeling segment.

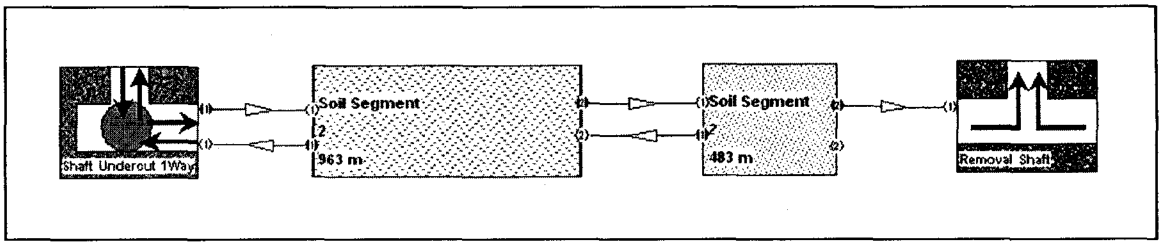


Figure 4-2: Simulation Modeling for NEST

The input parameters for the simulation model are updated twice a month: mid-month and at the end of the month. Since actual TBM penetration rates for some time periods are missing, updating could not be done during those periods and thus the update dates for each month may slightly vary. Using Bayesian updating, prior information about the TBM penetration rate is updated as the tunnel construction proceeds. The updated information is called posterior information.

Figure 4-3 shows the actual overall productivity and the progress chart for the NEST project. The learning curve effect is supported with a finding that the lower productivity rates were recorded at early stages of the project and that the overall productivity becomes stable from August 31, 2001 once approximately 19% of the entire tunnel section was completed.

Dates appearing in this chart indicate the overall milestone for updating the distributions for simulation input parameters. It should be noted that there were some periods when valid sample TBM penetration rates were not available and therefore updating was not done during that period. The first updating was done on August 15, 2001 once approximately 9% of the tunnel sections were completed. There were seventy-one sets of sample data for TBM penetration rates and commercial software was used to fit the distribution. The result shows that normal distribution was the distribution best suited for the TBM penetration rates.

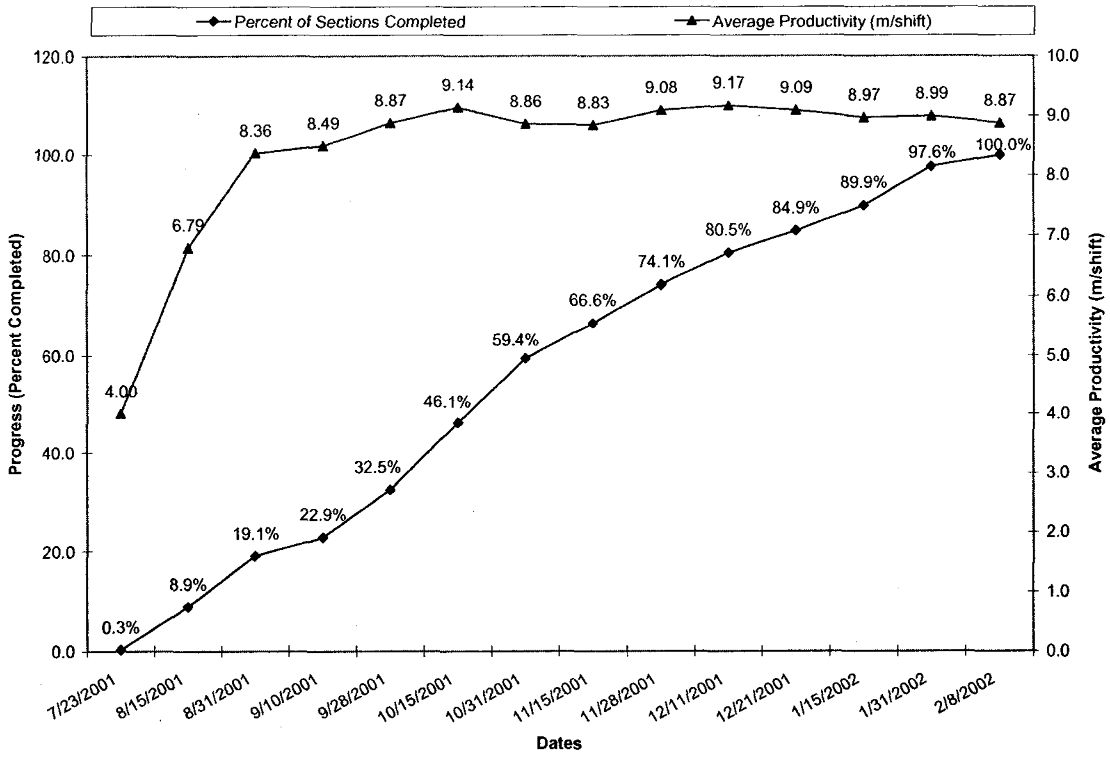


Figure 4-3: Percent Completion and Average Productivity for NEST Project

4.4.1 Updating TBM Penetration Rates

As discussed in an earlier section, the original model assumed a uniform distribution for the TBM penetration rate ranging from 2 to 4 m/hour. For mathematical simplicity, it was decided that in the case of the Bayesian updating application the uniform distribution would be transformed into a normal distribution for prior information. It is assumed that the mean TBM penetration rate lies between 2 and 4 m/hour with a 99% confidence interval. The mean of this distribution is 3 m/hour, and the variance can be calculated using a standard normal distribution table and the confidence interval. The calculated standard deviation σ of this normal distribution is 0.39.

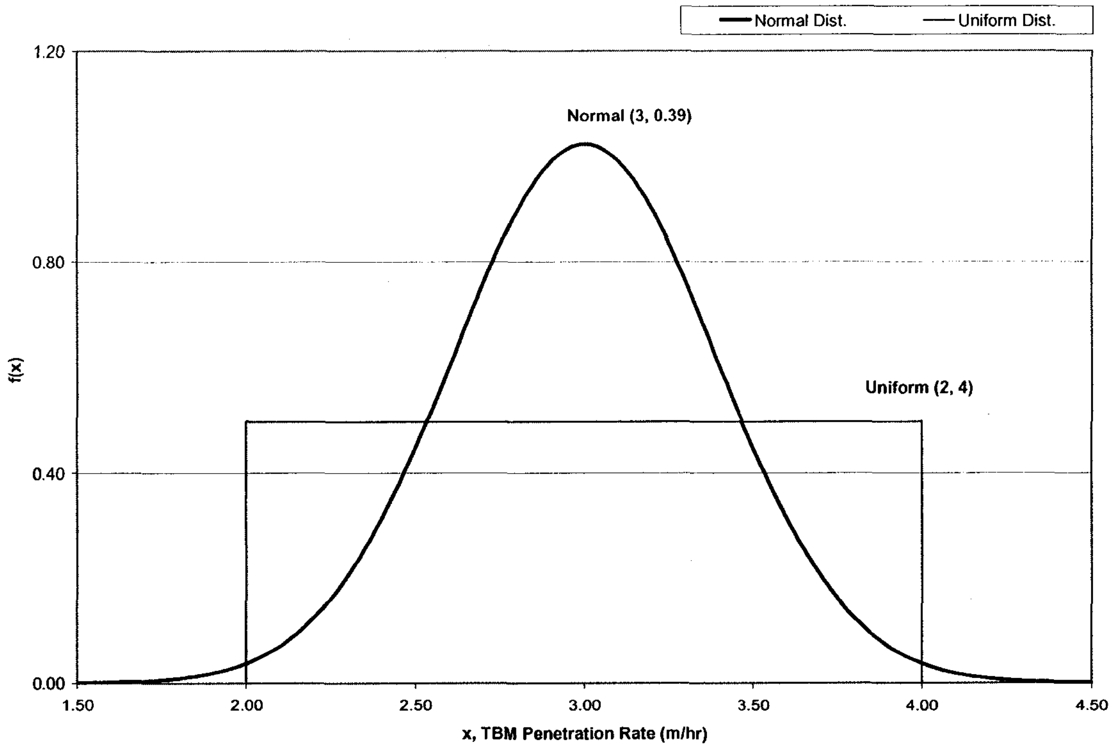


Figure 4-4: Transforming Uniform into Normal Distribution for TBM Rate

Figure 4-4 shows the normal distribution with a mean of 3 m/hr and a standard deviation of 0.39, which was transformed from the uniform distribution ranging from 2 to 4 m/hr. Since the prior distribution is assumed to be a normal distribution, the posterior distribution obtained from Bayesian updating can employ the same mathematical form as the prior. The formulas for calculating posterior distribution parameters are obtained from the following equations:

Prior information (subjective): $\mu' = 3.0$ and $\sigma' = 0.39$

Likelihood function (sample on August 15, 2001): $\bar{x} = 4.74$, $\sigma = 1.37$, and $n = 71$

Using equations,

$$\mu'' = \frac{\bar{x}(\sigma')^2 + \mu'(\sigma^2/n)}{(\sigma')^2 + (\sigma^2/n)} = \frac{4.74 \times 0.39^2 + 3.0 \times (1.37^2/71)}{0.39^2 + (1.37^2/71)} = 4.48$$

$$\sigma'' = \sqrt{\frac{(\sigma')^2(\sigma^2/n)}{(\sigma')^2 + (\sigma^2/n)}} = \sqrt{\frac{0.39^2 \times (1.37^2/71)}{0.39^2 + (1.37^2/71)}} = 0.15$$

Therefore, the posterior distribution updated on August 15, 2001 is the normal distribution with a mean of 4.48 and a standard deviation of 0.15. Figure 4-5 shows the comparisons of prior, likelihood function, and posterior distribution updated on August 15, 2001.

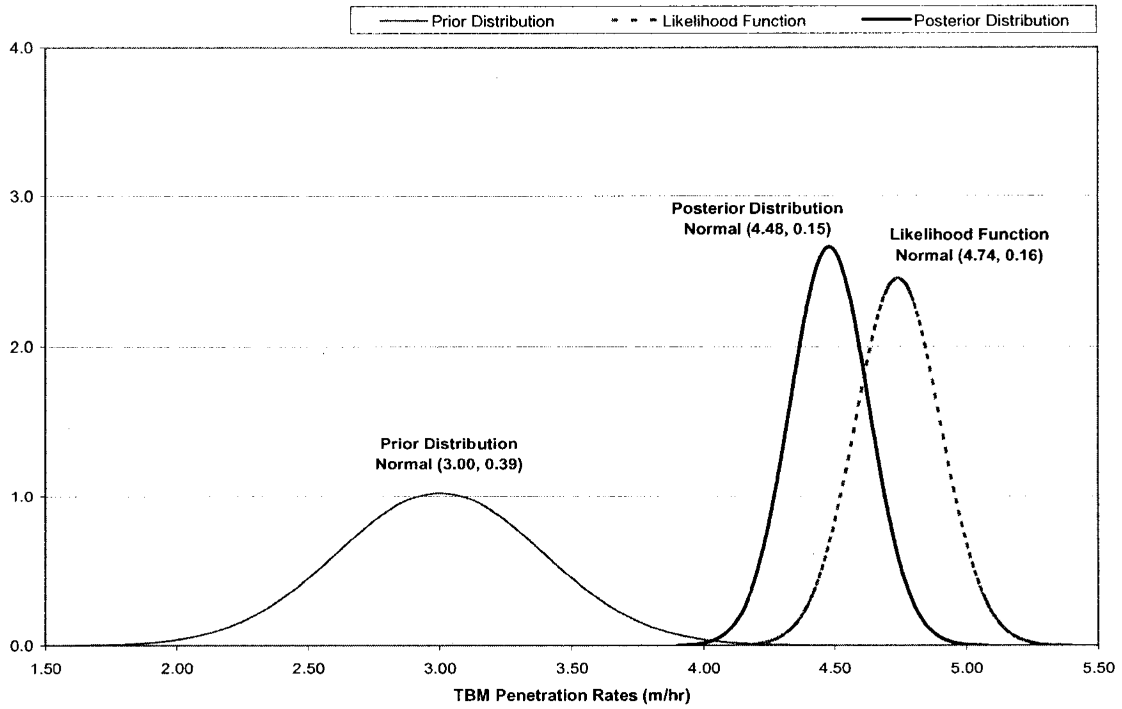


Figure 4-5: Updating TBM Penetration Rates on August 15, 2001

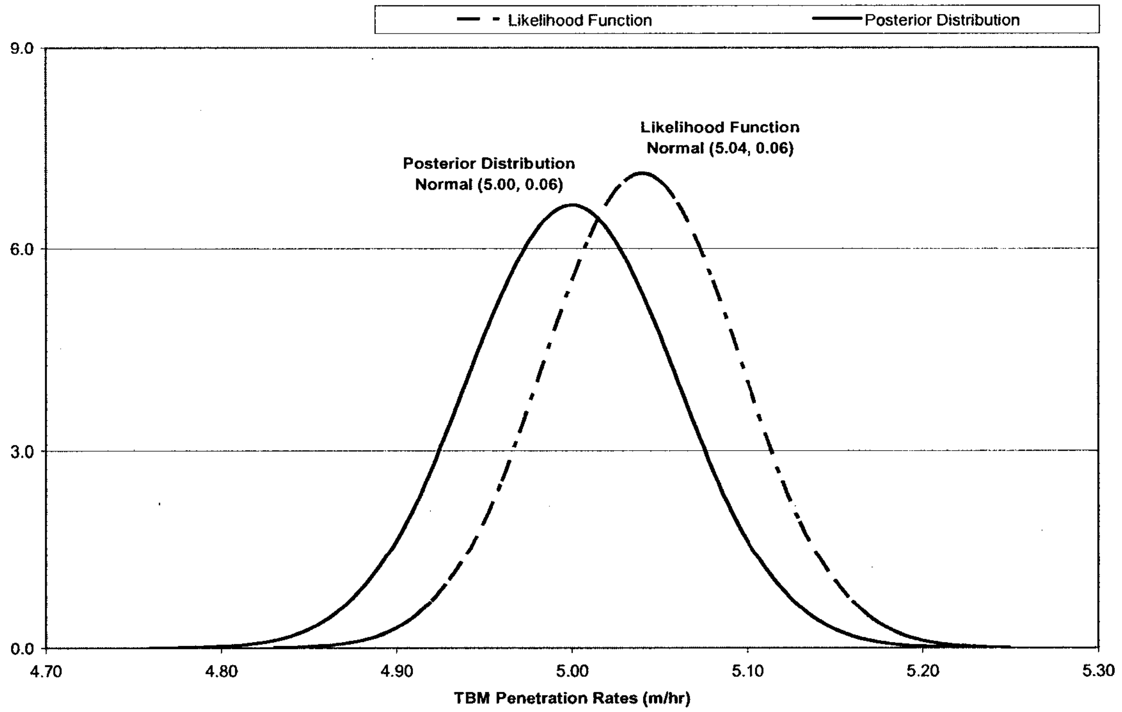


Figure 4-6: Updating TBM Penetration Rates on February 8, 2002

Successive updating can also be done if the sample data are consistently gathered during the entire project. However, this approach was not suitable for this project due to many data points missing for the TBM penetration rates, especially in the middle stage of project. The distributions for TBM penetration rates on later dates were therefore updated independently, not successively. That is, the original assumption was used as the same prior information for each update on later dates. Figure 4-6 shows the updated posterior distribution at the completion of the project on February 8, 2002. The result shows that the updated posterior distribution with a mean of 5.00 and a standard deviation of 0.06 was very close to the actual distribution with a mean of 5.04 and a standard deviation of 0.06. It is believed that simulation results based on information updated at a later date provide more accurate predictions than those made at an earlier date, since the amount of sample data increases at the later date. The distributions of other input parameters such as the time between TBM breakdowns described by the exponential distribution can also be updated using Bayesian techniques.

4.4.2 Simulation with Updated Input Parameters

Simulations were conducted on specified time intervals and the simulation results were compared with the updated mean TBM penetration rates and actual productivities, as shown in Figure 4-7. The actual productivity increases until December 11, 2001, then slightly decreases after December 11, 2001. This trend in productivity may be related to the different soil conditions since a similar trend is also shown in the average TBM penetration rates.

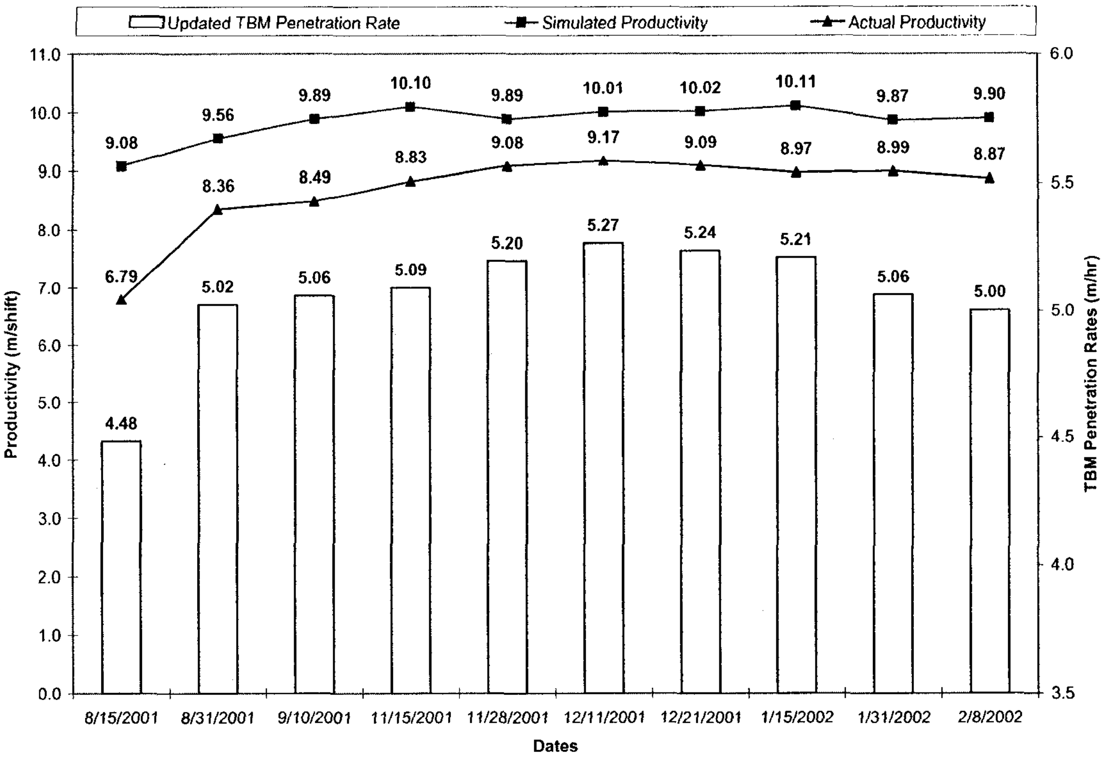


Figure 4-7: Comparison of Productivities between Actual and Simulation Results

The results show that the productivity predicted in simulation tends to be somewhat higher than the actual productivity. These results are probably due to other factors affecting productivity such as rock drilling, since these modeling elements are not included in the current tunnel simulation template and were not modeled for this project.

The productivity and duration between the actual and simulation results for the completed sections were compared. Consistent differences between actual and simulated results still exist and the effects of some factors related to productivity, such as rock drilling, need to be analyzed. The total time spent for rock drilling in each time period was obtained and the actual productivity was adjusted by subtracting the rock drilling hours from the total work-hours. For instance, by eliminating the effects of the total rock drilling time of 105 hours, the adjusted actual productivity of 9.56 m/hr was obtained at the end of the project instead of the actual rate of 8.87 m/hr, as shown in Figure 4-8. It is important to notice that as the total rock drilling time increases, the adjusted productivity increases and becomes quite close to the simulation results. This trend indicates that the time spent on rock drilling has a significant effect on overall productivity. This finding is consistent with the result of the regression model discussed previously as rock drilling was one of the major factors affecting productivity. It is concluded that the productivity predicted from simulation can be used as an ideal productivity, and some factors, such as rock drilling, need to be considered to reflect the productivity loss.

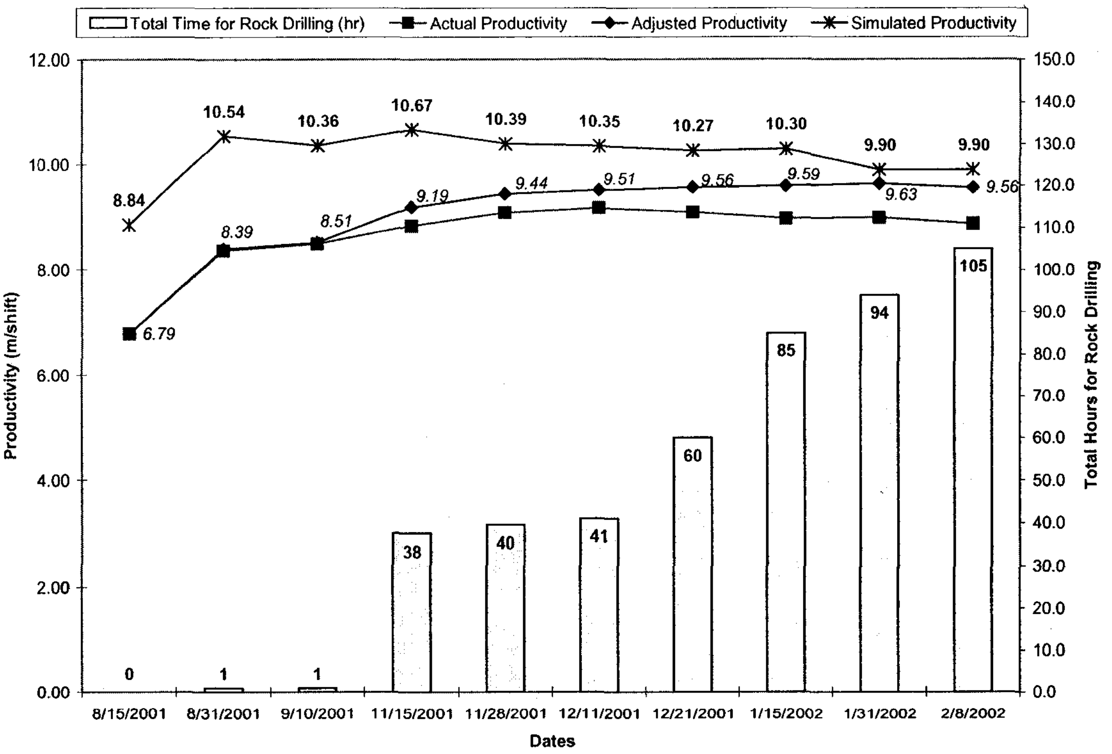


Figure 4-8: Comparison of Productivity for the Exclusion of Rock Drilling Hours

4.4.3 Simulation Results for the Remaining Sections

Figure 4-9 compares the actual and simulation productivity for the remaining sections. TBM penetration rates were updated using Bayesian techniques in the simulation model. Two trend-lines considering the time intervals compare the remaining durations for the actual project with those predicted from the simulation. The same results are also shown in Table 4-5. When simulation was conducted in preparation for the project, input parameters were assumed without any updating. This initial simulation experiment predicted a total duration of 177 shifts with an average productivity of 8.17 m/shift while the actual duration was 163 shifts with an average productivity of 8.87 m/shift. On August 15, 2001, the first simulation with the updated input parameters predicted 145 shifts for the remaining section. This predicted result is very close to the actual duration of 144 shifts. Thus, the difference between actual and simulated durations for the remaining section was considerably reduced from the initial simulation conducted before the project. The comparisons of the two trend-lines at later dates do not show any significant deviation between these two results except for the 9-shift difference on September 10, 2001. Simulations conducted during construction predict better project durations than those conducted before the project. These results indicate that Bayesian techniques were successfully applied to update the distribution of the input parameter.

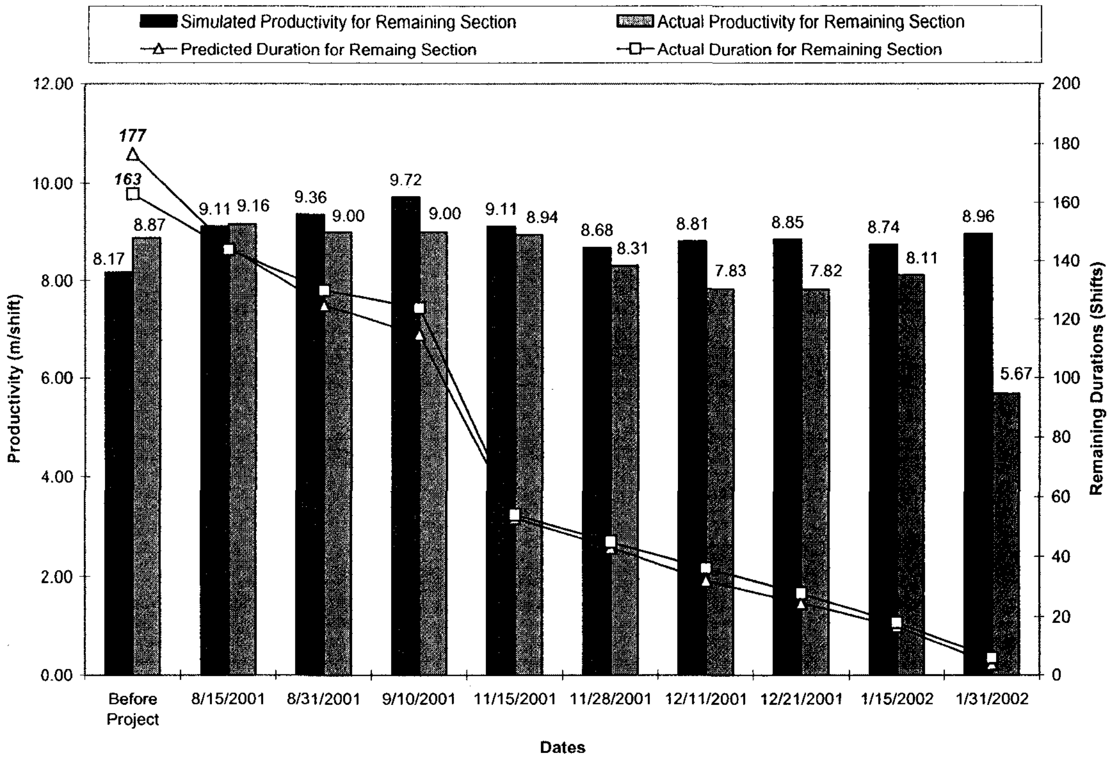


Figure 4-9: Comparison of Productivity and Duration for the Remaining Sections

Table 4-5: Comparison of Remaining Shifts between Actual and Simulation Results

Year	Before	Year 2001					Year 2002	
Date	**Project**	**8/15**	**8/31**	**9/10**	**11/15**	**12/11**	**1/15**	**1/31**
Sections Completed (%)	0	8.9	19.1	22.9	66.6	80.5	89.9	97.6
Actual (Shifts)	163	144	130	124	54	36	18	6
Predicted (Shifts)	177	145	125	115	53	32	17	4
Difference (Shifts) (Predicted – Actual)	14	+1	-5	-9	-1	-4	-1	-2

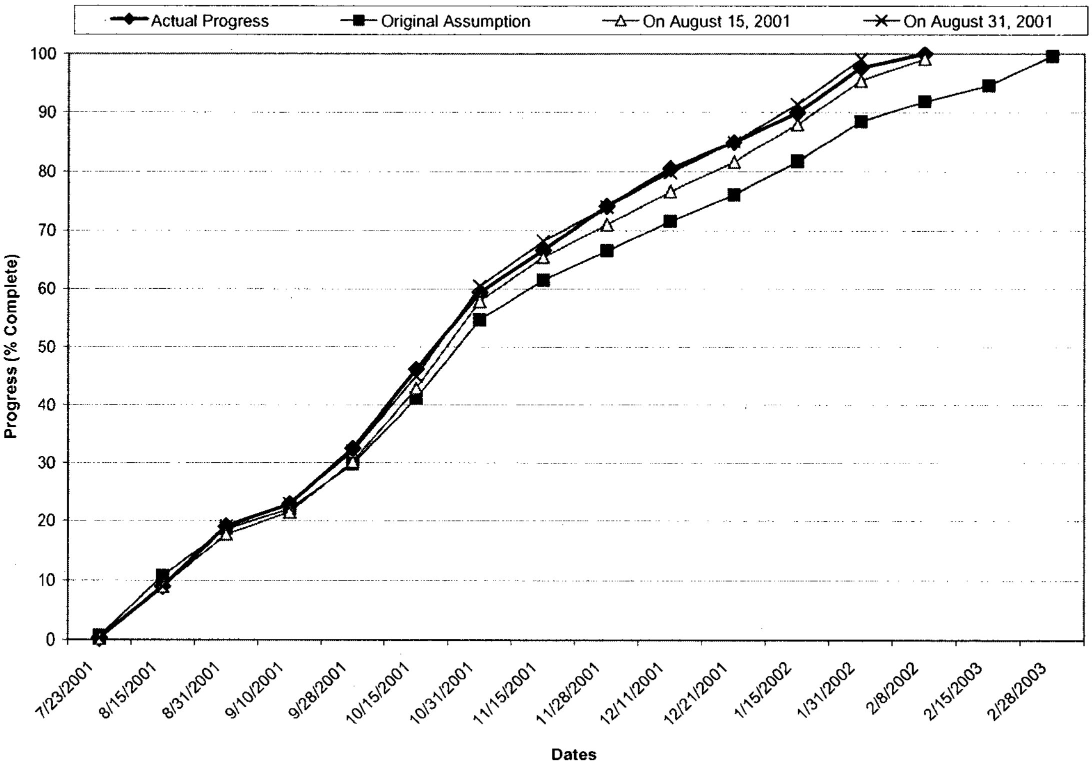


Figure 4-10: Comparison of Progress Charts

It was also determined that updating the input parameters even in the very early stages of a project can provide good simulation results. Based on the average productivity obtained from simulation, the progress charts were updated and the results were compared with the actual progress, as shown in Figure 4-10. These results were obtained from three simulations based on early assumptions: August 15 and August 31. The calculation of the percentage complete was based on the average productivity obtained from simulation. Progress charts on August 15 and August 31 were continuously updated from the original. A comparison of these progress charts indicates that updated progress charts on both August 15 and August 31 are very close to the actual chart. This result leads to the conclusion that even early updates during construction can significantly improve the prediction of project performance by eliminating uncertainty in the original assumption.

4.4.4 Validity of Normal Distribution Assumption

Early input updates with more accurate predictions will be beneficial for project managers who utilize simulation as a tool for project control. If the data obtained at an early stage of the project are reliable enough to update the input parameters, the simulation results will serve as accurate predictions. However, a certain amount of data is required for the underlying assumption of the Central Limit Theorem: as a rule of thumb, at least thirty sample data sets are needed to meet the assumption (Devore, 1995). For instance, thirty-six sample data sets for TBM penetration rates on August 9, 2001 were gathered and the results of the distribution fitting software show that beta and uniform distributions were the best fit. Similarly, data collected on later dates were also fit into distributions. The results are shown in Table 4-6. On August 14th, the normal distribution became the best distribution rather than the uniform distribution. The histogram comparison also shows that the distribution becomes approximately normal on later dates as shown in Figure 4-11. This finding suggests that the larger the amount of sample data, the better the approximation for the Central Limit Theorem. Therefore, these results lead to the conclusion that the sample data on August 15, 2001 were valid for updating the distribution of the input parameters for simulation. For this specific project, approximately 14% of sample data for TBM penetration rates were obtained and used to update the input parameters once approximately 9% of the total tunnel section was completed. While the total number of sample data should be more than thirty as a rule of thumb, the results of this project show that sample data greater than fifty were best for meeting the assumption.

Table 4-6: Fitting Distributions for TBM Penetration Rates on Different Dates

Dates	Number of Sample Data	Percent of Sample Data	Best Distributions From BestFit
Aug. 9, 2001	36	6.9 %	Beta, Uniform
Aug. 13, 2001	47	9.0 %	Beta, Uniform
Aug. 14, 2001	57	10.9 %	Beta, Normal
Aug. 15, 2001	71	13.6 %	Beta, Normal
Aug. 16, 2001	80	15.4 %	Beta, Normal
Sep. 10, 2001	267	51.2 %	Normal, Beta
Nov. 15, 2001	289	55.5 %	Normal, Beta
Dec. 11, 2001	364	69.9 %	Normal, Beta
Jan. 15, 2002	408	78.3 %	Normal, Beta
Feb. 8, 2002	521	100 %	Normal, Beta

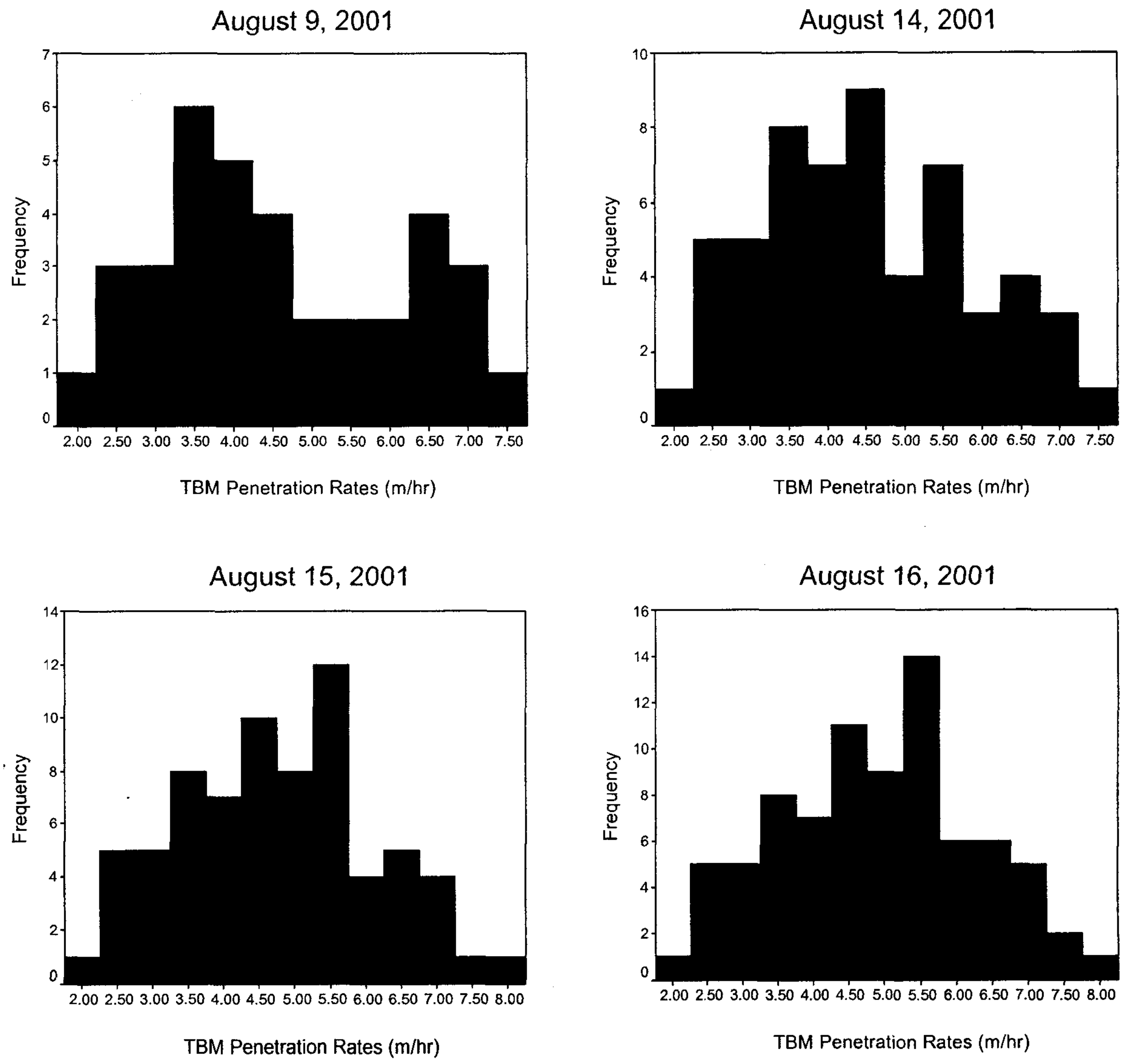


Figure 4-11: Distributions of TBM Penetration Rates

4.5 Conclusions

Since tunneling projects usually contain many unforeseen factors, such as geological conditions, simulation can be used as a powerful tool to experiment with multiple scenarios instead of resorting to costly experimentation in the field. Simulation has been traditionally used to make predictions prior to construction. Some input data are mainly traditionally used to make predictions prior to construction. Some input data are mainly obtained based on assumptions rather than on actual data; simulation results may therefore be inaccurate and lead to erroneous predictions for the project. A proper updating process for simulation during construction can reduce uncertainty and improve simulation prediction. Furthermore, the renewed predictions can serve to improve overall project control over schedule and cost.

This chapter described Bayesian techniques to update the distributions of input parameters for a tunnel simulation model of the North Edmonton Sanitary Trunk Project. It showed a formal approach for combining original assumptions with sample data obtained during construction. TBM penetration rates were selected as an example to show how the distribution is updated. The simulation results show that even early updates during construction can significantly improve the prediction of a project's performance by eliminating the uncertainty contained in the original assumption. In this project, it is determined that the earliest time to update the distribution for TBM penetration rates properly is once approximately 9% of the total tunnel section is completed and more than fifty sets of sample data are gathered. These results can be used as a guideline for similar tunneling projects when simulation is applicable and proper simulation updates are required.

CHAPTER 5: BAYESIAN INFERENCE FOR TUNNEL SIMULATION INPUT PARAMETERS

5.1 Introduction

In Chapter 4, Bayesian techniques were utilized to update the distributions of input parameters for the tunnel simulation model of the NEST. As a formal approach for combining original assumptions with sample data obtained during construction, the application of Bayesian updating techniques to the planned simulation model demonstrated a remarkable improvement in the schedule prediction of the remaining portion of the tunneling in the early stages of the project's lifecycle.

A Bayesian statistical approach offers many benefits. It is a way of improving estimation in sparse data sets by borrowing strength and offers a full distributional profile of a parameter such as mean, median, and percentiles without the assumption of normality underlying classical estimation methods such as maximum likelihood. With the combined sources of information (prior and data based on the accumulated knowledge), the posterior estimate thus has greater precision. The recent developments of computer intensive sampling methods of estimation also have revolutionized the application of Bayesian methods in a variety of fields such as biostatistics, econometrics, and genetic mapping (Congdon 2001).

This chapter discusses the application of a sampling-based Bayesian inference for estimation of major input parameters for a tunnel simulation model including TBM penetration rates, encountering rocks, and surveying activity. The objective is to obtain the enhanced estimation of current input parameters with a use of a Bayesian method based on sample of the actual tunnel project, NEST.

This chapter is organized as follows: Section 5.2 explains the Bayesian inference methodology. The procedures and results for estimating the input parameters for the simulation model using the sampling-based Bayesian inference method were presented in detail in Section 5.3. Section 5.4 discussed the application of the obtained results into an actual tunneling project. The conclusions are then presented in Section 5.5.

5.2 Background in Bayesian Inference

5.2.1 Overview of Bayesian Inference

According to Gelman et all (2003), a Bayesian inference is defined as the process of fitting a probability model to a set of data and summarizing the result by a probability distribution on the parameters of the model and on unobserved quantities such as predictions for new observations. The joint probability density function is a product of two densities, prior distribution $p(\theta)$ and the sampling distribution $p(y|\theta)$:

$$p(\theta, y) = p(\theta)p(y|\theta). \tag{5.1}$$

Conditioning on the known value of the data y using Bayes' rule, the posterior density follows:

$$p(\theta|y) = \frac{p(\theta, y)}{p(y)} = \frac{p(\theta)p(y|\theta)}{p(y)}, \tag{5.2}$$

where $p(y) = \int p(\theta)p(y|\theta)d\theta$ in the case of continuous θ.

Due to the complex numerical integrations, the computer intensive sampling methods of estimation have been employed for Bayesian inference. The core of the

Bayesian inference for the estimation of the parameters is to use iterative methods to take repeated samples of θ from the posterior density, $p(\theta|y)$ after prior assumptions $p(\theta)$ about the density of θ is combined with the sampling distribution $p(y|\theta)$.

Currently, Markov Chain Monte Carlo (MCMC) methods are utilized to sample from posterior densities. The main idea in Markov chain simulation is to create a Markov process whose stationary distribution is the specified $p(\theta|y)$ and run the simulations long enough that the distribution of the current draws is close enough to this stationary distribution. The package BUGS (Bayesian Inference Using Gibbs Sampling) developed from the MRC Biostatistics Unit in Cambridge has become the most popular tool for Bayesian inference. The BUGS uses a particular Markov chain algorithm, Gibbs sampling. For the Markov chain simulation, it is important to check the convergence of the simulated sequences (Gelman et all. 2003).

5.2.2 Inference on Normal Distribution when Mean and Variance Unknown

The normal distribution is also central to statistical inference in Bayesian perspective. It is common that the value of both mean and variance for the normal distribution is unknown for many cases. The common practice in Bayesian inference is simply to assume that the mean and variance can be estimated independently of each other. Thus, when the priors on these parameters are specified, two independent priors $p_1(\mu)$ and $p_2(\sigma^{-2})$ needs be assumed. For appropriate prior distributions for precisions $\tau = \sigma^{-2}$, any density confined to positive values can be used such as the uniform over the positive part of the real line and the gamma. A typical non informative but proper prior for the precision is a gamma with small but positive values of the shape (*a*) and scale (*b*) parameter. For example, if $a=b=0.0001$, the prior of precision τ will be approximately $p(\tau) \propto 1/\tau$. This prior on the precision is known as Jeffrey's prior. Similarly, a non informative prior for the mean can be specified as a normal density N(0,10000) located at zero and with low precision (high variance) (Congdon 2001).

5.2.3 The *t* Density as an Alternative to the Normal Distribution

The *t* density is a robust alternative to the Normal when sample sizes are small (namely samples less than 50) and outliers are suspected in the data. The density has the form

$$p(y|\mu,\tau,\kappa) \propto (1+\tau(y-\mu)^2/\kappa)^{-(\kappa+1)/2} \tag{5.3}$$

where μ , τ , and κ are the mean, variance, and the degrees of freedom parameter. The degree of freedom determines the extent of overdispersion. For the density expected to have outliers might be described by a t density with smaller values of κ (under 10) while values of κ over 100 result in a density indistinguishable from the normal distribution (Congdon 2001).

5.3 Sampling-Based Bayesian Inference for Estimation of Parameters

5.3.1 TBM Penetration Rates

Figure 5-1 demonstrates the scatterplot of the TBM penetration rates along the tunnel path. There were missing data points for the tunnel section of 363 to 895 m. As mentioned in Chapter 3, those data were identified as inadequate data points and removed during the data cleaning process. For those tunnel sections, the major soil types were type 5, type 9, and a mixed soil condition of type 5 and type 9. Therefore, from the NEST project, the TBM penetration rates can be obtained from five different soil types (Type 2, 5, 6, 8, and 9) except a mixed soil condition of type 5 and type 9. Further analysis will focus on finding the TBM penetration rates depending on soil characteristics for each soil type.

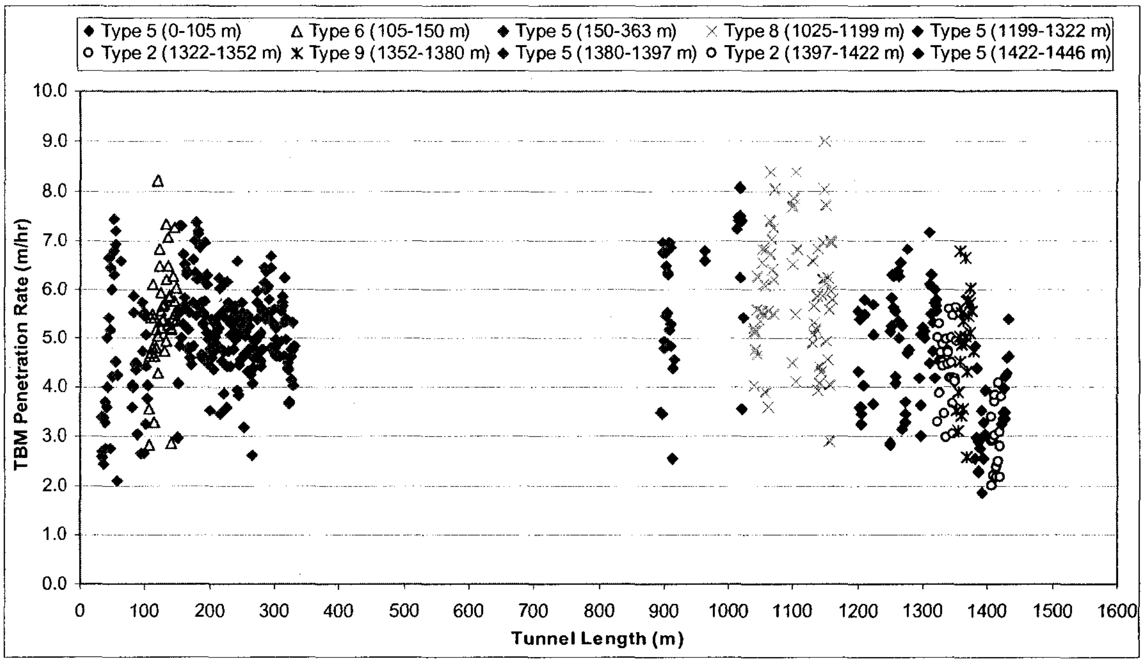


Figure 5-1: Scatterplot of TBM Penetration Rates along the Tunnel Path

Frequent soil transitions were detected especially at the end of the tunnel portion with an overall tendency that TBM penetration rates gradually decreased. For the tunnel section of 1025 to 1199 m containing soil type 8, the higher TBM rates were recorded while the lower TBM rates were found for the final portion of the tunnel. It is believed that the hard soil formations were major reasons for the low TBM rates on those tunnel sections. The plots of the TBM penetration on those segments clearly illustrate the apparent soil transitions.

It is decided that the Bayesian statistical analysis should be conducted to obtain the TBM penetration rates for each soil type for various soil conditions. One of major objectives is to establish whether there are significant differences in TBM penetration rates in each soil type. It is also of interest to see if one of the major soils, type 5, which makes up about 56 % of the total tunnel length, has a consistent TBM rates for the different locations of the tunnel. The obtained information from the statistical analysis can be utilized as inputs for various soil conditions for tunnel simulation models.

The data set for TBM penetration rates for two different soils, type 5 (clay till) and 2 (clay shale) are first compared to find the overall differences in rates. As mentioned previously, soil type 5 was one of the major soils while soil type 2 represents the hard soil formation, which is expected to have lower TBM rates than type 5. In order to evaluate the overall difference in rates for both soil types, data sets are combined into one group for each soil type 5 and 2, respectively.

The two assumptions about the sampling distribution with the two data sets are made: the normal distribution and *t* density. After 10,000 iteration from WinBUGS program, the result shows a 95 % posterior interval for the difference in TBM rates between soil type 5 and type 2, (0.849, 1.511) when normal distributions are assumed for two different soil types. A *t* density with a preset 5 degrees of freedom produces a very similar result of a 95 % credible interval for the difference in means of (0.806, 1.505). Therefore, it can be concluded that there is a significant difference in means for TBM rates between soil type 5 and 2. Table 5-1 compares the statistics for two different soils in case of normal distribution assumptions.

Table 5-1: Comparison of TBM Rates between Soil Type 5 and Type 2

Parameter	Statistics	Type 5	Type 2
Mean (μ)	Mean	5.074	3.895
	2.5 %	4.951	3.584
	Median	5.074	3.895
	97.5 %	5.198	4.202
Standard Deviation (σ)	Mean	1.131	1.030
	2.5 %	1.047	0.834
	Median	1.129	1.020
	97.5 %	1.224	1.289

Statistical analysis was subsequently conducted to evaluate means within each soil type. Based on the location of the soil type along the tunnel path, independent data sets including six different sub-groups for soil type 5 and two different sub-groups for soil type 2 are obtained. Due to the limited number of data points for the last two data sets of soil type 5, these two sets are combined into one sub-group (soil 5-5) and the results from the Bayesian inference are compared in Figure 5-2. The comparison of the mean and 95% credible interval for each soil type indicates that wide ranges of means were found even for the same soil type. For instance, the means for soil type 5 vary ranging from 3.446 to 5.857 m/hr. The variation in means for each soil may be related to the state and characteristics of soil such as the presence of water and rocks. The findings lead to a conclusion that detailed level of data should be used as input for TBM penetration rates for the simulation model since the use of one single mean rate for each soil type may produce inadequate and erroneous simulation results.

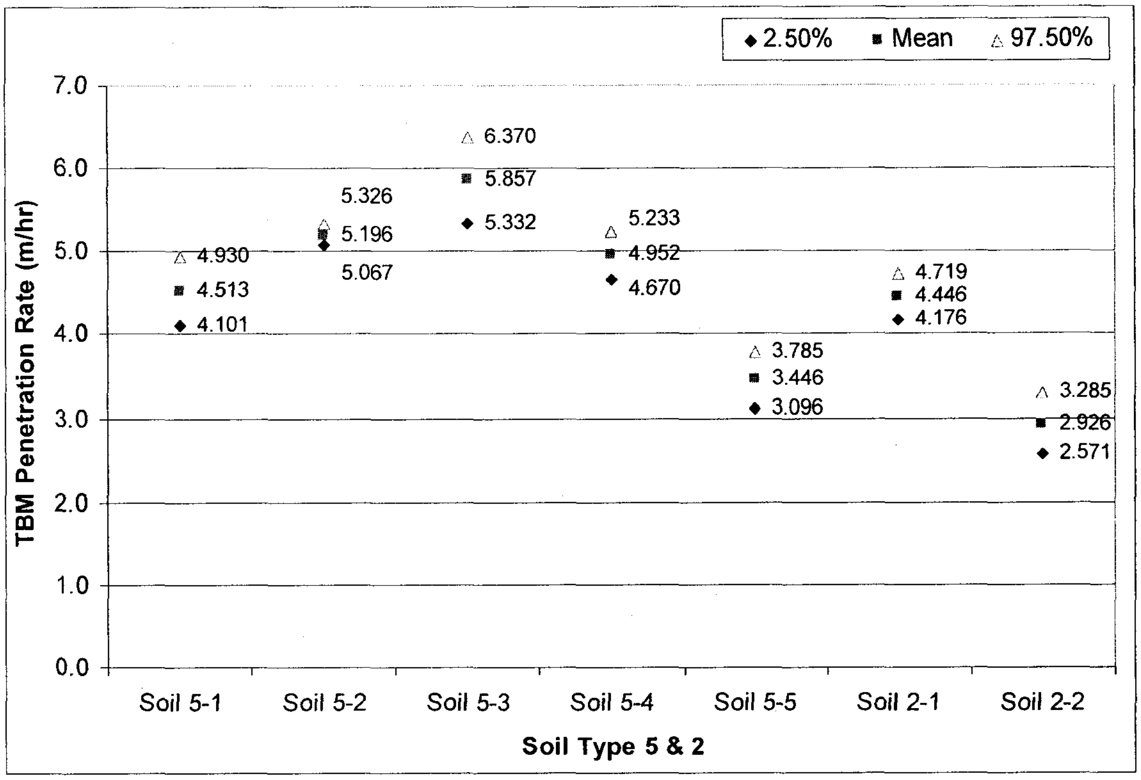


Figure 5-2: Comparison of TBM Rates for Soil Type 5 and Type 2

The visual inspection of the scatterplot in Figure 5-1 suggests the classification of several groups for TBM penetration rates for each soil type. A soil group 5-2 (150-363 m) demonstrates clustered data points indicating a steady soil state. A soil group 5-4 (1199-1322 m) also demonstrates somewhat a steady state of data points while other groups for soil type 5 show sparse and dispersed data distributions.

The comparison of means in TBM rates between soil 5-2 and soil 5-4 shows a 95 % credible interval for the difference in means of (-0.069, 0.554). It is concluded that two groups do not have significant difference in means and can be grouped as one group. It should be noted that the statistical results for both groups are independent since these soils were located separately. It is concluded that the overall rates obtained from combining these two sets of data can represent typical soil type 5 without soil transition where soil condition was not significantly influenced by other soil types.

However, significant deviations from the typical rate are detected for soil 5-3 and 5-5. It seems that these soils are considerably affected by the soil conditions on the adjacent soil segment. For instance, a higher rate for soil 5-3 may be affected by the adjacent soil segment with soil 8 while a lower rate for soil 5-5 may be somewhat related to the one with soil 2 (clay shale). Although two adjacent soil segments have different soil types, some common characteristics due the coexisting factors such as the presence of water and rocks may give rise to the similarity in TBM penetration rates for both soil groups.

After 10, 000 iterations from the WinBUGS, statistical results including mean and 95% confidence intervals are obtained for each soil group. Table 5-2 compares means for TBM penetration rates for each soil type while Table 5-3 compares standard deviations. Rates for soil 6 and 9 are within the range of soil 5. A 95 % confidence interval for the mean TBM rates for soil 8 is very close to the one for the high rate group of soil 5. The results lead to a conclusion that TBM rates for soil type 5 should be carefully selected after soil status and characteristics are determined. However, rates for soil type 6, 8, and 9 were only based on data points from one single tunnel section from this case study. More data need to be collected from other similar tunneling projects to generalize the TBM penetration rates for those soil types. The comparison of means and standard deviations in Table 5-2 and 5-3 illustrates that as the means for TBM rates decrease standard deviations also tend to decrease. This finding suggests that TBM rates with a higher mean tend to have more variability or dispersion than ones with a lower mean.

Table 5-2: Comparison of Means for TBM Rates for Each Soil

Soil	Type 5			Type 2		Type 6	Type 8	Type 9
Level	High	Mid	Low	High	Low	N/A	N/A	N/A
2.5 %	5.332	5.013	3.096	4.173	2.568	5.107	5.593	4.466
Mean	5.858	5.133	3.446	4.445	2.926	5.428	5.916	4.908
97.5 %	6.370	5.255	3.785	4.719	3.287	5.749	6.242	5.347

Table 5-3: Comparison of Standard Deviations for TBM Rates for Each Soil

Soil	Type 5			Type 2		Type 6	Type 8	Type 9
Level	High	Mid	Low	High	Low	N/A	N/A	N/A
2.5 %	1.134	0.857	0.683	0.564	0.495	0.895	1.128	0.840
Mean	1.452	0.937	0.893	0.734	0.707	1.101	1.338	1.113
97.5 %	1.897	1.027	1.191	0.973	1.039	1.361	1.605	1.501

Table 5-4: TBM Rates based on the Industry Experts' Opinion (Ruwanpura 2001)

Soil Type	Description	Input Distribution	Mean
5	Glacial till	Triangular (3.50, 3.70, 4.20)	3.80
1, 2	Bed rock	Triangular (2.00, 2.60, 3.00)	2.53
3, 4	Saskatchewan gravel and sand	Triangular (1.75, 1.90, 2.00)	1.88
6	Glacial sand and gravel	Uniform (1.00, 2.00)	1.50
7, 8, 9, 10	Lake Edmonton clay	Triangular (3.75, 4.25, 5.00)	4.33

For input modeling for TBM penetration rates in tunnel simulation, it is of interest to obtain and compare the current simulation practice with the results obtained from this research study. Ruwanpura (2001) uses tunnel simulation models based on his prediction model for soil transition. Table 5-4 shows input distributions for TBM rates used for his study. These input parameters were mainly obtained from the industry expert's opinion. It is obvious that these rates were conservatively estimated with very small variances when compared to the results from the actual case study.

The comparison of means for soil type 2 demonstrates the similarity between two rates. That is, the mean of 2.53 m/hr for his study was quite close to the one of 2.926 m/hr for the low rate group for soil 2, which represents hard soil formations where rock drillings were frequently and considerably required. For soil type 5, a mean of 3.80 m/hr from the experts' opinion was quit close to one of 3.446 m/hr from the low group for this study. However, there is a considerable difference between experts' rate for soil type 5 and an overall mean of 5.074 m/hr based on the actual sample. Thus, one single rate for soil type 5 from the experts' opinions may not well represent various soil conditions. It is believed that the TBM penetration rates based on sample from this study can be utilized as a valuable guideline for selecting appropriate TBM rates for different soil types.

5.3.2 TBM Penetration Rates for Soil Transitions

The accurate prediction of soil transitions are major concerns for project planners since exact soil profiles are never known prior to construction. Because soil samples are usually obtained from vertical boreholes spaced about 300-500 m apart for typical utility tunnel construction, a typical industry practice to predict the soil profiles between boreholes is mainly based on linear approximations or interpolations (Ruwanpura et all, 2004).

To trace the soil transitions based on the TBM penetration rates for NEST project, the last portion of tunneling with a length of 605m was focused on since it demonstrates clear soil transitions due to existence of hard soil conditions (clay shale). Soil transitions follow as soil type 5-8-5-2-9-5-2-5 along the tunnel path. After the mean and 95 % confidence interval from the sample for each soil was obtained from WinBUGS, the results are plotted as shown in Figure 5-3.

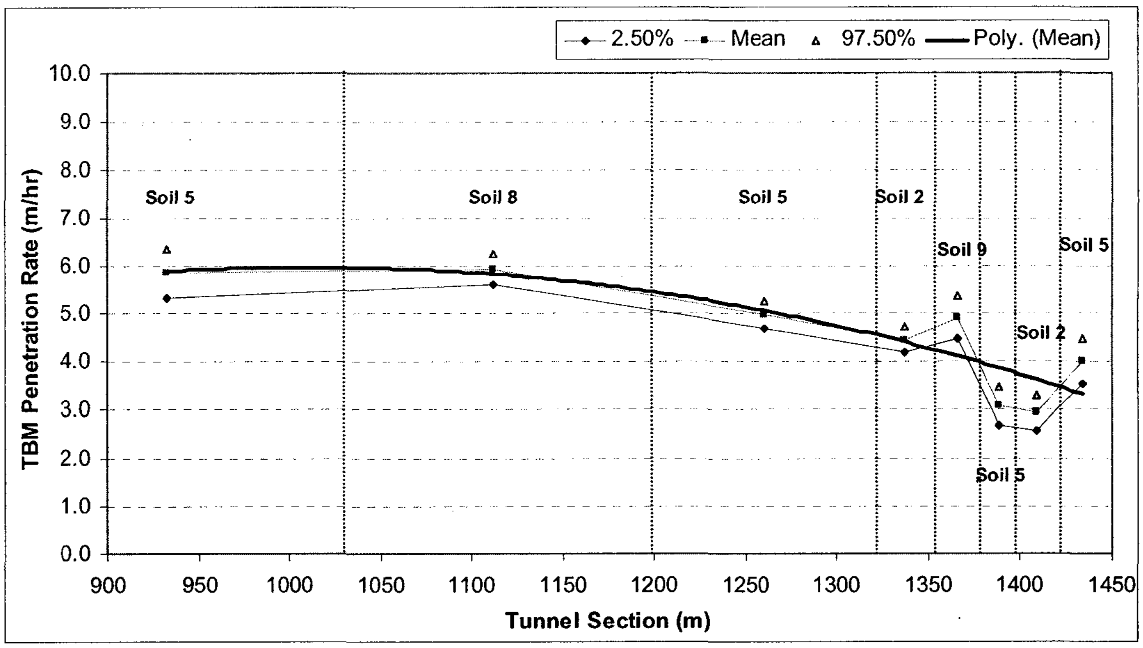


Figure 5-3: TBM Rates for Soil Transition for NEST Project

The plot of TBM rates along the tunnel path indicates that overall TBM penetration rates gradually decreased with frequent soil changes especially at the end portion of the tunneling. The highest rate of 5.915 m/h was achieved in soil type 8 while the lowest rate of 2.926 m/h was recorded in soil type 2. The significant difference between two extreme rates demonstrates the TBM advancement was considerably affected by the soil conditions.

The TBM penetration rates in soil type 5 vary depending on the location of the soil segments. The highest rate achieved was 5.857 m/h while the lowest rate recorded was 3.064 m/h. Those obtained rates are quite similar to ones in adjacent soil segments with soil type 8 and 2, respectively. These findings are consistent with the results in the previous section that similar TBM rates were found for two adjacent soil segments having different soil types. Review of the project progress report indicates that the TBM frequently encountered rocks along those tunnel paths regardless of soil types. It is concluded that the presence of rocks for those tunnel portions is a major factor affecting the TBM advancement and determining the soil transitions.

5.3.3 Encountering Rocks

When hard soil layers such as rock boulders can not be bored with the TBM, drilling and/or jack hammering should be employed to break these layers. The probability of encountering these soil layers is considered a high risk factor causing significant schedule delays and costs because the TBM cannot proceed at its normal productivity in this situation. Due to the geological uncertainty, predicting the exact probability of encountering these types of soil layers is a very challenging task especially at the planning stage of tunnel construction.

According to the NEST project report, TBM encountered the rock boulders frequently and considerable amount of times were spent on drilling and splitting these rocks. In order to see overall trend in rock encountering occurrences in time series, A

Poisson regression model was used to find the point where change occurs in frequency of encountering rocks. The occurrence of encountering rocks for total 163 shifts for the NEST project are analyzed and a change-point model for the Poisson means via a log-link is as follows:

$$
\begin{aligned}
&Y_t \sim Poi(\mu_t) \\
&\log(\mu_t) = \beta_1 + \beta_2 \times \delta(t-\tau) \\
&\beta_j \sim N(0, a_j), j = 1,\ 2
\end{aligned}
\tag{5.4}
$$

The function $\delta()$ is defined as 1 if its argument is zero or positive, and 0 otherwise. After 10,000 iterations, estimates of mean and median for the shift change (τ) were about 110th and 118th shift, respectively. Figure 5-4 shows a plot of the posterior density of the parameter and there apparently seems to be a higher rate of encountering rocks after the obtained shifts. From the project progress report, the soil transition from type 5 to 8 occurred from 115th shift (tunnel section starting from 1025th m). It is decided that two different probabilities for two different tunnel sections are calculated. That is, a lower rate from the first section (a section from 0 to 1025th m) and a higher rate from the second section (a section from 1025th to 1446th m).

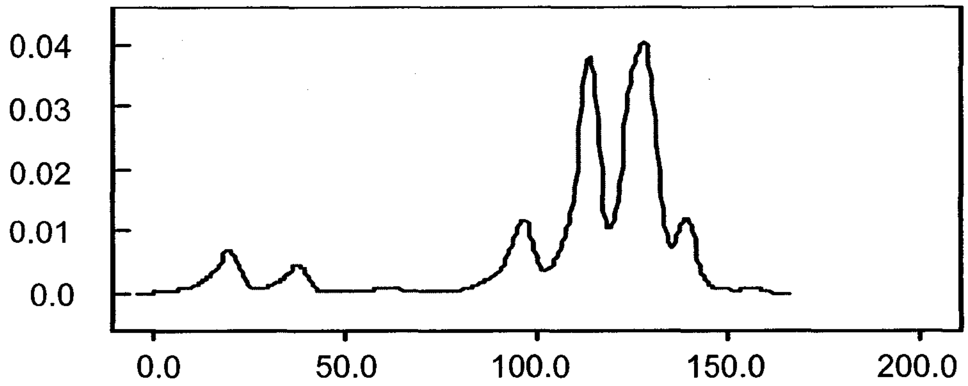


Figure 5-4: Posterior for Change Shift for Rock Encountering

A Poisson model was utilized for the calculation of the rates for rock encountering. The number of the occurrence of rock encountering is assumed to follow a Poisson distribution

$$x \sim Poisson(\theta t)$$

where θ is the rate for the occurrence of rock encountering and t is the length of tunnel section completed (in meters). A prior distribution of $\theta = Gamma(\alpha, \beta)$ was assumed and Hyperparameters, $\alpha \sim Exponential(1.0)$ and $\beta \sim Gamma(0.1,\ 1.0)$ were used (George et al. 1993). After 10,000 iterations, a mean rate in the first section was estimated to be 0.014 with a 95% credible interval (0.008, 0.022) while a higher mean rate of 0.053 with a 95% credible interval (0.033, 0.077) was estimated for the second section containing rock soil conditions. These results demonstrate there is a significant difference in probabilities of encountering rocks between two sections. It suggests that a higher rate may represent the probability for tunnel sections with rock soil conditions while a lower rate may represent the probability for the normal soil condition.

It is also of interest to see if two different tunnel sections with different probabilities of the rock occurrence also have different average times (in minutes per each occurrence) required for drilling and splitting rocks. Because two data sets only contain 12 and 20 data points, respectively, the sampling distributions with those data sets are assumed to be t density. A t density a degree of freedom as random parameter of uniform (2, 100) produces a mean of 162.7 minutes with a 95% credible interval (92.94, 254.2) for the first tunnel section while a mean of 199.7 minutes with a 95% credible interval (141.9, 257.6) was estimated for the second section. A difference of about 40 minutes in the average duration indicates that higher average time was spent on rock drilling and splitting for the tunnel section containing rock soil conditions. From this result with the higher probability of encountering rocks found in hard soil formations, it can be concluded that the TBM advancement also should be affected by both frequency and degree of rock soil conditions

5.3.4 Surveying Activity

The different interval of surveying activities is implemented for the tunnel sections. For instance, more frequent surveying activities should be employed for the curvature section while the frequency of these activities will be reduced for the straight section. From the NEST project progress report, there were 26 times of surveying activities recorded for the first 338 m tunnel section indicating the surveying activity needs to be repeated for every 13 meter on average. The current simulation input for this activity based on the industry expert's opinion is every 15 m for the tunnel section with more frequent surveying while the interval of every 50 m can be assumed for the section with less frequency. The current assumption for the activity seems to be reasonable and is used for further simulation analysis.

For the duration of the surveying activity, the sampling distribution was assumed to be *t* density. After 10,000 iterations, a *t* density with a degree of freedom as random parameter of uniform (2, 100) produces a mean of 113 minutes with a 95% credible interval (95, 132). However, a slight difference in the duration of survey activity has been found between the obtained result and current practice in simulation. The duration is currently assumed to have a uniform distribution ranging from 120 to 180 minutes. It was decided that the obtained estimation of major input parameters using a sampling-based Bayesian inference is utilized for another tunneling project.

5.4 Case Study for Tunnel Simulation Application

A case study was conducted to see if the use of the input parameters obtained from the sampling-based Bayesian inference in the previous section can enhance the simulation outputs for the different tunneling project where samples for major input parameters such as TBM penetration rates are not available. The Glencoe Storm Sewer Upgrade project was selected as a case study since both projects have a similar tunnel diameter and common soil characteristics for some tunnel portions. This project started with a segment containing soil type 5 (clay till). However, soil changes occurred after about 37% completion of the tunnel portion and the remaining segment was mainly composed of hard sandstone.

5.4.1 Description of the Case Study

In order to increase storage capacity during storm period, the City of Calgary proposed the 930-meter-long storm storage tunnel having a diameter of 2.9 meter after conducting a drainage study for the Glencoe Basin due the overland flooding and sewer backup problems during heavy rainstorms. The installation depth of the tunnel varies from 16 m at the working shaft to 45 meter at the retrieval shaft. The project is an infrastructure Canada-Alberta (ICAP), a joint partnership between the Federal Government, the Government of Alberta, and its municipalities.

The total length of 864 meter tunnel was excavated by using the TBM and the tunnel excavation started on August 10, 2005 and was completed on March 21, 2006 with the overall tunnel productivity of 6.25 m/shift.

For the total tunnel length of 864 meter, the entire tunnel path was divided into three tunneling segments considering different soil conditions. The first segment with a length of 316 meter contains clay till and sand. The second segment with a length of 90 meter containing some sandstone with water is considered as a transition segment. The third segment, 458 m, is composed of hard and dry sandstone, which will cause very low TBM advancement.

5.4.2 Input Modeling for Simulation

Input data for simulation are normally obtained from assumptions based on the experts' opinion when actual data are not available. Although these subjective inputs can be used as a starting point, simulation results may not be reliable if simulation inputs and outputs are not thoroughly validated with the actual project outcomes.

The soil conditions for this project are very distinctive with one segment having clay till and the other segment having sandstone. Overall project information such as daily productivity was recorded during the actual tunnel construction while critical simulation input data such as TBM penetration rates and delay information were not thoroughly recorded. For many tunnel construction projects, these data are not available and assumptions for the simulation model are simply made based on the superintendent's expert opinion since the data collection especially for TBM penetration rates may be time-consuming and costly. The primary objective is to establish whether the input models developed from the actual project can be successfully utilized into the simulation model for other similar projects to improve the accuracy of simulation results.

Three tunnel segments were selected for the simulation model in *Simphony*. For the first segment, soil type 5 is selected for major soil condition while soil type 2 represents soil condition for the third segment. The analysis from the NEST project showed that the average TBM penetration rate for soil type 5 varies ranging from 3.446 to 5.858 m/hr. A thorough analysis of the TBM penetration rates for soil type 5 indicated that the TBM advancement was strongly affected by the soil conditions on the adjacent soil segment. It was decided that a low mean rate of 3.446 m/h was more suitable for the first segment due to the succeeding segments having hard sandstone.

The selection of the mean TBM rate for the third segment having sandstone should be carefully made. According to experts' opinions, the rates for soil type 2 can be divided into two major groups: shale with a triangular distribution (2.5, 2.7, 3.0) and sandstone with a triangular distribution (1.75, 1.90, 2.00). In the previous section, the result of the sampling-based Bayesian inference for clay shale illustrated a mean of 2.926 m/h with a 95% credible interval of 2.568 and 3.287 (in a low level in Table 3). This result for clay shale is quite consistent with the expert opinion. It is thus decided to follow the expert's opinion on the input distribution for the sandstone for the third segment.

The second segment with a relatively shorter length of 90 m was assumed to be a transition segment because the TBM started to encounter some sandstone on this segment according to the project progress report. A mean TBM rate of 2.665 m/h on the second segment was chosen based on the assumption of the gradual soil transitions from the first to the third segment. Table 5-5 demonstrates input models for TBM penetrations for three segments.

Table 5-5: Input Models for TBM Rates for Case Study Project

	1st Segment	2nd Segment	3rd Segment
Tunnel Length	316 m	90 m	458 m
Soil Type	clay shale	clay shale with some sandstone	sandstone
Distribution for TBM Rates	Normal (3.446, 0.893)	Normal (2.665, 0.605)	Triangular (1.75, 1.9, 2.0)

5.4.3 Simulation Output Analysis

Simulation analysis was conducted after appropriate input parameters for various tunnel activities were selected. Major input parameters for activities such as surveying and rock drilling are based on results from the sampling-based Bayesian inference from the NEST project. Since the durations for some activities are random with a small number of data sets, it is decided that uniform or triangular distribution using the 95% credible interval of the means from the Bayesian inference is utilized for the duration of these activities.

For the first segment of the Glencoe tunnel, ten simulations assuming no rock drilling were first run. With the obtained means from the simulation, WinBUGS was run for Bayesian inference for the tunnel productivity. After 10,000 iterations, WinBUGS produces a mean of 8.421 m/shift with a 95 % credible interval (8.355, 8.485). This obtained result was very close to the actual productivity of 8.29 m/shift for the first segment. It should be noted that simulation analysis was based on the assumption of no significant TBM delays such as rock drilling for this segment.

The daily productivity generated from one of the simulation runs were plotted and compared with the actual productivity in Figure 5-5. The mean productivity for this simulation run was 8.43 m/shift with a standard deviation of 1.39. The comparison of both productivities shows the simulation results are quite close to the actual trend. It is thus concluded that the simulation result validates major input models such as surveying activity used for this case study. It also supports the use of the lower mean TBM penetration rate of 3.446 m/h for the soil condition instead of the typical rate of 5.133 m/h for soil type 5.

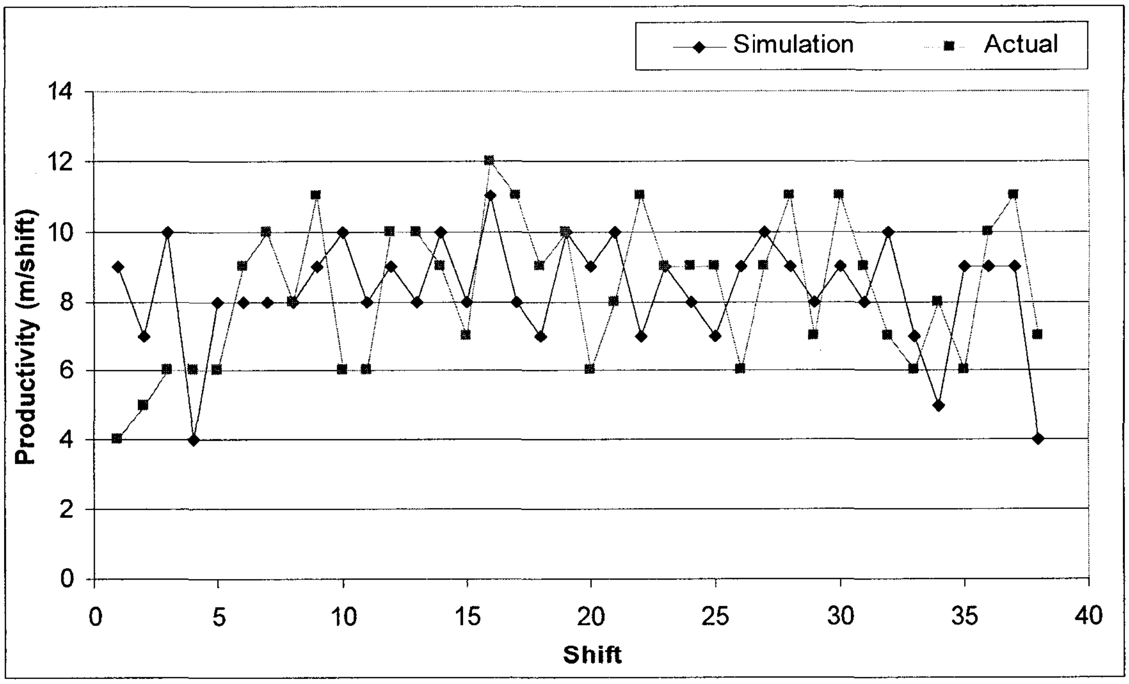


Figure 5-5: Comparison of Productivity between Actual and Simulation Result for the First Segment

Similarly, after ten simulations were run for the second segment, a mean of 7.465 m/shift with a 95 % credible interval (7.374, 7.557) was obtained from WinBUGS. The actual productivity for this segment with soil transitions was 7.5 m/shift with a standard deviation of 2.15. The comparison indicates that the mean TBM rate assumed for the transition was appropriate. The finding also supports the assumption that the TBM rates gradually decrease as the soil transition occurs along the tunnel path.

For the third segment, several cases were assumed for the occurrence of the TBM stoppage mainly due to the activity of rock drilling. The assumption was based on the finding from the NEST tunnel project that TBM encountered rocks more frequently on the hard ground conditions such as clay shale requiring significant times for drilling and splitting.

In order to evaluate the effects of the rock drilling on the overall tunnel productivity, ten simulations were first run with the assumption that TBM does not encounter any rock. The results show a mean of 6.564 m/shift with a 95 % credible interval (6.520, 6.607) for this case. Subsequently, simulation assuming various intervals for the rock drilling occurrence was run. An exponential distribution ranging from 750 to 1500 min was used for the occurrence of rock encountering in *Simphony.*

Table 5-6 illustrates the result of means and 95 % credible intervals for each assumption. The result indicates that the mean of 5.159 m/shift assuming an exponential distribution of 750 min was very close to the actual one of 5.205 m/shift. The result of this simulation analysis showed that the average productivity was significantly affected by the occurrence of the rock drilling activity and the productivity loss of about 1.41

m/shift occurred due to frequent rock drilling activities (for instance, about 46 times of rock drilling with an average duration of 200 min each occurrence)

Table 5-6: 95 % Credible Intervals for Mean Productivity for the Third Segment

Average No. of Rock Drilling	Distribution for Interval	Productivity (m/shift)		
		2.5 %	Mean	97.5 %
0	NA	6.520	6.564	6.607
22.2	Exponential (1500)	5.738	5.797	5.857
31.2	Exponential (1000)	5.429	5.558	5.686
46.2	Exponential(750)	5.044	5.159	5.274

5.5 Conclusions

This chapter discussed the estimation of major simulation input parameters using the sampling-based Bayesian inference method. The major input parameters include the TBM penetration rates for various soil types, rock encountering, and surveying activities. The TBM penetration rates as one of the most important factors affecting the productivity were first analyzed depending on the five different soil types (Type 2, 5, 6, 8, and 9). After the patterns of soil transitions along the tunnel path were determined, sample for TBM penetration rates of different soil types were categorized and the results from Bayesian inference including the mean and 95% credible interval of each soil group were obtained and summarized.

The comparison of those statistics between the soil type 5 and type 2 demonstrated that there is a significant difference in means for TBM rates. However, TBM penetration rates even for the same soil type also vary depending on the location of soil. For instance, the means for soil type 5 range from 3.446 to 5.857 m/h. The variation in means for each soil may be related to the state and characteristics of soil such as the presence of water and rocks. The findings lead to a conclusion that the detailed level of data should be used as input for TBM penetration rates for the simulation model since the use of one single mean rate for each soil type may produce inadequate and erroneous simulation results. It is also found that although two adjacent soil segments have different soil types, some common characteristics due to the coexisting factors such as the presence of water and rocks may give rise to the similarity in TBM penetration rates for both soil groups.

After a Poisson regression model was utilized, the overall trend in rock encountering occurrences in time series was determined. The results indicated the higher probability of encountering rocks were found in hard soil conditions (clay shale) with a higher average time required for drilling and splitting the rocks.

A case study was conducted to see if the use of the input parameters obtained from the sampling-based Bayesian inference can enhance the simulation outputs. Since sample for major input parameters such as TBM penetration rates was not available for the Glencoe Storm Sewer Upgrade project chosen as a case study, input parameters obtained from Bayesian inference were utilized for the simulation model of the case study. Based on the results of the comparison between the simulation and actual performance, it is determined that major input parameters used for the simulation model were valid. These results demonstrated the successful applications of the sampling-based Bayesian inference for estimating major input parameters of the simulation model.

CHAPTER 6: TUNNEL PRODUCTIVITY MODELING WITH A MULTIPLE REGRESSION TECHNIQUE

6.1 Introduction

The tunnel productivity has been utilized as one of major criteria to determine the base project schedule. Industry practitioners usually predict the tunnel productivity based on their own experience using historical data. However, those estimates as a deterministic approach may be inaccurate and subjective especially when various project conditions are not well reflected.

As an alternative, simulation can be used as a powerful means for improving the accuracy of the productivity prediction. One of the major advantages of simulation is that its users can experiment various project scenarios using statistical input distributions for various activities. However, many industry practitioners are still hesitant to implement the simulation as a planning tool due to the lack of their knowledge in simulation modeling. The use of a good quality simulation input is also essential since inaccurate simulation inputs may produce the erroneous simulation outputs.

This chapter presents the development of the simulation-based tunnel construction productivity model using the actual tunneling project: the North Edmonton Sanitary Trunk (NEST). Data are first generated from simulation experiment with various site conditions and a multiple regression technique is utilized to develop the productivity model. With the proposed productivity model, tunnel productivity can be easily and accurately predicted by identifying and quantifying the effects of factors on the productivity. The approach is as follows:

1. Divide the tunnel path into several segments based on the geological conditions.
2. Determine the statistical distributions for simulation input parameters such as TBM penetration rates, survey activity, rock drilling, and TBM breakdown for each segment.
3. Identify and quantify the effects of major factors on the overall productivity with simulation experiments for each segment
4. Conduct a multiple regression analysis with generated data sets from simulation experiments.
5. Validate the productivity model by comparing its results with ones from the actual and simulation runs.

Experimental design is first implemented to evaluate the factors such as TBM penetration rates, rock encountering, and survey interval for three different geological zones determined from the soil profile assumptions from borehole samples. In simulation, experimental design provides an efficient and structured way of selecting simulation configurations for the target factors with the minimum simulation runs. Thus, a "hit-or-miss" sequence of simulation runs unsystematically trying a number of alternative configurations can be avoided (Law and Kelton, 2000). After determining the simulation configurations for major factors in tunnel construction operations, the simulation–based tunnel productivity model is developed with the multiple regression technique.

This chapter is organized as follows: Section 6.2 explains background information on experimental design, regression technique, and geological zones used for simulation.

Section 6.3 describes the application of experimental design for the NEST. Productivity analysis using simulation is explained in Section 6.4. Section 6.5 discusses the proposed tunnel productivity modeling and conclusions are then presented in Section 6.6.

6.2 Background

6.2.1 Overview of Experimental Design in Simulation

The experimental design in simulation is an efficient methodology to evaluate the effects of factors in the responses. It is also useful to determine whether the effect of one factor depends on the levels of the other factors (interaction effect). In order to reduce the number of simulation runs required, a 2^k factorial design is an economical strategy: with two levels for each factor, simulation runs at each of 2^k possible factor-level combinations are needed. Usually, a minus sign (-) is associated with one level of a factor (for instance, pessimistic condition) and a plus sign (+) is associated with the other (the optimistic condition). For instance, if three factors are considered ($k = 3$), the total eight configurations ($2^3 = 8$) are required and each response variable is the value of response with different levels of factors corresponding to design matrix (Law and Kelton, 2000).

The main effect of factor j is the average change in the response when the factor j moves from the (-) level to the (+) level while all other variables are held constant. When the interaction exists between two factors, the effect of the one factor depends in some degree on the level of some other factor. The degree of the interaction by the two-factor (or two-way) interaction effect can be defined as half the difference between the average effect of factor j_1 when factor j_2 is at its (+) level (while holding all other factors fixed) and the average effect of j_1 when factor j_2 is at its (-) level (Law and Kelton, 2000).

6.2.2 Overview of Measuring Casual Effects with a Regression Technique

A Regression technique is one of the most common statistical approaches. The primary objectives of the regression analysis are for explaining how the explanatory variables impact the response variable and making predictions. This section briefly reviews the use of the regression model for the measure of casual effect.

Table 6-1: Examples of Measures of Casual Effect (Stolzenberg and Land, 1983)

	Casual Effects of X_1 on Y	
Specification	Metric Effect $\frac{\partial Y}{\partial X_1}$	Standardized Effect $\frac{\partial Y/\sigma Y}{\partial X_1/\sigma X_1}$
1. $\hat{Y} = a + \sum_{i=1}^{I} b_i X_i$	b_1	$b_1 \frac{\sigma X_1}{\sigma Y}$
2. $\hat{Y} = a + b_1 \ln(X_1) + \sum_{i=2}^{I} b_i X_i$	$\frac{b_1}{X_1}$	$\frac{b_1}{X_1} \frac{\sigma X_1}{\sigma Y}$
3. $\hat{Y} = a + b_0 X_1 + b_1 X_1^2 + \sum_{i=2}^{I} b_i X_i$	$b_0 + 2b_1 X_1$	$(b_0 + 2b_1 X_1)\frac{\sigma X_1}{\sigma Y}$
4. $\hat{Y} = a + \sum_{i=1}^{I} b_i X_i + b_{I+1} X_1 X_2$	$b_1 + b_{I+1} X_2$	$(b_1 + b_{I+1} X_2)\frac{\sigma X_1}{\sigma Y}$

Table 6-1 illustrates the major mathematical equations corresponding to common casual relations. The casual effect of one variable on another is defined as the extent to which variation in the first variable results in variation in the second. As an approach to measures of casual effect, a rate-of-change based on partial derivatives (when there is more than one casual variable) is used to measure the average number of units of change in the effect variable associated with a change of one unit in the casual variable. In Table 6-1, it should be noted that the unstandardized effect, $\partial Y/\partial X_1$ is the rate of change in Y per change in X_1 while the standardized effect measures changes in one of these standardized units by dividing it by the variable's standard deviation (Stolzenberg and Land, 1983).

6.2.3 Three Different Geological Zones for the Tunnel Simulation

The soil segment elements in *Simphony* allow the users to define the geological zones for tunnel simulation modeling. Three different soil segments are determined based on the soil profile assumptions from borehole samples for the NEST. The length of three different soil segments is 105, 1038, and 303 m, respectively. The first segment, 105 m, is created assuming lower advance rate due to the learning curve effect. The second segment, 1038 m, is considered as a typical soil segment with major soil type of clay till. The third segment, 303 m, represents a harder soil formation that will reduce the TBM advance rate. Table 6-2 shows the actual soil compositions of each zone. It was found that frequent soil changes occurred on third segment. The existence of the soil type 2 indicates harder soil formation resulting in the lower TBM advance on this segment.

The selection of zones is a subjective decision and different decision (the number and length of zones) can be made. However, the creation of too many soil segments with a short tunnel length for the tunnel simulation model may produce inappropriate simulation results due to the shortage of data points generated from the simulation.

Table 6-2: Actual Soil Compositions of Each Zone

Zone	Length	Major Soil Types
Zone 1	105 m	Type 5 (clay till): 100 %
Zone 2	1038 m	Type 5 (clay till) and Type 9 (clay silt): 84 %
Zone 3	303 m	Type 5 (clay till): 55% and Type 2 (clay shale): 18 %

Total sample for TBM penetration rates consists of 521 data points. The sample data is divided into three groups for each zone and the descriptive statistics are compared in Table 6-3. Samples available for TBM penetration rates represent 44.8%, 28.8%, and 57.8% of the length of each zone, respectively. The results demonstrate zone 2 has somewhat higher rates than zone 1 and 3. These results are logically consistent with the assumption that the first and third zone will reduce TBM penetration rates due to learning curve effect and harder soil condition, respectively.

Table 6-3: Comparison of TBM Penetration Rates for Tunnel Zones

	Zone 1	Zone 2	Zone 3
Number of Data	47	299	175
% of Sample	44.8 %	28.8 %	57.8 %
Mean	4.514	5.410	4.557
Std. Dev.	1.436	1.068	1.329
25 Percentile	3.374	4.746	3.469
50 Percentile	4.343	5.335	4.551
75 Percentile	5.517	6.097	5.543
Distribution	Beta (1.12, 1.36, 2.08, 7.46)	Beta (3.14, 3.30, 2.57, 8.39)	Beta (2.20, 3.63, 1.85, 9.01)

Statistical distributions of the TBM penetration rates for each zone were fitted based on the sample data using distribution fitting software (BestFit). This parameter is believed to play an important role in the accuracy of simulation modeling and also affect the overall tunnel productivity. The beta distribution was selected for the TBM penetration rates since it allows more flexibility to attain many different shapes while the normal distribution only allows the bell shape. Four parameters for beta distribution fitted for the each zone (the first and second parameters are shape parameters and third and fourth parameters are the end points) are shown in Table 6-3. Figure 6-1 compares the distributions for zone 2 and 3. The zone 2 has a bell-shape distribution with a mean of 5.41 m/hr while the distribution for the zone 3 is slightly positively skewed with a mean of 4.56 m/hr. It is believed that the lower mean TBM penetration rate for the zone 3 is mainly due to the soil condition (existence of clay shale). It is also supported with a finding from the project progress report that more frequent rock encounters were recorded for the zone 3 than the zone 2. The percentages of actual time spent on rock drilling for the zone 2 and 3 were 4 % and 19 % of the entire duration for each zone, respectively.

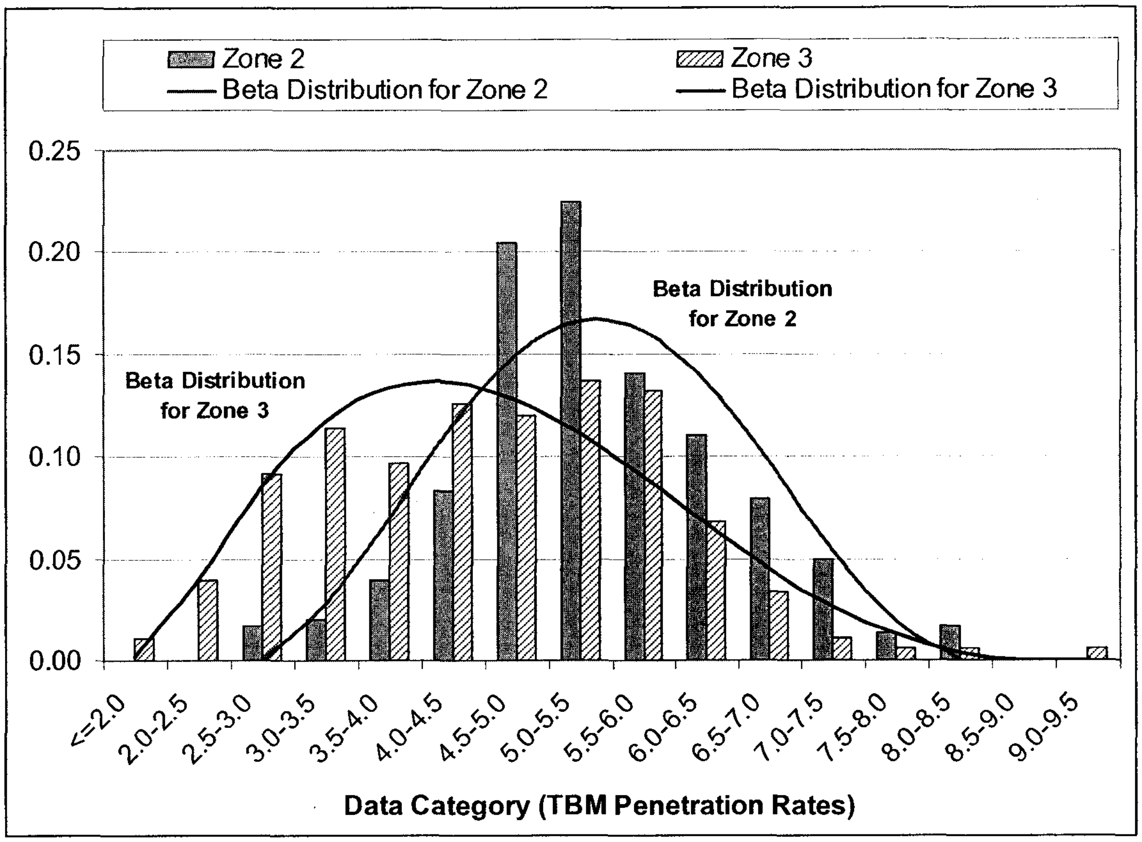


Figure 6-1: Distributions for the TBM penetration rates for Zone 2 and 3.

6.3 Experimental Design for NEST Project

The experimental design in simulation was conducted to evaluate how different levels of factors affect the productivity in different zones. Four major factors potentially affecting productivity were selected: (1) TBM penetration rates, (2) frequency of rock encountering, (3) duration of rock drilling, and (4) Survey interval. Table 6-4 shows the main factors and two different levels of each factor. The low and high levels of each factor were mainly determined by comparing data from the second and third zone determined in the previous section. The low levels for factors other than survey interval were chosen from the third zone. Although some other factors affecting productivity may exist, four major ones are first considered since the number of design points for the experimental design increase at the rate of 2^k. Table 6-5 shows the design matrix for the 2^4 factorial design and for each factor combination. Five independent responses were replicated to construct 100(1-α) percent confidence intervals for the expected effects using the t distribution with n-1 df (Law and Kelton, 2000). Therefore, with $k = 4$ factors leading to $2^4 = 16$ design points, five replications at each design point would require 80 replications in total.

Table 6-4: Factors for the 2^k factorial design

Factor Number	Factor		Low (-)	High (+)
1	TBM Rates (m/hr)	Mean	4.557	5.410
		Dist.	Beta	Beta
		Parameter	(2.20, 3.63, 1.85, 9.01)	(3.14, 3.30, 2.57, 8.39)
2	Freq. of Rock Encountering (min)	Mean	1140	4166
		Dist.	Exponential	Exponential
		Parameter	(1140)	(4166)
3	Duration of Rock Drilling (min)	Mean	218.3	165.0
		Dist.	Beta	Beta
		Parameter	(1.08, 1.50, 28, 482)	(0.51, 1.39, 28, 540)
4	Survey Interval (Every m)	Parameter	15	50

Table 6-5: Design Matrix for a 2^4 factorial design

Design Point	Factor 1	Factor 2	Factor 3	Factor 4	Response
1	-	-	-	-	R_1
2	+	-	-	-	R_2
3	-	+	-	-	R_3
4	+	+	-	-	R_4
5	-	-	+	-	R_5
6	+	-	+	-	R_6
7	-	+	+	-	R_7
8	+	+	+	-	R_8
9	-	-	-	+	R_9
10	+	-	-	+	R_{10}
11	-	+	-	+	R_{11}
12	+	+	-	+	R_{12}
13	-	-	+	+	R_{13}
14	+	-	+	+	R_{14}
15	-	+	+	+	R_{15}
16	+	+	+	+	R_{16}

The main effect of factor j is the average change in the response when the factor j moves from the (-) level to the (+) level while all other variables are held constant. According to Law and Kelton (2000), the main effect can be easily calculated by applying the signs in the factor j column to the corresponding R_l's, adding them up, and dividing by 2^{k-1}. For the interaction effect of factor i and j, the signs of the R_l's can be determined by multiplying the lth sign in the factor i by the lth sign in the factor j. As with main effects, the divisor is 2^{k-1}. For example, in the 2^4 factorial design of Table 6-5, the two-factor (or two-way) interaction effect, e_{13} is

$$e_{13} = \frac{R_1 - R_2 + R_3 - R_4 - R_5 + R_6 - R_7 + R_8 + R_9 - R_{10} + R_{11} - R_{12} - R_{13} + R_{14} - R_{15} + R_{16}}{8}$$

Figure 6-2 demonstrates the results of the 2^4 factorial design including four mains effects and ten interaction effects. Each plot of the effect shows the mean and a 90% confidence interval. It is found that there is lack of significant interactions in comparison with the main effects since all interactions are close to the zero. Thus, it is decided that the main effects are directly interpreted without consideration of interactions. Table 6-6 shows the means and 90% confidence intervals for the main effects of each factor.

The main effect of factor 1 (TBM Rates) is significant indicating that the increase of the mean TBM rates from 4.557 (zone 3) to 5.410 m/hr (zone 2) would lead to the productivity increase of 0.740 m. More frequent rock encountering (zone 3 in this case) would significantly reduce the productivity by 1.075 m while the difference of about 53 minutes for the duration for the rock drilling seems to somewhat moderately affect the productivity.

The main effect of factor 4 (Surveying) is also strong indicating that the less surveying activity (every 50 m) would increase the productivity by 0.977 m. From the results of the experimental design, it is concluded that the higher productivity for the zone 2 was attainable due to the main effects of factor 1, 2, and 3 while it was offset by the factor 4. The review of the actual productivity for the two different zones shows that the productivity of 9.61 m/shift was recorded for the zone 2 while the one of 7.97 m/shift was recorded for the zone 3. The actual productivity difference of 1.64 m/shift was compared to the one of 1.08 obtained from the experimental design. The actual difference can be somewhat explained by the factors from the experimental design. However, there is still some difference unexplained by the factors in the experimental design. This may be due some other factors omitted in the experimental design.

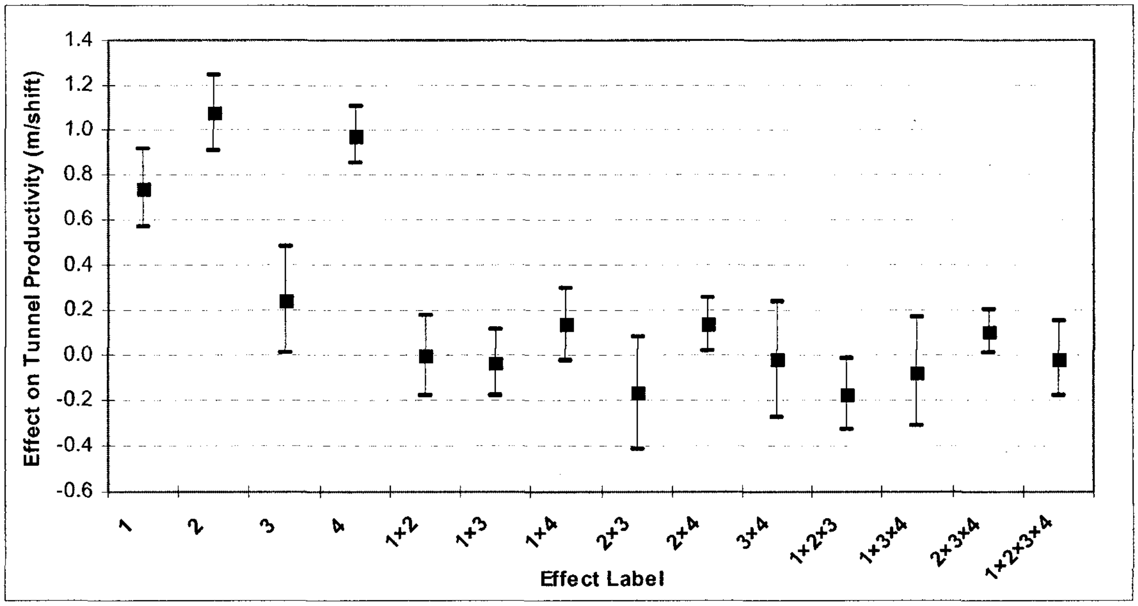


Figure 6-2: Main Effects and Interactions for Experimental Design

Table 6-6: Main Effects for Experimental Design

Factor Number	Factor Description	Mean Effect	90% Confidence Interval
1	TBM Rates	0.740	(0.566, 0.914)
2	Freq. of Rock Encountering	1.075	(0.905, 1.245)
3	Duration of Rock Drilling	0.245	(0.010, 0.480)
4	Survey Interval	0.977	(0.854, 1.100)

Using the data of 5 independent replications at each of the 16 design points in the full 2^4 factorial design, a regression was conducted. The overall F statistic for the regression was significant, $F(14, 65)=15.67$, $p<.001$, with $R^2=0.77$ and adjusted $R^2=0.72$

while the individual *t* ratio statistics for each coefficient for all interactions were not significant as with the results from the experimental design. The regression model excluding interactions was then run and the overall *F* statistic for the regression was significant, $F(4, 75)=53.59$, $p<.001$, with $R^2=0.74$ and adjusted $R^2=0.73$. Table 6-7 shows the regression results indicating the obtained coefficients for all factors are equivalent to the results from the experimental design as shown in Table 6-6.

Table 6-7: *t* Ratio Statistics for Each Coefficient for Main Factors

Factor	Coefficient	Standard error	*t*	Significance
Factor 1	0.740	0.113	6.572	<0.001
Factor 2	1.075	0.113	9.547	<0.001
Factor 3	0.245	0.113	2.176	0.033
Factor 4	0.977	0.113	8.677	<0.001

6.4 Productivity Analysis using Simulation for NEST Project

6.4.1 Simulation Inputs for the Tunnel Simulation

In order to evaluate the differences in the effects of factors, it is decided that simulation experiment for each zone will be conducted separately, focusing on the second and third zone. The second zone with a length of 1038 m was considered as a typical soil segment with major soil type of clay till. For the TBM penetration rates for the second zone, a beta distribution was fitted with a mean of 5.41 m/hr and a standard deviation of 1.07. The third zone with a length of 303 m was assumed for the hard soil formation. Based on the actual sample for the TBM penetration rates, the third zone has a lower mean of 4.56

m/hr than the second zone with one of 5.41 m/hr. It is believed that the lower TBM penetration rate for the third zone was due to the hard soil condition (clay shale).

Based on the project progress report, major factors potentially affecting the overall tunneling productivity were also recognized. These factors include survey activity, TBM breakdown/teeth replacement, and rock drilling. These factors directly affect the tunnel productivity because the activities related to these factors interrupt the TBM advancement. The current tunneling template in *Simphony* has a modeling element for the TBM breakdown. This element allows users to model the situation when the TBM is not advancing due to the delays mainly associated with the TBM breakdown. It is decided that all activities resulting in the TBM stoppage are combined into one element called "TBM delays". Table 6-8 shows the distributions fitted for each parameter for two different zones for the NEST project.

Table 6-8: Distributions of TBM delays for each zone

Parameter		**Zone 2**	**Zone 3**
TBM Breakdown	Interval	Exponential (4486)	Exponential(6840)
	Duration	Beta (0.32, 1.09, 29, 421)	Uniform (120, 180)
Rock Drilling	Interval	Exponential (4166)	Exponential (1140)
	Duration	Beta (0.51, 1.39, 28, 540)	Beta (1.08, 1.50, 28, 482)
TBM Delays	Interval	Exponential (2160)	Exponential (977)
	Duration	Beta (0.46, 1.61. 30, 540)	Beta (1.16, 1.76, 28, 482)

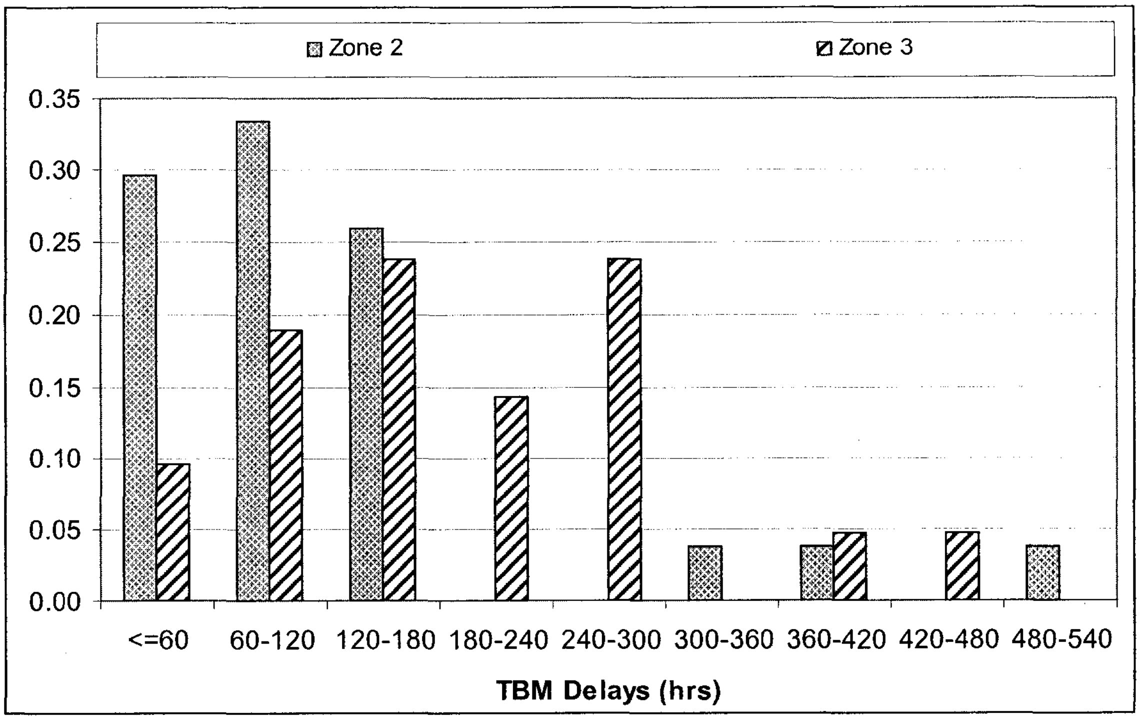


Figure 6-3: Comparisons of TBM Delays for Zone 2 and 3

Figure 6-3 compares the distributions of the TBM delays for zone 2 and 3. More frequent TBM delays occurred for the zone 3 with a higher mean duration of 208 hours while the zone 2 has the one of 142 hours. The percentage of the actual TBM delay time for the zone 2 and 3 was 6.5 % and 21.3 % of the entire duration for each zone, respectively. The total TBM delay time for the zone 2 is composed of 60 % of the rock drilling and 40 % of the TBM breakdown while one for the zone 3 has 90 % and 10 %, respectively. It is concluded that the TBM advancement for the zone 3 was more severely affected by the rock soil conditions. Simulation analysis is thus required to compare two different zones by quantifying the impacts of the different TBM rates due to the different soil conditions. It is also of interest to see how the simulation model by adding an element for TBM delays can improve the accuracy of the simulation output.

6.4.2 Project Analysis using Simulation

Using the input parameters discussed in the previous section, multiple simulations for each zone were run. Due to the randomness of the exponential distribution related to the occurrence of the TBM delays, it was decided that 10 independent replicates for each zone were generated for the simulation experiment.

Table 6-9: Simulation Results for Zone 2 and 3

Zone	Occurrence of the TBM Delays			Productivity (m/shift)	
	Distribution used	**Simulation Occurrence**	**Actual Occurrence**	**Simulation 95% C. I.**	**Actual Mean**
Zone 2	Exp (2160)	24.4	27	(10.13, 10.43)	9.61
Zone 3	Exp (977)	13.5	21	(8.80, 9.78)	7.97

Table 6-9 compares the simulation results with the actual. It was found that there were some discrepancies for the occurrence of the TBM delays between the actual and simulation results leading to the overestimation of the simulation productivity especially for the zone 3. These results indicate that simulation input parameters used for the occurrence of the TBM delays were not very accurate.

However, instead of selecting one mean value of the exponential distribution, it is decided that simulation data points are generated from the wide range of mean values for the exponential distribution to see if there is a relation between the occurrence of the TBM delays and overall productivity. For the occurrence of the TBM delays, the exponential distribution was used for various mean values ranging from 1500 to 25000 minutes for the zone 2 while the zone 3 has the ones ranging from 500 to 5000 minutes. For each mean of the exponential distribution, 10 independent replicates were generated from the simulation producing 50 and 40 data points for each zone 2 and 3, respectively.

The data points plotted in Figure 6-4 show that there is a strong relation between TBM delays and tunnel productivity for each zone. Using the regression equation based on the data point generated from the simulation experiment, it is found that the linear relationships are fit with R^2 of 0.837 and 0.935 for each zone 2 and 3, respectively.

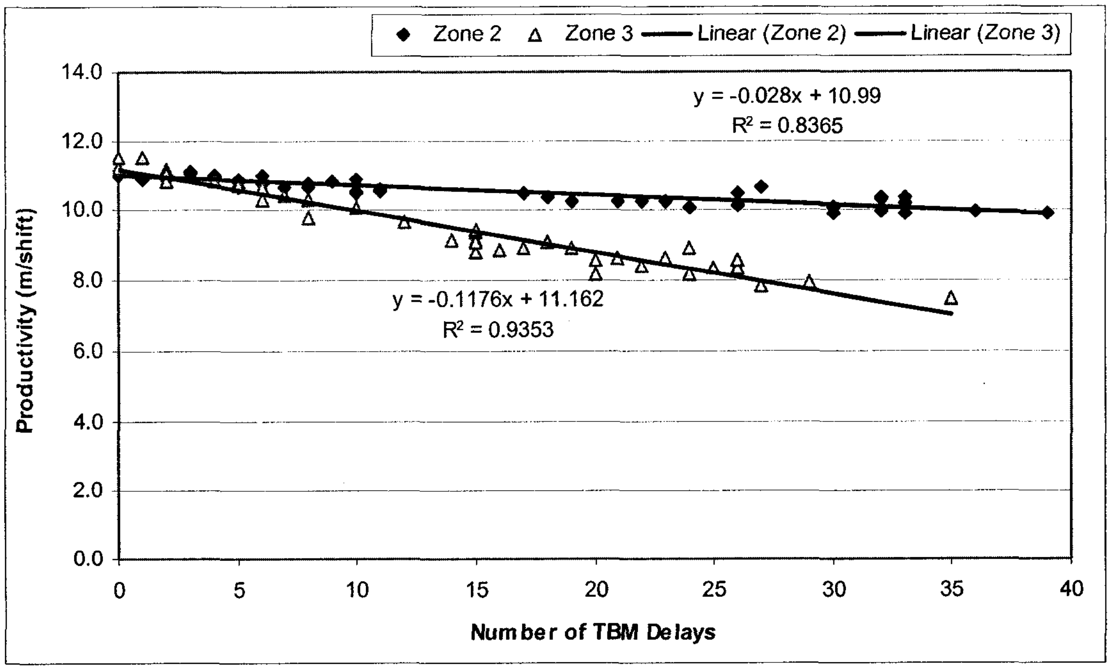


Figure 6-4: Comparison of Scatterplots of Mean Productivity from the Simulation

When the total number of 27 TBM delays occurred for the zone 2 were taken account, the estimated productivity from the regression for the zone 2 was 10.23 m/shift while the actual one was 9.61 m/shift. The comparison indicates the predicted productivity from the simulation experiment was quite close to the actual one although some minor difference exists. The review of the project progress report indicates that there were four shifts with a very low productivity affected by some activities other than the rock drilling and TBM breakdown. These include three shifts with zero productivity and one shift with a productivity of 2 m/shift. By excluding the productivity data for three shifts with zero productivity, the recalculated actual mean productivity of 9.89 m/shift is closer to the predicted one.

For the zone 3, the estimated productivity from the regression model considering the total occurrence of 21 TBM delays was 8.69 m/shift, which is also close to the actual one of 7.97 m/shit. As mentioned in the previous section of the experimental design, when the productivity between the zone 2 and 3 were compared there was some difference unexplained by the factors in the experimental design. That is, there was a productivity difference of 1.08 m/shift found between the zone 2 and 3 in the experimental design while the actual difference was 1.64 m/shift. However, in the experimental design, rock drilling described by one mean value of the exponential distribution was only considered without showing the overall relation between the occurrence of the TBM delays and productivity. With the regression models based on the simulation experiments, the productivity difference between the zone 2 and 3 was 1.54 m/shift, which is very close to the actual one of 1.64 m/shift.

Figure 6-5 compares distributions for the tunnel productivity for the effects of the TBM delays for the zone 2. One of the simulation experiment results assuming no TBM delays was fitted as a normal distribution with a mean of 11.01 m/shift and a standard deviation of 1.73. For the actual case with 27 occurrences of the TBM delays, the beta distribution with shape parameters of 3.59, 1.92 and the two end points of 0 and 15 was better fitted with a mean of 9.89 m/shift and a standard deviation of 2.94. The productivity difference of 1.12 m/shift for the zone 2 can be considered as the lost productivity mainly due to the TBM delays.

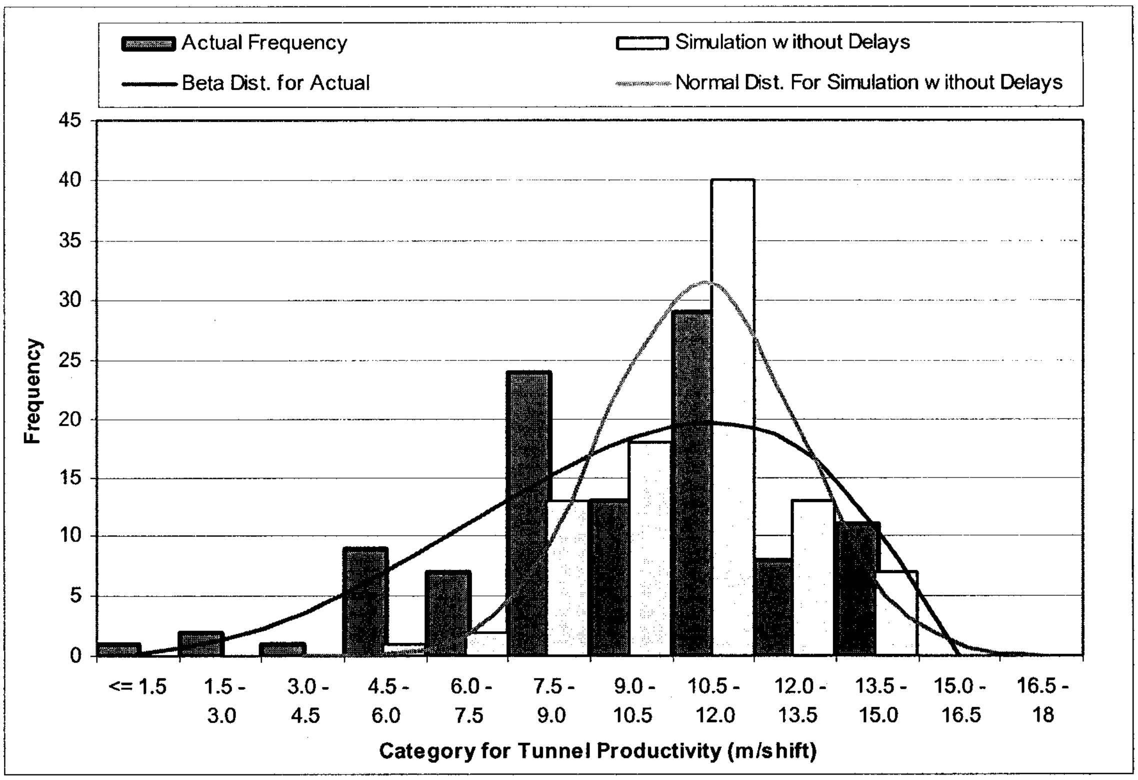


Figure 6-5: Comparison of the distributions for the tunnel productivity considering the effects of the TBM delays

Table 6-10 illustrates that when there was no TBM delays assumed for two zones, the zone 3 has a higher productivity than the zone 2 although the zone 3 has a lower TBM penetration rates. This is due to the combined effects of TBM rates and survey interval. The results of the experimental design demonstrated the mean effect of survey interval (0.977 m/shift) outweighs the one of TBM rates (0.740 m/shift). Thus, in the case of no TBM delays, a slightly higher productivity can be estimated for zone 3 with a lower TBM rates but less survey interval. The estimated productivity difference due to both effects was 0.237 and 0.378 m/shift from the experimental design and regression model, respectively. In spite of minor differences, both results lead to the consistent conclusion that the effect of survey interval on the productivity was somewhat higher than the one of TBM rates. However, as the number of TBM delays increases for both zones, the more significant productivity loss occurs for the zone 3 due to more frequent occurrence of the TBM delays with the relatively shorter length of the tunnel. Table 6-10 shows that due to the TBM delays, the productivity decreases by 24.7 % for the zone 3 while it decreases only by 7.6 % for the zone 2.

Table 6-10: Comparison of Productivity for the Effects of TBM Delays

Zone	Tunnel Length (m)	TBM Delays		Simulation Productivity (m/shift)		
		Frequency	% based on length	without Delays	with Delays	Percent Decrease
Zone 2	1038	27	2.60 %	11.05	10.21	7.6 %
Zone 3	303	21	6.93 %	11.43	8.61	24.7 %

The comparison of the simulation and actual results leads to the conclusion that the simulation modeling considering the occurrence of the TBM delays due to the TBM breakdown and rock drilling improved the accuracy of simulation results. These results also imply that the effects of TBM delays on the overall productivity are significant and should not be neglected for estimating the tunnel productivity. As with the experimental design results discussed in the previous section, it was found that the effects of factors on the productivity should be carefully analyzed, interpreted and applied to the future productivity estimate.

6.5 Simulation-based Tunnel Productivity Model

6.5.1 Soil Segments by TBM Penetration Rates

In the previous section, three different zones were selected and utilized for the simulation models. The divisions of the tunnel segments were based on the soil profile assumptions from borehole samples. However, from the visual inspection of actual TBM penetration rates as shown in Figure 6-6, six different segments are determined based on the patterns in the TBM rates and soil types. Table 6-11 describes each segment including the location, data availability, and soil composition. The second and fourth segment show somewhat higher TBM rates compared to the third segment, which is considered as a typical soil segment with clay till (type 5). It seems that the higher mean rates with higher variability were mainly found in soil type 6 and type 8. The fifth segment has the TBM rate patterns similar to the third segment while the rates at the end of the tunnel portion seem to be decreasing due to the soil type 2 and 9. There was a significant decrease in the TBM rates found in the sixth segment which represents a harder soil formation.

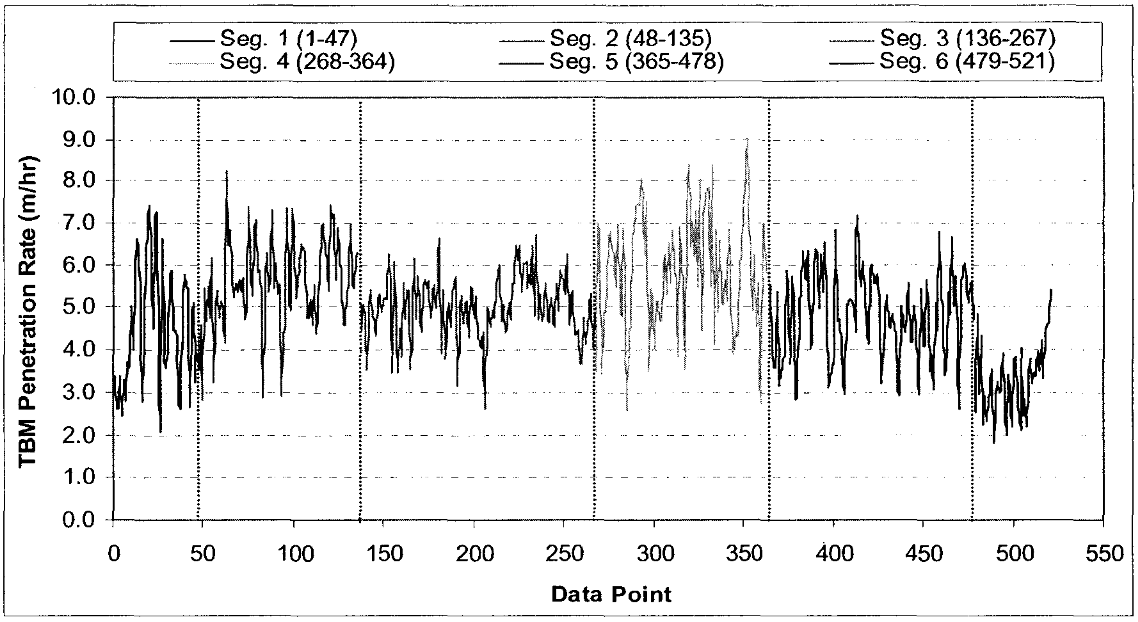


Figure 6-6: TBM Penetration Rates for Each Segment

An interesting trend was found that even the same soil type has a different range of TBM rates. For instance, TBM rate pattern in soil type 5 having a wide ranges of means seem to be more closely related to the adjacent soil such as type 6, 8, and 2. This implies that TBM rates tend to be affected by the soil characteristics such as presence of water and inclusion of rock boulders and the soil type itself should not be a single factor for determining the TBM rates.

Table 6-11: Description of Tunnel Segments

Segment	Location	Length	Percent of TBM Rates	Soil Composition
1	0 - 105th m	105 m	44.8 %	Type 5 (100 %)
2	105th -196th m	91 m	96.7 %	Type 6 (51.1%), 5 (48.9%)
3	196th – 363rd m	167 m	79.0 %	Type 5 (100%)
4	895th – 1199th m	304 m	31.9 %	Type 5 (32.0%), 8 (68.0%)
5	1199th – 1380th m	181 m	63.0 %	Type 5 (53.5%), 2 (24.6%), 9 (21.9%)
6	1380th – 1446th m	66 m	65.2 %	Type 5 (62.8%), 2 (37.2%)

Table 6-12: Descriptive Statistics for TBM Penetration Rates for Each Segment

	Segment					
	Seg. 1	Seg. 2	Seg. 3	Seg. 4	Seg. 5	Seg. 6
No. of Data	47	88	132	97	114	43
% of Data	44.8 %	96.7 %	79.0 %	31.9 %	63.0 %	65.2 %
Mean	4.514	5.594	5.011	5.897	4.819	3.252
Std. Dev.	1.436	1.048	0.725	1.346	1.032	0.831
Min.	2.100	2.820	2.600	2.570	2.600	1.850
Max.	7.430	8.200	6.700	9.010	7.190	5.390
25 Percentile	3.374	4.956	4.607	4.921	4.097	2.558
50 Percentile	4.343	5.531	5.002	5.963	4.984	3.054
75 Percentile	5.517	6.295	5.476	6.853	5.566	3.836

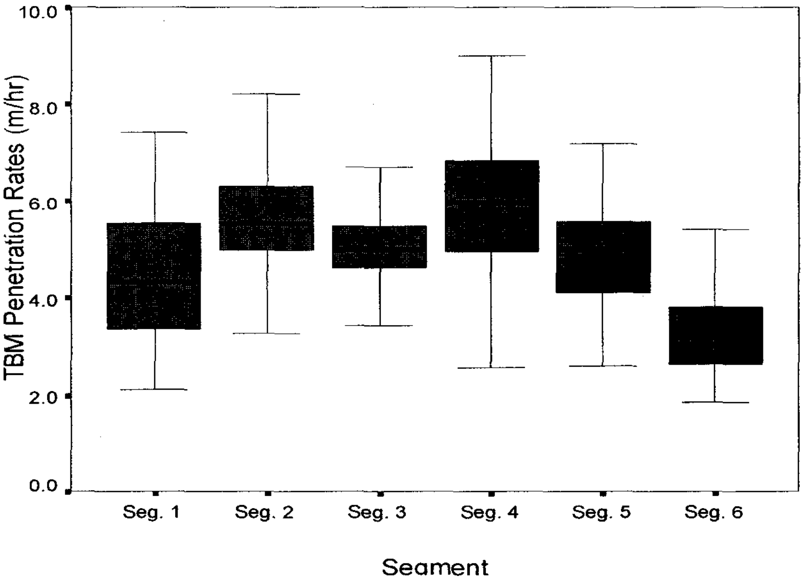


Figure 6-7: Boxplot of TBM Penetration Rates for Each Segment

6.5.2 Simulation Input Parameters

Based on the sample for TBM penetration rates consisting of 521 data points, it was divided into six different groups for each segment and statistical distributions for each segment were fitted using distribution fitting software (BestFit). Since the first segment created due to learning curve effect is exactly the same as the first zone for three zones in the previous section, it was excluded for this section. Table 6-13 shows the input parameters for TBM rates and survey activity for each segment. The beta distribution allowing more flexibility for many different shapes was selected for the TBM rates for the sixth segment due to its positive skewness. For other segments, the normal distribution seems to be the reasonable assumption. For the second and third segment, there were more frequent survey activities occurred with an interval of every 15 meter while less frequent survey with every 50 meter interval was used for the fourth, fifth, and sixth segment.

Table 6-13: Input Parameters for TBM Rates and Survey Activity

Segment	TBM Rates (m/h)	Survey	
		Interval	Duration (min)
Seg. 2	Normal (5.59, 1.05)	15 m	Uniform (95, 132)
Seg. 3	Normal (5.01, 0.73)	15 m	Uniform (95, 132)
Seg. 4	Normal (5.90, 1.35)	50 m	Uniform (95, 132)
Seg. 5	Normal (4.82, 1.03)	50 m	Uniform (95, 132)
Seg. 6	Beta (1.33, 2.03, 1.85, 5.40)	50 m	Uniform (95, 132)

As with the TBM penetration rates and survey activity, factors such as rock drilling and TBM breakdown are believed to play important roles in simulation modeling and also significantly affect the overall tunnel productivity causing schedule delays because the TBM cannot proceed at its normal productivity for those occurrences. For instance, when hard soil layers such as rock boulders can not be bored with the TBM, drilling and/or jack hammering should be employed to break these layers. Table 6-14 describes the input parameters for rock drilling for each segment including the percent of the occurrence and the duration. The percent of the rock drilling occurrence was based on the tunnel length for the simplicity of the comparison between each segment. It was found that more frequent rock drilling occurred with a higher average duration of 3.6 hr per occurrence in the fifth and six segments. It should be noted that the percentages of occurrence in the third and fourth segment were very consistent while the sixth segment has somewhat higher one than the fifth segment. These results are also consistent with the ones in the previous section that tunneling in the third zone was more affected by the hard soil layers resulting in the more frequent rock encounters.

Table 6-14: Input Parameters for Rock Drilling

Segment	Percent of Occurrence	Duration (Hour)		
		Distribution	Mean	Std. Dev.
Seg. 2	0 %	Beta (0.77, 1.27, 0.44, 6.06) Weibull (1.81, 2.90)	2.56	1.56
Seg. 3	1.8 %			
Seg. 4	1.7 %			
Seg. 5	5.5 %	Beta (0.98, 1.38, 0.46, 8.04) Weibull (1.88, 4.05)	3.60	2.04
Seg. 6	7.6 %			

Table 6-15 illustrates the input parameters for the TBM breakdown. For this parameter, data for TBM breakdown and teeth replacement were combined to fit the distribution for the duration. From the fourth to sixth segment, each percent of the occurrence seems to be very consistent. However, a higher rate of TBM breakdown was recorded in the second segment since more frequent TBM teeth replacement was required at the early stage of the tunnel construction for this project.

Table 6-15: Input Parameters for TBM Breakdown

Segment	Percent of Occurrence	Duration (Hour)		
		Distribution	Mean	Std. Dev.
Seg. 2	3.30 %	Beta (0.50, 1.75, 0.50, 7.00) Weibull (1.47, 2.17)	1.94	1.50
Seg. 3	0.60 %			
Seg. 4	1.66 %			
Seg. 5	1.66 %	Uniform (2, 3)	2.50	0.29
Seg. 6	1.52 %			

6.5.3 Actual Tunnel Productivity for Each Soil Segment

According to the project progress report, the daily productivity recording started on July 23, 2001, and ended on February 8, 2002. The total number of working days and accumulated shifts were 139 and 163, respectively and there were two shifts per day for 24 working days. The overall average productivity was 8.87 m/shift with a standard deviation of 3.42. Among the total 163 shifts, the highest daily production rate of 15 m/shift was achieved for four shifts while a zero production rate was recorded for six shifts.

Due to the interruption by some activities such as pouring shaft, undercut, and patching blocks, very low production rates were mainly recorded on these shifts. Since these activities were not directly related to the TBM performance, the inclusion of those data may result in the underestimation of the actual productivity. Therefore, it was decided to exclude production rates ranging from 0 to 2 m/shift for shifts when the major interruption other than machine breakdown and rock drilling occurred.

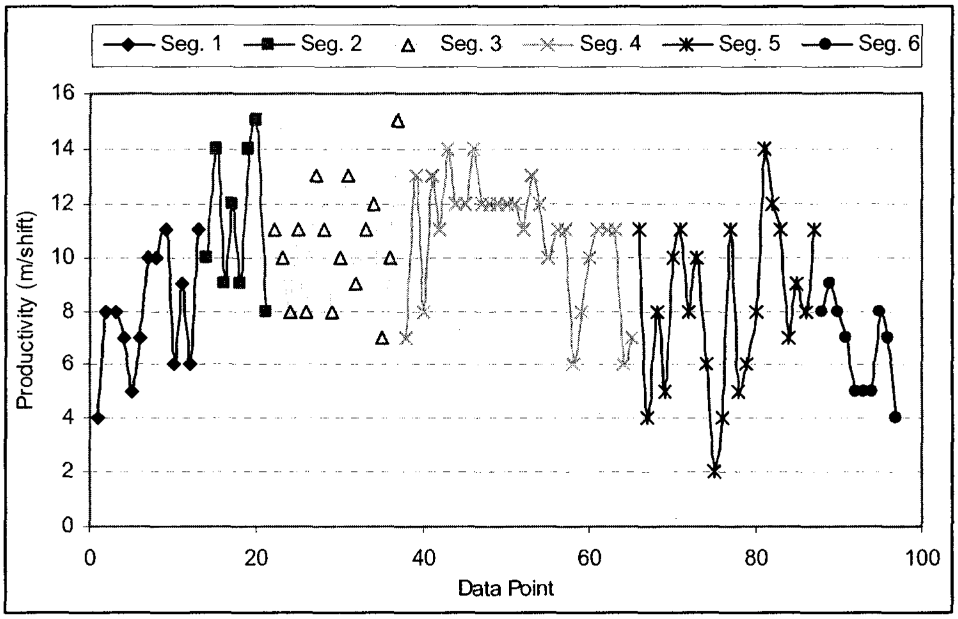


Figure 6-8: Tunnel Productivity for Each Segment

Table 6-16: Comparison of Productivity for Each Segment

Segment	Mean	Std. Dev.	95 % Confidence Interval
Seg. 1	7.846	2.267	(6.476, 9.216)
Seg. 2	11.375	2.722	(9.099, 13.651)
Seg. 3	10.438	2.159	(9.287, 11.588)
Seg. 4	10.786	2.267	(9.907, 11.665)
Seg. 5	8.277	3.085	(6.859, 9.595)
Seg. 6	6.600	1.713	(5.375, 7.825)

Figure 6-8 shows the actual tunnel productivity for each segment and the means and 95% confidence intervals for the productivity were shown in Table 6-16. It should be noted that obtained mean productivity for each segment varies ranging from 6.60 to 11.38 m/shift although the overall productivity for this project was 8.87 m/shift. There was an overall trend that the productivity was related to the TBM rates. That is, lower production rates were mainly recorded for the first, fifth and sixth segment which also have lower TBM rates. Higher production rates were recorded for the second, third and fourth segment. It is interesting that the highest production rate was achieved for the second segment with a mean TBM rate of 5.59 m/hr lower than the fourth segment with one of 5.90 m/hr. The comparison of the third and fifth segment also shows that there is a significant mean difference in productivity although two segments have similar TBM mean rates. These findings imply that tunnel productivity is also affected by other factors such as survey, TBM breakdown, and rock drilling activity as well as TBM penetration rates. It is thus decided that simulation studies for these segments under various conditions should be conducted to identify the effects of those factors on the overall tunnel productivity.

6.5.4 Simulation Experiments

Simulations with input parameters discussed in the previous section were conducted for each segment. Major input parameters include the TBM penetration rates, survey, TBM breakdown, and rock drilling activity. There are also other factors potentially affecting tunnel productivity such as liner installation and dirt removal. Due to the lack of data for these elements for simulation, the input parameters were based on the experts' opinion.

For each segment, an ideal productivity without major delays first needs to be established to identify and calculate the productivity loss due to the interruption. For instance, using the input parameters for the second segment, the simulation without major TBM delays produced the mean productivity of 11.70 m/shift. For the same segment, simulation considering actual condition of no rock drilling and 3.3 % of TBM breakdown produced a lower mean productivity of 11.35 m/shift, which is very close to the actual one of 11.38 m/shift. Therefore, it can be concluded that the productivity loss of 0.35 m/shift was mainly due to the TBM breakdown.

For the third segment, which is considered as a typical soil segment of clay till (type 5), the ideal productivity from the simulation was determined as a mean of 11.38 m/shift while the productivity considering 1.8 % of rock drilling and 0.6 % of TBM breakdown produced the mean productivity of 10.31 m/shift. The obtained simulation result was also close to the actual one of 10.44 m/shift. In this case, the productivity difference of about 1 m/shift can be explained from the effect of the combination of rock drilling and TBM breakdown.

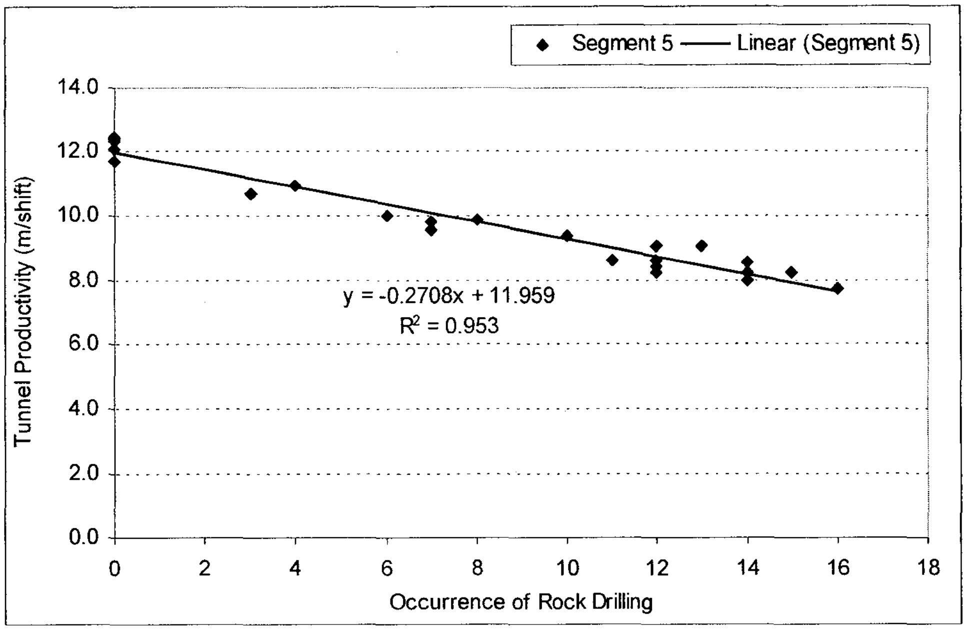


Figure 6-9: Scatterplot of Mean Productivity for the Fifth Segment

The mean TBM rate of 4.89 m/h for the fifth segment is close to one of 5.01 m/h for the third segment. However, the ideal productivity of 12.16 m/shift for the fifth zone was much higher than one of 11.38 m/shift for the third segment. The productivity difference between two segments shows that the survey interval was also a key factor affecting the productivity. With similar TBM rates, more frequent survey (every 15 meter) for the third zone results in a productivity decrease of about 0.78 m/shift. When the actual delay including 1.7 % of TBM breakdown and 5.5 % of rock drilling was considered for the fifth segment, the productivity of 9.25 m/shift was attainable from the regression equation fitted from data as a result of multiple simulation runs as shown in Figure 6-9. There is a mean difference of about 1.0 m/shift between actual (8.28 m/shift) and obtained result (9.25 m/shift). However, the obtained result seems to be reasonable since the mean of 9.25 m/shift from simulation results is within the 95 % confidence interval (6.86, 9.60) of the actual productivity in Table 6-16.

The sixth segment with a low TBM rate of 3.25 m/h was affected by hard soil layers where more frequent rock drillings were required. Simulation produced the ideal productivity of 10.15 m/shift for this segment only considering the TBM rates and survey interval. However, when the actual condition of 1.5 % of the TBM breakdown and 7.6 % of the rock drilling was considered, the result of multiple simulation runs shows a mean productivity of 7.38 m/shift, which is also within the 95 % confidence interval (5.38, 7.83) of the actual productivity. The simulation results imply that productivity for the sixth segment decreases by about 27 % due to the effect of the TBM breakdown and rock drilling.

For each segment with specific conditions, the simulation produces the results quite similar to the actual performance. The result of simulation clearly explains the variation in productivity under the different conditions by identifying the effects of various factors. It is concluded that the input data collected and used for this study is validated and simulation outputs can be utilized as an excellent source for productivity model for future projects. It was thus decided that tunnel productivity model should be developed using the obtained simulation results.

6.5.5 Tunnel Productivity Models with Regression Technique

The previous simulation experiment successfully identified key factors and effects of these on the overall tunnel productivity. These factors include the TBM penetration rates, survey interval, each percentage of the TBM breakdown and rock drilling occurrence, and the duration of rock drilling. In this section, the major objective is to develop tunnel productivity models considering the effects of each factor. Factors may influence the productivity independently or interactively.

Table 6-17: Unchanged Input Parameters for Simulation Model

Element	Simulation Input Parameter	Value
Trains	Empty speed (km/hr)	5
	Loaded speed (km/hr)	5
	Number of muck cars	3
	Number of material cars	1
	Muck car capacity (m^3)	4.2
TBM	Excavation Diameter (m)	3.2
	Resetting time (min)	Uniform (2,4)
	Liners installation time (min)	Triangular (15,18,25)
Hoisting	Muck car cycle	Uniform (4.00,7.00)
	Material car cycle	Uniform (7.00,10.00)
Shift control	Start time	800
	Mobilization time (min)	Uniform (10,15)
	Coffee break at	1000
	Coffee break time (min)	Uniform (25,35)
	Lunch break at	1200
	Lunch break time (min)	Uniform (40,50)
	Finish time	1700

It should be noted that there are other simulation input parameters that remained unchanged as shown in Table 6-17 since the simulation experiment was based on a single tunnel project, NEST. Tunnel productivity is obviously affected by various factors such as excavation diameter, type of TBM machine, and quality of its operating crew.

Although their importance cannot be neglected for robust tunnel productivity model for its application into various projects with different circumstances, the effects of those factors are not considered due to the scope of this research.

A multiple regression analysis was conducted using SPSS to establish the tunnel productivity model. The independent variables were each factor discussed in the above and its interactions with other factors if applicable while the dependent variable was the productivity (m/shift). It should be noted that the data used for this regression model were results of multiple simulation runs for each segment in the previous section. The descriptions of each independent variable are shown in Table 6-18. For the variable of "Survey" and "Duration of Rock Drilling", dichotomous variables (0 or 1) are used as the classifications of these variables were discussed in the previous section.

Table 6-18: Descriptions of Independent Variables for Regression Models

Independent Variables	Descriptions of Variables
TBM Rates (m/hr)	TBM penetration rates ranging from 3.25 to 5.90 m/hr
Survey Interval (0 or 1)	0 if every 50 m, 1 if every 15 m
TBM Breakdown (%)	Percent of the TBM Breakdown occurrence
Rock Drilling (%)	Percent of the rock drilling occurrence
Duration of Rock Drilling (0 or 1)	0 if average duration of 2.56 hr, 1 if average duration of 3.6 hr

The overall F statistic for the regression was significant, $F(7, 102)=384.214$, $p<.001$, with $R^2=0.963$ and adjusted $R^2=0.961$. Table 6-19 shows the individual t ratio statistics for each coefficient for all independent variables. The use of the logarithmic function for the TBM rates indicates the effect of the TBM penetration rates is stronger for low rates than for high rates. For the variable of "Survey", "Rock Drilling", and "Duration of Rock Drilling", an interaction term between each variable and the variable "TBM rates" was required as the effects of these variables vary depending on the value of TBM rates. Since the coefficient for the quadratic term, *(Rock Drilling)²* is significantly different from zero, there is an evidence that the relation between overall productivity and the percent of the rock drilling occurrence is nonlinear and that this relation is fitted more accurately by a parabola than by a straight line. That is, the rate of change in productivity for the rock drilling decreases as the occurrence of the rock drilling increases.

Table 6-19: Summary of Regression Outputs

Predictors	Coefficients	Standard Error	t	Significance
Constant	4.819	0.536	8.999	<0.001
Ln(TBM Rates)	4.609	0.318	14.478	<0.001
TBM Breakdown	-0.177	0.027	-6.511	<0.001
(TBM Rates) × (Survey)	-0.184	0.020	-9.134	<0.001
(TBM Rates) × (Rock Drilling)	-0.101	0.006	-15.773	<0.001
(Rock Drilling)^2	8.072×10^{-3}	0.002	4.651	<0.001
Duration of Rock Drilling	-1.164	0.538	-2.163	0.033
(TBM Rates) × (Duration of Rock Drilling)	0.232	0.115	2.025	0.046

6.5.6 Validation of Tunnel Productivity Models

In order to validate the tunnel productivity models developed in the previous section, it was decided to compare the results from these models with actual simulation results using information from the first segment. It should be noted that simulation results from the first segment were not utilized to develop the productivity models. If the results from the tunnel productivity model are close to the ones from multiple simulation runs, it can be concluded that the developed tunnel productivity model is valid and can be utilized for the further analysis.

Using actual information from the first segment such as TBM rates, survey, and TBM breakdown, it was assumed to have a low percentage of rock drilling occurrence similar to the third and fourth segment. Based on major input parameters as shown in Table 6-20, multiple simulations assuming two major scenarios were run. The first scenario assumed no major TBM delays such as TBM breakdown and rock drilling while the second scenario assumed the moderate levels of those occurrences.

Table 6-20: Input Parameters for Simulation

Input Parameters	Distribution	Mean
TBM Rates (m/hr)	Beta (1.12, 1.36, 2.08, 7.46)	4.51 m/hr
Survey with every 15 meter (min)	Uniform (95, 132)	113.5 min
Occurrence of TBM Breakdown	Exponential (1700)	1.76 %
Occurrence of Rock Drilling	Exponential (2600)	2.06 %

Ten independent replicates for each scenario were generated from the simulation experiment to construct a 95 % confidence interval for the expected productivity. The mean and 95 % confidence interval for the first scenario assuming no major TBM delays was 10.62 ± 0.389 m/shift. However, assuming 1.76 percent of TBM breakdown and 2.06 % of rock drilling, the simulation predicted the productivity of 9.72 ± 0.590 m/shift. Based on same input parameters, the estimated productivity from the productivity model for each scenario was 10.93 and 9.72 m/shift, respectively. The obtained results for each scenario were within the confidence interval and the productivity predicted from the regression model for the second scenario was equivalent to the one from actual simulation runs. Thus, it is concluded that the developed productivity model with the regression technique is valid and the effects of each factor on the productivity are evaluated in the next section.

6.5.7 Effects of Major Factor on the Productivity

From the regression model in Table 6-19, it is found that TBM penetration rates is one of key factors affecting the productivity. The use of the logarithmic function for the TBM rates implies the effect of the TBM penetration rates is stronger for low rates than for high rates. The statistical significance of its interaction with other factors such as survey, and the occurrence and duration of rock drilling indicates that effects of these factors vary depending on the TBM rates.

Figure 6-10 illustrates the effects of survey interval for various TBM rates assuming no major TBM delays from TBM breakdown and rock drilling. Based on data points generated from the regression model, logarithmic regression lines were fitted for the survey interval of 15 and 50 meter, respectively in order to identify the effect of the survey frequency. The comparison of two regression lines shows the difference in productivity increases as the TBM rates also increases. For the lowest mean TBM rate of 3.25 m/hr, the productivity differs by about 0.60 m/shift. However, its difference increases up to 1.09 m/shift for the highest mean TBM rate of 5.90 m/hr.

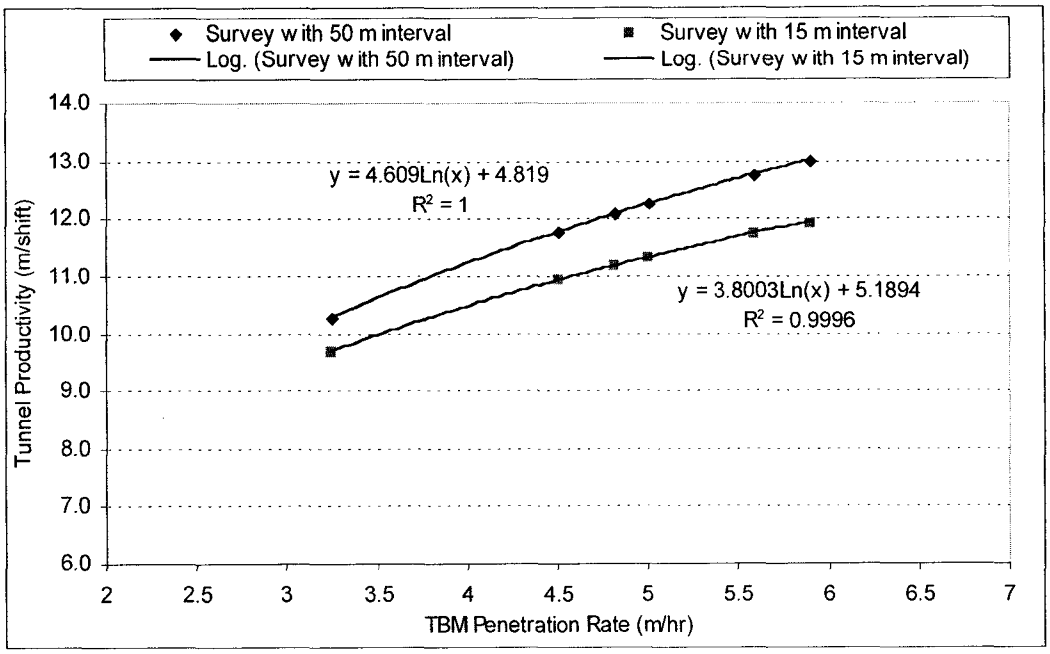


Figure 6-10: Effects of Survey Interval Depending on the TBM Rates

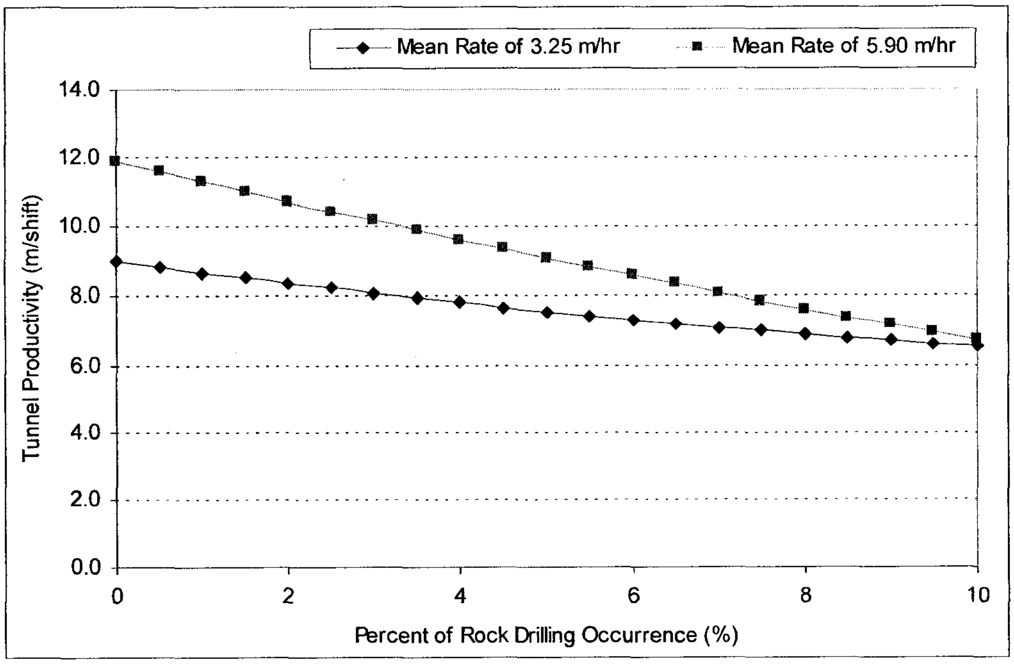


Figure 6-11: Effects of Rock Drilling Occurrence on the Productivity

Figure 6-11 compares the relation between the tunnel productivity and rock drilling occurrence for the mean TBM penetration rate of 3.25 and 5.90 m/hr. Data points were generated from the productivity model assuming a survey interval of every 15 m, 1.32 % of the TBM breakdown, and the average rock drilling duration of 3.6 hr for both TBM rates. With no rock drilling, the productivity difference of 2.88 m/shift is mainly due to the effect of TBM penetration rates because other conditions are held constant. However, as the percent of rock drilling occurrence increases, the productivity difference decreases. The productivity for a higher TBM rate was more severely affected by the occurrence of the rock drilling.

Table 6-21: Comparison of the Productivity with Rock Drilling Occurrence

TBM Rates	Percent of Rock Drilling Occurrence					
	0%	2%	4%	6%	8%	10%
3.25 m/hr	9.01	8.39	7.83	7.33	6.90	6.53
5.90 m/hr	11.89	10.73	9.63	8.60	7.63	6.73
Prod. Diff. (m/shift)	2.88	2.34	1.80	1.27	0.73	0.20

6.5.8 Examples of Calculating Tunnel Productivity Considering the Factors

In order to demonstrate how the productivity with the developed model can be calculated considering the effects of factors, the third and fifth segments in the previous section are selected. The third segment as a typical soil segment of clay till (type 5) has a mean TBM rate of 5.01 m/hr. The fifth segment consisting of 53.5 % of type 5, 24.6% of type 2, and 21.9 % of type 9 also has a similar TBM rate of 4.82 m/hr. However, both segments have different survey intervals, TBM breakdown rates, and rock drilling occurrences as shown in Table 6-22.

Table 6-22: Comparison of Factors affecting Productivity

Input Parameters	Segment	
	Segment 3	Segment 5
TBM Penetration Rates	5.01 m/hr	4.82 m/hr
Survey Interval	Every 15 m (1)	Every 50 m (0)
% of TBM Breakdown	0.6 %	1.66 %
% of Rock Drilling	1.8 %	5.5 %
Avg. Duration of Rock Drilling	2.56 hr (0)	3.60 hr (1)

Table 6-23: Summary of Productivity Calculation with Effects of Factors

	Segment 3	Segment 5
Base Productivity (m/shift)	12.246	12.068
Productivity Loss		
Survey Interval	-0.922	0
% of TBM Breakdown	-0.106	-0.294
% of Rock Drilling	-0.896	-2.633
Duration of Rock Drilling	0	-0.046
Total Productivity Loss	-1.924	-2.973
Total Productivity (m/shift)	10.322	9.095

A base productivity for each segment needs to be determined based on the TBM penetration rate without considering other delay factors. The obtained base productivity of 12.246 m/shift for the third segment was somewhat higher than one of 12.068 m/shift for the fifth segment due the minor difference in TBM rates. Since, for factors of both survey interval and duration of rock drilling, the dichotomous variables (0 or 1) are used, a productivity loss only occurs when the variable is 1 (for the survey interval of every 15 meter and average rock drilling duration of 3.6 hr). Due to the interaction between survey interval and TBM rates, the effect of the survey interval on the productivity varies with value of TBM penetration rates. For the third segment, a productivity loss of 0.922 m/shift occurs due to the more frequent survey interval. However, for the fifth segment, a higher TBM breakdown rate causes a productivity loss of 0.294 m/shift while a relatively less productivity loss of 0.106 m/shift occurs for the third segment.

More frequent occurrences of rock drilling resulted in a significant productivity loss of 2.633 m/shift for the fifth segment. However, a minor productivity loss of 0.05 m/shift from the effect of rock drilling duration for the fifth segment indicates that the difference of about one hour in the rock drilling duration did not have a strong impact on the productivity. It was determined that the occurrence of rock drilling was a major factor affecting the overall productivity loss for the fifth segment while the productivity loss for the third segment was mainly due to effects in combination of the survey interval and the occurrence of rock drilling.

6.6 Conclusions

A tunnel construction project is considered as one of high risk projects due to the uncertainty mainly related to geological conditions. Although significant geological investigations are normally conducted prior to the tunnel construction, it is almost impossible to precisely predict the soil characteristics. Furthermore, the effects of unforeseeable conditions such as rock encounters and machine breakdowns are attributed to the significant loss of the tunnel productivity by making it more difficult for project planners to accurately estimate the schedule and cost.

In this chapter, the review and analysis of data from the actual tunnel project of North Edmonton Sanitary Trunk (NEST) determined six different geological zones based on the actual soil types and TBM penetration rate samples collected. The second and fourth segment show somewhat higher TBM rates compared to the third segment, which is considered as a typical soil segment with clay till (type 5). These results indicate that the higher mean rate with higher variability was found on soil type 6 and type 8. There was a significant decrease in the TBM rates recorded in the sixth segment which represents a harder soil formation containing soil type 2. As with the TBM penetration rates, major factors such as survey interval, a percent of rock drilling occurrences, an average duration of rock drilling, and a percent of TBM breakdown occurrences were considered as major factors exerting a significant influence on the overall productivity.

The results of the simulation experiment successfully demonstrated the effects of those factors on the productivity. Simulation model and its inputs were validated by comparing the obtained simulation results with the actual. Based on the simulation results, a tunnel productivity model using a multiple regression technique was established and validated. The developed productivity model can clearly identify the effects of uncertainty factors and predict the productivity corresponding to the specified project circumstances. It is believed that the developed model can be utilized to analyze the tunnel productivity in a more systematic and scientific manner by quantifying the uncertainty inherent to various project conditions.

CHAPTER 7: INFERENCE OF TBM RATES AND SOIL TRANSITIONS USING PRODUCTIVITY MODELS

7.1 Introduction

The performance of the tunnel construction projects is significantly influenced by the uncertainty factors related to the geological conditions. Factors affecting overall tunnel productivity were identified and quantified with a use of simulation techniques. The tunnel productivity model based on the multiple regression technique was then developed and validated in Chapter 6. The development of the tunnel productivity model leads to improvement in many areas. The uncertainty factors such as TBM breakdown and rock encountering were easily and accurately quantified to predict the tunnel productivity from the proposed methodology. In this approach, the tunnel productivity model was built on the data sets generated from the simulation experiment under various site conditions of an actual project. The comparison of both the prediction of tunnel productivity model and simulation results also validated the developed framework.

For the purpose of the simulation application for tunneling, TBM penetration rates were traditionally assumed simply based on the industry experts' opinions. A thorough analysis of the TBM penetration rates based on the actual samples collected during the NEST project demonstrates that some discrepancies existed between the actual sample and experts' opinion. During the data collection and cleaning process explained in Chapter 3, it also turned out that the procedure for obtaining the sample for TBM penetrations is tedious and tremendous efforts for the data cleaning for many inadequate data points and outliers were required. In addition, the TBM penetration rates sample collected for the NEST project were 521 data points making up only 36 % of the entire tunnel length. The limited sample data for some tunnel sections thus makes it impossible to recognize a relation between the TBM penetration rates and the overall productivity.

This chapter presents a methodology to predict the TBM penetration rates, which is considered as the single most important factor for determining the overall tunnel productivity. Since the developed productivity model was built with independent variables, which are mainly available from the daily report logs of the actual project, one of the independent variables, TBM penetration rates, can be determined with accurate inputs for those variables and actual tunnel productivity data as a dependent variable. In order to make inferences of the TBM penetration rates, the entire tunnel length of 1446 m for the NEST was divided into 11 tunnel segments, which were primarily determined by the soil conditions recorded on the daily report logs. Segments in the absence of the sample are first focused on to predict the TBM penetration rates. Then, rates for remaining segments are inferred and compared with the actual sample. After the results are validated, TBM penetration rates for soil transitions along the entire tunnel path are recognized, plotted, and compared with the tunnel productivity transitions.

This chapter is organized as follows: Section 7.2 explains the use of a regression technique for calculating the lost productivity. Section 7.3 presents the methodology to make inferences of TBM penetration rates with the use of productivity models developed in Chapter 6. Section 7.4 discusses soil transition models along the tunnel path and summary and conclusions are then presented in Section 7.5.

7.2 Use of a Regression Technique for Calculating Lost Productivity

The data cleaning process for removing many inadequate data points and outliers resulted in missing data for the TBM penetration rates for the tunnel section of 363 to 841 m. The major soil types for that section were type 5 and 9. In order to predict the TBM penetration rates and make inferences of soil transitions, the entire tunnel length was divided into 11 segments depending on the soil types as shown in Table 7-1. According to this classification, segments from 4th to 6th contain the missing data for TBM penetration rates. The 4th segment is composed of a mixed soil condition of type 5 and type 9 while the 5th and 6th segment has type 5 and type 9, respectively.

Table 7-1: Description of Tunnel Segments by Soil Types

Segment	Location	Length	Soil Type	Percent of Sample TBM Rates
1	0 – 105th m	105 m	Soil 5	44.8 % (47)
2	105th - 150th m	45 m	Soil 6	100% (45)
3	150th – 363rd m	213 m	Soil 5	82.2% (175)
4	363rd – 576th m	213 m	Soil 5 & 9	0%
5	576th – 709th m	133 m	Soil 5	0%
6	709th – 841st m	132 m	Soil 9	0%
7	841st – 1025th m	184 m	Soil 5	16.8% (31)
8	1025th – 1199th m	174 m	Soil 8	37.9% (66)
9	1199th – 1322nd m	123 m	Soil 5	49.6% (61)
10	1322nd – 1380th m	58 m	Soil 2, 9	91.4% (53)
11	1380th – 1446th m	66 m	Soil 5, 2	65.2% (43)

Figure 7-1 shows the actual productivity plots from the 3rd to 6th segment. It demonstrates the lower productivity pattern for the 6th segment was apparent when compared to the other segments. Table 7-2 compares statistics for each tunnel segment.

The overall productivities for both the 3rd and 4th segment are exactly the same under the similar conditions for the major delays of the TBM breakdown and rock drilling occurrence. However, the same productivities for both segments do not indicate that these segments should have the identical mean TBM penetration rates since both segments have different survey intervals. If the effects of delay factors on productivity such as survey intervals are accurately measured and then eliminated by adding the lost productivity to the actual productivity, the productivity can be adjusted to the one that was not affected by the delays. It is thus believed that the adjusted productivity should represent actual soil characteristics more precisely.

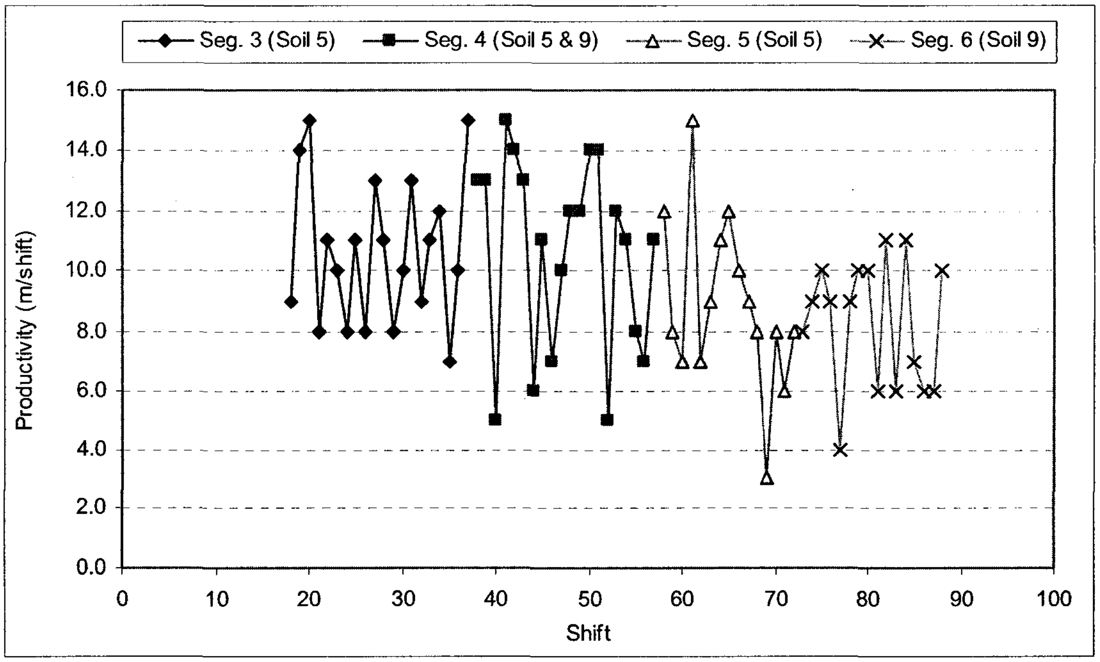


Figure 7-1: Actual Productivity Plots from the 3rd to 6th Segment

Table 7-2: Comparison of Statistics from the 3rd to 6th segment

	Seg. 3	Seg. 4	Seg. 5	Seg. 6
Productivity (m/shift)	10.65	10.65	8.87	8.25
Section Length (m)	213	213	133	132
Survey Interval (m)	15 m	50 m	50 m	50 m
TBM Breakdown (%)	0.47 %	1.41 %	3.76 %	3.03 %
Rock Drilling (%)	1.41 %	1.41 %	1.50 %	0.00 %

A multiple regression analysis based on the daily production recording from the project progress report was conducted to calculate the effects of the factors on the productivity on the shift. The independent variables were the time spent on TBM delays and rock drilling and different tunnel segments divided by major soil types, while the dependent variable was the production per shift (m/shift). Ten dummy variables for the eleven different tunnel segments were included as independent variables and the first segment was chosen as a reference variable and excluded in this model. Delays for TBM breakdown and TBM teeth change were combined into one variable, "TBM delays" since no significant differences in statistics for both factors were found from the daily report logs of the actual project.

Table 7-3 shows the results of the Bayesian regression model. It was determined that the TBM delays and rock drilling significantly affect the productivity and the effects of these factors on productivity is equivalent to the coefficients for each factor. Thus, to calculate the adjusted productivity excluding the effects of these factors, the productivity loss due to each factor should be first calculated by multiplying the coefficients of each factor by the duration for the relevant factor. Since the obtained results are the productivity loss incurred for each factor, the actual productivity can be adjusted by changing the sign and adding the obtained results to the actual productivity. For instance, on September 19, 2001 (40th Shift in Figure 7-1), the actual productivity was 5 m/shift while the time spent on the machine breakdown was 7 hrs. It should be noted that the productivity on that shift was extremely low when compared to ones on the other shifts from 38th to 43rd shift. By eliminating the effects of the machine breakdown, the adjusted actual productivity was 11.70 m/shift, rather than the actual one of 5 m/shift. Figure 7-2 illustrates the adjusted productivity plots by eliminating productivity loss due to effects of factors. Especially, on the 4th segment, significant differences in the productivity pattern from original productivity plots in Figure 7-1 were found. It also seems that eliminating the effects of factors makes productivity pattern clearer and overall productivity tends to be decreasing from the 4th to 6th segment. This finding indicates that using actual productivity without considering specific project circumstances may mislead productivity estimates for future projects.

Table 7-3: Summary of Regression Outputs

	Mean	SD	2.5%	Median	97.5%
Constant	8.140	0.563	7.033	8.141	9.237
TBM Delay	-0.957	0.151	-1.252	-0.957	-0.666
Rock Drilling	-0.833	0.124	-1.074	-0.834	-0.587
Seg. 2	3.704	1.158	1.448	3.711	6.008
Seg. 3	2.748	0.722	1.341	2.745	4.162
Seg. 4	3.576	0.721	2.179	3.567	5.012
Seg. 5	1.763	0.762	0.270	1.755	3.266
Seg. 6	0.709	0.759	-0.789	0.701	2.195
Seg. 7	3.231	0.751	1.769	3.230	4.727
Seg. 8	3.066	0.754	1.612	3.056	4.563
Seg. 9	1.839	0.808	0.294	1.831	3.405
Seg.10	2.076	1.019	0.083	2.075	4.089
Seg.11	-0.132	0.875	-1.868	-0.123	1.595

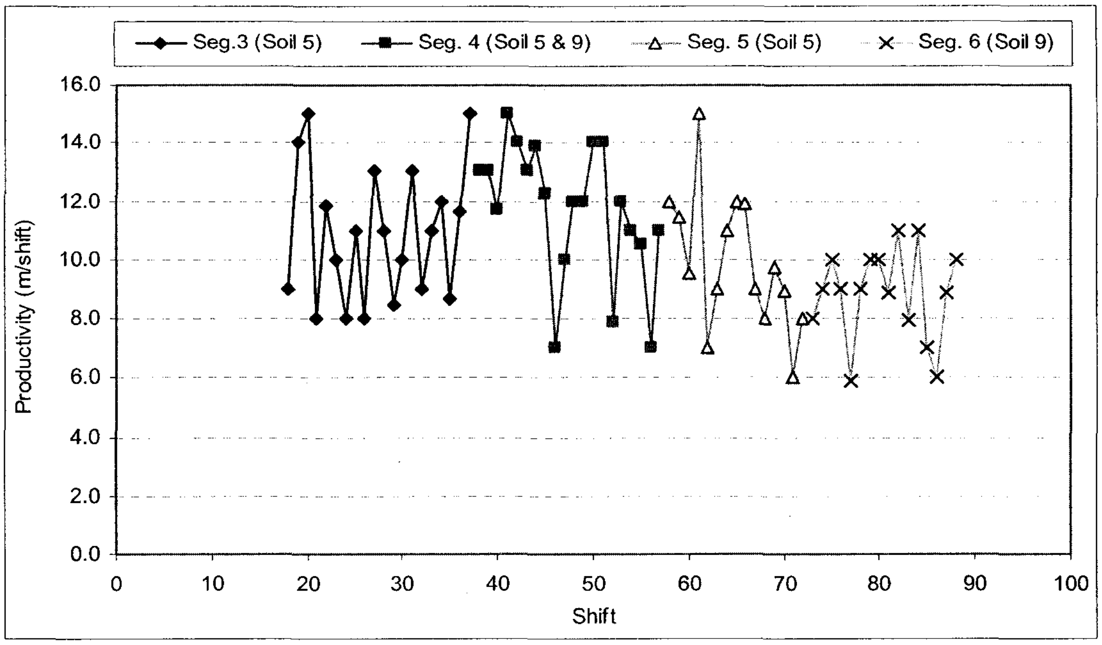


Figure 7-2: Adjusted Productivity Plots eliminating Effects of Delay Factors

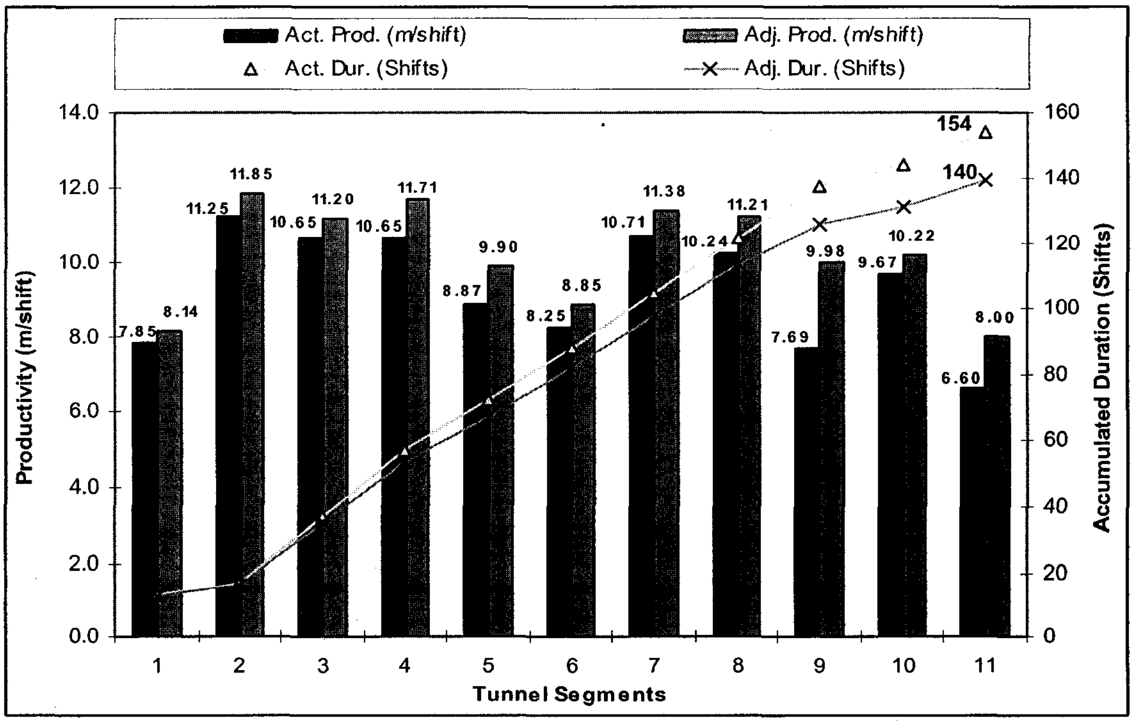


Figure 7-3: Comparison of productivity and duration for tunnel segments

Figure 7-3 compares actual and adjusted productivity for each tunnel segment. The actual and adjusted durations based on the productivity were first determined and accumulated durations for both actual and adjusted ones are then compared in Figure 7-3. Although actual productivities are equivalent for both the 3rd and 4th segment, adjusted productivity for the 4th segment was slightly higher than one for the 3rd segment. The results indicate that adjusted productivities for each segment are higher than actual productivities with the percent increase ranging from 3.7 to 29.9 %. The difference between both actual and adjusted productivity for each segment can be considered as the productivity loss incurred mainly due to the TBM breakdown and rock drilling. For entire tunnel segments with a total length of 1441 m, the actual productivity of 9.36 m/shift was compared to the adjusted one of 10.32 m/shift. The actual durations for entire tunnel construction was 154 shifts while ones determined from the adjusted productivity was 140 shifts. Therefore, it is determined that the total loss of about 14 shifts incurred due to the delays from the TBM breakdown and rock drilling. That is, it would be possible to complete the tunnel construction in 140 shifts for this project instead of the original duration of 154 shifts if there were no major delays.

7.3 TBM Rates Inference with the Use of Productivity Models

The division of 11 segments on the entire tunnel length determined that segments from the 4th to 6th (363rd to 1037th m) contained missing data for the TBM penetration rates. In this section, a methodology to make inferences of the TBM penetration rates using the tunnel productivity model developed in Chapter 6 is presented. The first objective is to predict the TBM penetration rates for the 4th, 5th and 6th segment in the absence of the samples. In similar ways, TBM rates for the remaining segments are then inferred from the developed model and compared to the actual samples collected for this study.

7.3.1 TBM Penetration Rates for Missing Data

In order to explain the methodology for TBM rates inference, the 3rd segment was chosen since it has a typical soil type 5 with a high percent of actual samples. The productivity model determined from the previous section is as follows:

$$\begin{aligned} y = 4.819 + 4.609\ln(X_{Rate}) - 0.177X_{Breakdown} - 0.184X_{Rate} \times X_{Survey} - 0.101X_{Rate} \times X_{Rock} \\ + 0.008072(X_{Rock})^2 - 1.164X_{Rock\_Dur} + 0.232X_{Rate} \times X_{Rock\_Dur} \end{aligned} \tag{7.1}$$

The mean TBM penetration rates as one of independent variables can be solved when the values of dependent variable (mean productivity) and other independent variables such as survey interval, a percent of TBM breakdown and rock drilling, and an average duration of rock drilling are substituted in Equation 7.1. With values of the productivity of 10.65 m/shift, survey interval for 1, rock drilling duration for 0, TBM breakdown rate of 0.47 %, and rock drilling rate of 1.41 %, the equation can be simplified and derived as follows.

$$4.609\ln(X_{Rate}) - 0.32625X_{Rate} - 5.89809 = 0 \tag{7.2}$$

Due to the existence of a logarithm term in the equation, a variable for X_{Rate} can be solved with the equation solver from the scientific calculator. The obtained value of X_{Rate} was 5.20 m/hr as a mean TBM penetration rate for the 3rd segment.

For the 3rd segment, the sample for TBM penetration rates with 175 data points is composed of 82.2 % for the segment length of 213 m. The histogram in Figure 7-4 shows the frequencies and distribution of the data. The average TBM penetration rate was 5.20

m/h with a standard deviation of 0.86. The highest rate achieved was 7.37 m/h while the lowest rate recorded was 2.60 m/h. It was found that the obtained value of 5.20 m/h for X_{Rate} from the productivity model was exactly the same as the mean from the sample. Thus, it was concluded that the methodology used for TBM penetration rate inference is valid and can be utilized for the missing data for the segments from 4th to 6th.

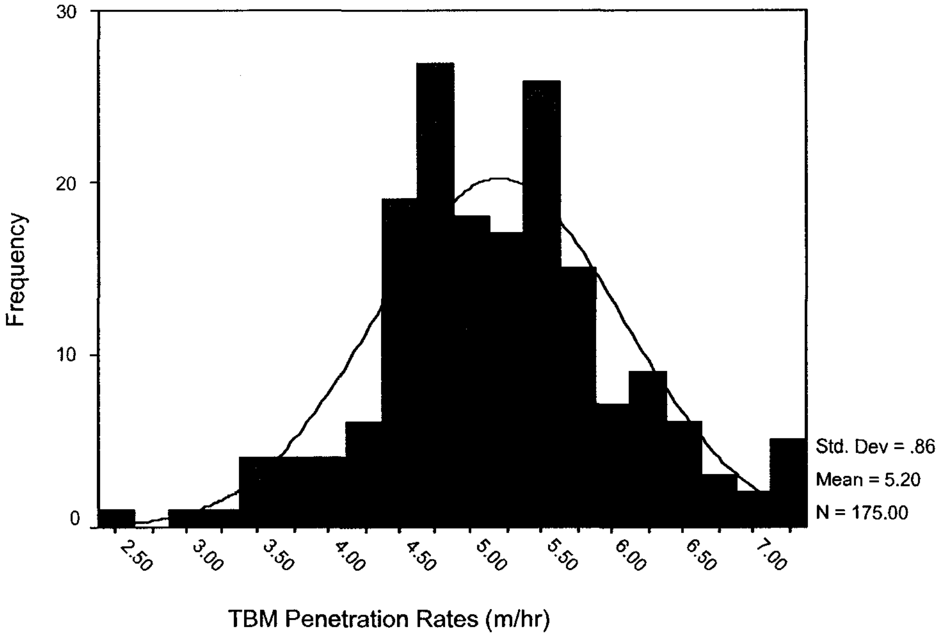


Figure 7-4: Histogram for TBM Penetration Rates for the 3rd Segment

Simulation was conducted to validate the obtained results for the 3rd segment. For TBM penetration rates, the normal distribution is a reasonable assumption from the distribution fitting software and is used as an input distribution with a mean of 5.20 and standard deviation of 0.86. Three cases were assumed for the simulation experiment. The first case represents the actual condition for the 3rd segment while the second and third case assumes no delays due to the TBM breakdown and rock drilling. However, the third case assumes less frequent survey interval of 50 m instead of 15 m assumed for the first and second case. It should be noted that the base productivity without the effects of major delays can be determined from the second case. Then, the comparison of productivities between the second and third case can produce the effect of survey interval on the productivity.

For each case, five independent replicates were generated from the simulation with major input parameters shown in Table 7-4. Table 7-5 summarizes the results of the simulation with means and 95% confidence intervals for the productivity of each case. The mean of 10.67 m/shift for the first case was almost equivalent to the actual one of 10.65 m/shift with the actual occurrence of 1 and 3 for the TBM breakdown and rock drilling, respectively.

Table 7-4: Simulation Inputs for Three Cases for the 3rd Segment

Parameters	Case 1	Case 2	Case 3
TBM Penetration Rates	Normal (5.20, 0.86)	Normal (5.20, 0.86)	Normal (5.20, 0.86)
Survey interval	15 m	15 m	50 m
TBM Breakdown Occurrence (min)	Exponential (9000)	Excluded	Excluded
Rock Drilling Occurrence (min)	Exponential (3000)	Excluded	Excluded

Table 7-5: Simulation Outputs for Three Cases for the 3rd Segment

Parameters	Case 1	Case 2	Case 3
TBM Breakdown Occurrence	1.4	0	0
Rock Drilling Occurrence	3.6	0	0
Mean Productivity	10.67	11.59	12.53
95% Confidence Interval	(9.878, 11.454)	(11.324, 11.852)	(12.530, 12.530)

The productivity model was utilized to make an inference of the TBM penetration rate for the 3rd segment. With the productivity model considering the TBM penetration rates of 5.20 m/hr and the survey interval of every 15 m, the base productivity of 11.46 m/shift can be determined. This result is also close to the base productivity of 11.59 m/shift obtained from the simulation (case 2 in Table). The mean productivity difference of 0.94 m/shift between the second and third case from the simulation in Table 7-5 shows the effect of the survey interval. The corresponding value from the productivity model can be determined by multiplying the coefficient of 0.184 by the TBM penetration rate of 5.20 m/h from the Equation 7.1. The obtained value of 0.957 m/shift was also very close to one of 0.94 m/shift from the simulation. The results lead to the conclusion that the developed productivity model is valid and the TBM penetration rates can be accurately inferred from this methodology. It was decided that same modeling concept is utilized to make inferences of the TBM penetration rates for the missing data.

TBM penetration rates were inferred from the productivity model for the tunnel section of 363rd to 1037th m (from the 4th to 6th segment). Figure 7-2 shows that the adjusted productivity tends to gradually decrease from the 4th to 6th segment. It is concluded that soil transitions occurred for the 4th and 5th segment while the soil status becomes stable on the 6th segment. Table 7-6 illustrates soil conditions, productivities, and TBM penetration rates inferred from the productivity model for those segments. It should be noted that although the overall productivities for the 3rd and 4th segment are quite similar there is a significant difference in TBM penetration rates due to the different survey interval. The base productivity of 11.461 m/shift for the 3rd segment can be adjusted to one of 12.418 m/shift when the survey interval of 50 m is assumed. A higher productivity trend from the first portion of productivity data points for the 4th segment in Figure 7-2 also supports the higher adjusted base productivity of 12.418 m/shift on the preceding segment since it is more logical that soil characteristics for adjacent segments should be somewhat related.

As with an overall trend of the gradual decrease in productivity from the 3rd to 6th segment, TBM penetration rates inferred from the productivity model also demonstrate a similar trend with the overall TBM penetration rate decrease from 5.20 to 2.365 m/h. The 6th segment with the soil type 9 having mainly fine sand and silt has a very low mean TBM penetration rate of 2.365 m/h. The review of the project progress report demonstrates that wet ground condition seems to be starting from the middle portion of the 4th segment and make TBM encounter more water on the 6th segment. Thus, it was assumed that the soil type with wet ground condition was a major reason for the very slow TBM advancement on the 6th segment.

It is also interesting that the TBM penetration rate on the 5th segment was considerably low when compared to the 3rd segment although two segments have the same soil type with similar percentages of the rock drilling occurrence. It is believed that a relatively low TBM penetration rate on the 5th segment should be related to the soil transition status and wet ground condition.

Table 7-6: TBM Penetration Rates Inference for the Missing Data

	Seg. 3	Seg. 4	Seg. 5	Seg. 6
Section Length (m)	213	213	133	132
Soil Types	Soil 5	Soil 5 & 9	Soil 5	Soil 9
Soil Status	Steady	Transit	Transit	Steady
Survey Interval (m)	15 m	50 m	50 m	50 m
TBM Breakdown (%)	0.47 %	1.41 %	3.76 %	3.03 %
Rock Drilling (%)	1.41 %	1.41 %	1.50 %	0.00 %
Base Productivity (m/shift)	11.461	11.648	10.412	8.786
Productivity (m/shift)	10.654	10.645	8.870	8.250
TBM Penetration Rates (m/h)	5.200	4.400	3.365	2.365

Simulation was conducted to validate the inferred TBM penetration rates. Five independent replicates were generated for the 4th and 5th segment while ten independent replicates were generated for the 6th segment. Table 7-7 summarizes the results of the simulation with means and 95% confidence intervals for the productivity of each segment. The obtained results are close to the actual productivity. It was concluded that the inferred TBM penetration rates used as inputs for simulation were validated and the proposed methodology can be effectively utilized as a means for determining the TBM penetration rates.

Table 7-7: Simulation Outputs for the Segments from 4th to 6th

Parameters	Seg. 4	Seg. 5	Seg. 6
TBM Breakdown Occurrence	2.6	3.0	3.0
Rock Drilling Occurrence	3.6	3.4	0.0
Mean Productivity	10.776	9.088	8.388
95% Confidence Interval	(10.061, 11.491)	(8.293, 9.883)	(8.199, 8.577)

7.3.2 TBM Penetration Rates for the Remaining Segments

In this section, TBM penetration rates for the remaining segments from the 7th to 11th for the tunnel section of 841st to 1446th m are predicted from the productivity model as the procedures for the TBM rates inference were described in the previous section. The obtained results from the productivity model are compared with the actual sample collected.

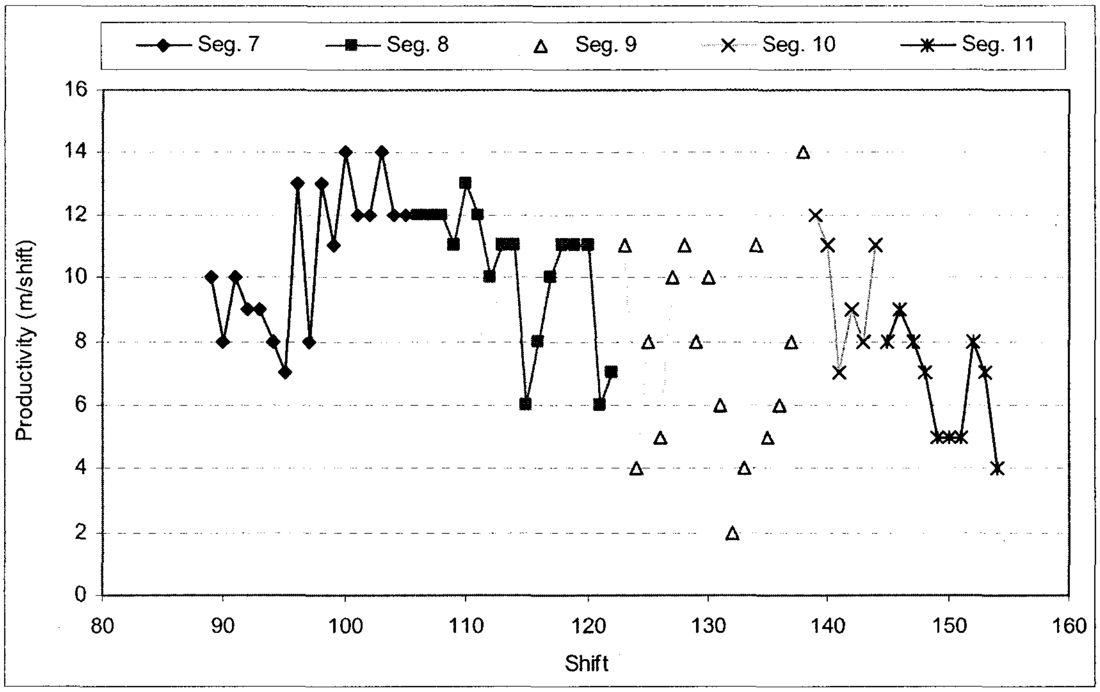


Figure 7-5: Actual Productivity Plots from the 7th to 11th Segment

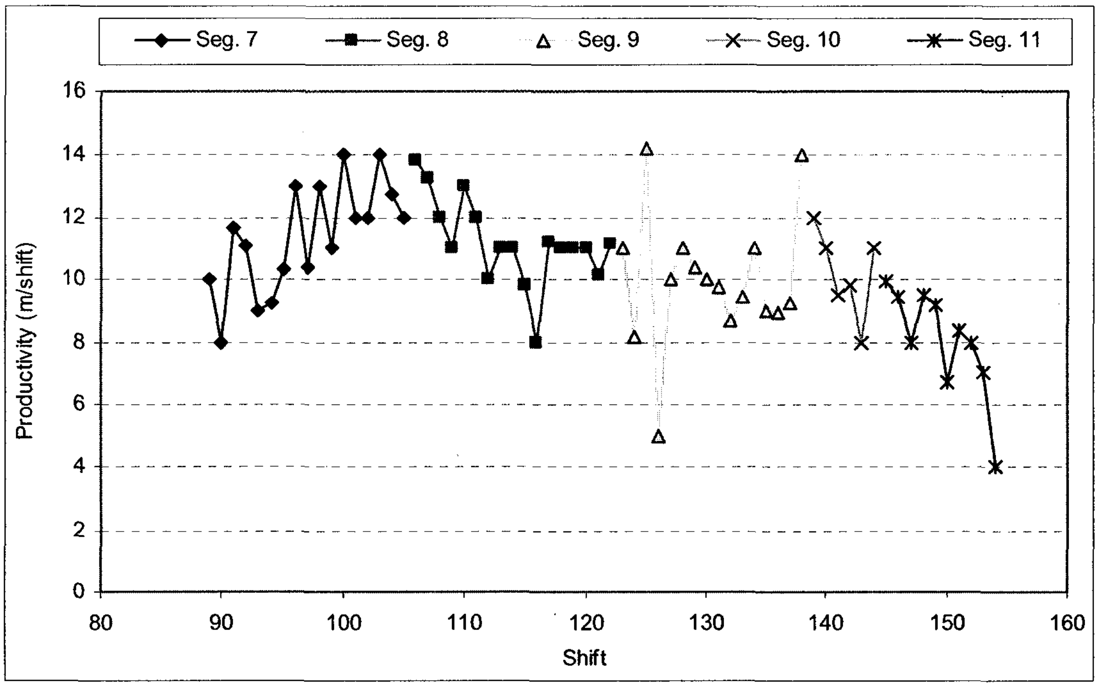


Figure 7-6: Adjusted Productivity Plots eliminating Effects of Delay Factors

Figure 7-5 shows the actual productivity plots from the 7th to 11th segment while the adjusted productivity plots excluding the effects of delays are illustrated in Figure 7-6. Both plots show a clear pattern for the productivity transition from the 7th to 8th segment. The comparison of both plots also demonstrates that productivity variation after excluding the effects of delays is considerably reduced for the 9th segment where the frequent rock drilling activities were required.

Table 7-8: TBM Penetration Rates Inference for the 7th and 8th Segment

	Seg. 7	Seg. 8
Section Length (m)	182	174
Soil Types	Soil 5	Soil 8
Soil Status	Transit	Transit
Survey Interval (m)	50 m	50 m
TBM Breakdown (%)	1.65 %	1.15 %
Rock Drilling (%)	1.65 %	2.87 %
Base Productivity (m/shift)	11.719	11.649
Productivity (m/shift)	10.706	10.235
TBM Penetration Rates Inferred (m/h)	4.469	4.401
Actual Sample Mean TBM Rates	5.856	5.917
% of Sample	16.8 %	37.9 %

Table 7-8 illustrates soil conditions, productivities, and TBM penetration rates inferred from the productivity model for the 7th and 8th segment. The productivity gradually increased on the 7th segment with soil type 5 while it decreased and became stable at the end portion of the 8th segment with soil type 8. Both segments also show the similar mean productivity and the percent of TBM breakdown occurrence while the 8th segment has a slightly higher rate for the rock drilling occurrence. TBM penetration rates inferred from the productivity model for the 7th and 8th segment were 4.469 and 4.401

m/h, respectively, while actual samples show somewhat higher rates of 5.856 and 5.917 m/h for each segment. Both results show similar rates between the 7th and 8th segment although there is a consistent difference in rates between the sample and inference method. Since the sample data for the 7th and 8th segment were based on 16.8 and 37.9 %, respectively, the finding implies the means for TBM penetration rates obtained from the sample may be somewhat overestimated.

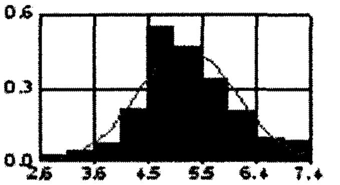
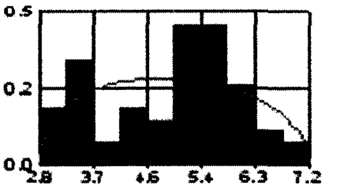
Table 7-9 illustrates soil conditions, productivities, and TBM penetration rates inferred from the productivity model for the segment from the 9th to 11th. As shown in Figure 7-6, the overall adjusted productivity seems to be stable on the 9th segment with soil type 5 while it gradually decreased on the 11th segment with soil type 5 and 2. Significant differences between actual and adjusted productivity for the 9th and 11th segment were found. Higher percentages of rock drilling for both segments indicate that the productivity loss for those segments was mainly due to the encounter of rocks.

Table 7-9: TBM Penetration Rates Inference for the 9th and 11th Segment

	Seg. 9	Seg. 10	Seg. 11
Section Length (m)	123	58	66
Soil Types	Soil 5	Soil 2, 9	Soil 5, 2
Soil Status	Stable	Stable	Transit
Survey Interval (m)	50 m	50 m	50 m
TBM Breakdown (%)	2.44 %	0 %	1.52 %
Rock Drilling (%)	6.50 %	3.45 %	7.58 %
Base Productivity (m/shift)	10.354	10.864	8.846
Productivity (m/shift)	7.688	9.667	6.600
TBM Penetration Rates Inferred (m/h)	3.323	3.712	2.396
Actual Sample Mean TBM Rates	4.953	4.665	3.252
% of Sample	49.6%	91.4%	65.2%

The 9th segment consisting of soil type 5 shows the mean TBM penetration rates of 3.323 m/h inferred from the productivity model while the mean of 4.953 m/h was obtained from 49.6 % of sample for that segment. It is interesting to compare the results with ones from the 3rd segment since both segments are composed of the typical soil type 5. Table 7-10 compares the distributions for the sample TBM penetrations for the two segments. The 3rd segment has a normal distribution with a mean of 5.197 m/hr while a beta distribution with a mean of 4.953 m/shift was better fitted for the 9th segment. Although two segments have different shapes of distributions, the statistics such as mean, minimum, and maximum values are quite close. These results imply that the sample for the 9th segment may be mainly composed of the rates that were not severely affected by the rocks. Relatively high frequencies in lower rates detected from the distribution for the 9th segment are another indications that sample data for that segment also seem to contain rates somewhat affected by the rocks.

Table 7-10: Comparison of Distributions for the 3rd and 9th segment

Segment	Distribution	Statistics
Seg. 3		Mean: 5.197 Std. Dev.: 0.861 Min.: 2.604 Max.: 7.372 Number of Sample: 175
Seg. 9		Mean: 4.953 Std. Dev.: 1.106 Min.: 2.833 Max.: 7.188 Number of Sample: 61

It is more logical that the overall TBM rates for harder soil are lower than ones for the normal soil condition. The percent of the rock drilling for the 3rd segment was 1.41 % indicating that the TBM advance was not strongly affected by the rocks while the 9th segment has 6.5 % of the rock drilling. Thus, it is believed that the sample data for the 9th segment do not represent the rates for the hard soil since there is no significant mean difference found for both segments. The mean rate of 3.323 m/h inferred from the productivity model seems to be more reasonable one for the 9th segment.

The 10th segment consisting of soil type 2 and 9 shows the mean TBM penetration rate of 3.712 m/h inferred from the productivity model while the one of 4.665 m/h was obtained from the sample data of 91.4 %. The normal distribution was fitted and the minimum and maximum data point was 2.6 and 6.804 m/h, respectively. It seems that the distribution fitted based on the sample data for the 10th segment is also close to one for the soil type 5 although the mean of 4.665 m/h for the 10th segment was somewhat lower than the one of 5.197 m/h for the 3rd segment. The rock drilling percent of 3.45 % shows that the 10th segment was relatively less affected by the rock conditions when compared to two adjacent segments of 9th and 11th with the one of 6.50 and 7.58 %, respectively. The inferred mean TBM penetration rate of 3.712 m/h on the 10th segment shows that the TBM advance was not strongly affected even for the soil type 2 when compared to the one of 3.323 m/h for the soil type 5 on the 9th segment.

However, the 11th segment consisting of soil type 2 and 5 seems to be severely affected by the hard rocks. The mean TBM penetration rate of 2.396 m/h was inferred from the productivity model while the one of 3.252 m/h was obtained from the sample of 65.2 %. The lower minimum and maximum data point of 1.853 and 5.390 m/h, respectively from the sample also indicate the TBM penetration rates are overall affected by the hard soil conditions.

7.3.3 Comparison of TBM Penetration Rates from the inference and sample

Table 7-11 compares the mean TBM penetration rates for the entire segment. For the 1st segment, a significantly lower mean TBM rate of 2.374 m/h from inference indicates the productivity model determines the TBM penetration rates as major causes for delays although the one of 4.514 from the sample was much higher. This comparison implies that delays were probably caused by learning curve effects due to some factors such as labor efficiency, which were not included in the productivity model for this study. Therefore, it was decided that the inferred TBM penetration rate for the first segment represents the one considering the learning curve effect. It is also a common practice for the tunnel simulation modeling that the lower TBM rates are normally assumed for the first segment, for instance, the first tunnel length of 100 m. For the second and third segment, there were no significant differences in TBM rates between the inference method and actual sample. However, some discrepancies in TBM rates for other segments were found between two different approaches.

Figure 7-7 compares the productivities and average durations for the TBM advancement for each segment. The average durations for the TBM advancement were based on the mean TBM penetration rates. The adjusted productivity is the rate excluding the effects of the delay factors such as rock drilling and TBM breakdowns as calculated in the previous section. The comparison of both actual and adjusted productivity for each segment shows that significant differences were found on the 9th and 11th segment indicating that the rock drilling was a leading cause for the delay. The comparison of the average durations determined from the sample and inference also indicates that differences in both durations on the 9th and 11th segment increased when compared to other segments. Thus, these findings lead to a conclusion that the difference in both rates are strongly related to the rock drilling and further analysis were required for the effects of rock drilling on the TBM penetration rates.

Table 7-11: Comparison of the Mean TBM Rates between Sample and Inference

Segment	Length	Soil Type	% of Rock Drilling	Mean Rates from Sample	Mean Rates from Inference
1	105 m	Soil 5	0.0	4.514	2.374
2	45 m	Soil 6	0.0	5.429	5.468
3	213 m	Soil 5	1.41	5.200	5.200
4	213 m	Soil 5 & 9	1.41	NA	4.400
5	133 m	Soil 5	1.50	NA	3.365
6	132 m	Soil 9	0.0	NA	2.365
7	184 m	Soil 5	1.65	5.856	4.469
8	174 m	Soil 8	2.87	5.917	4.401
9	123 m	Soil 5	6.50	4.953	3.323
10	58 m	Soil 2, 9	3.45	4.665	3.712
11	66 m	Soil 5, 2	7.58	3.252	2.396

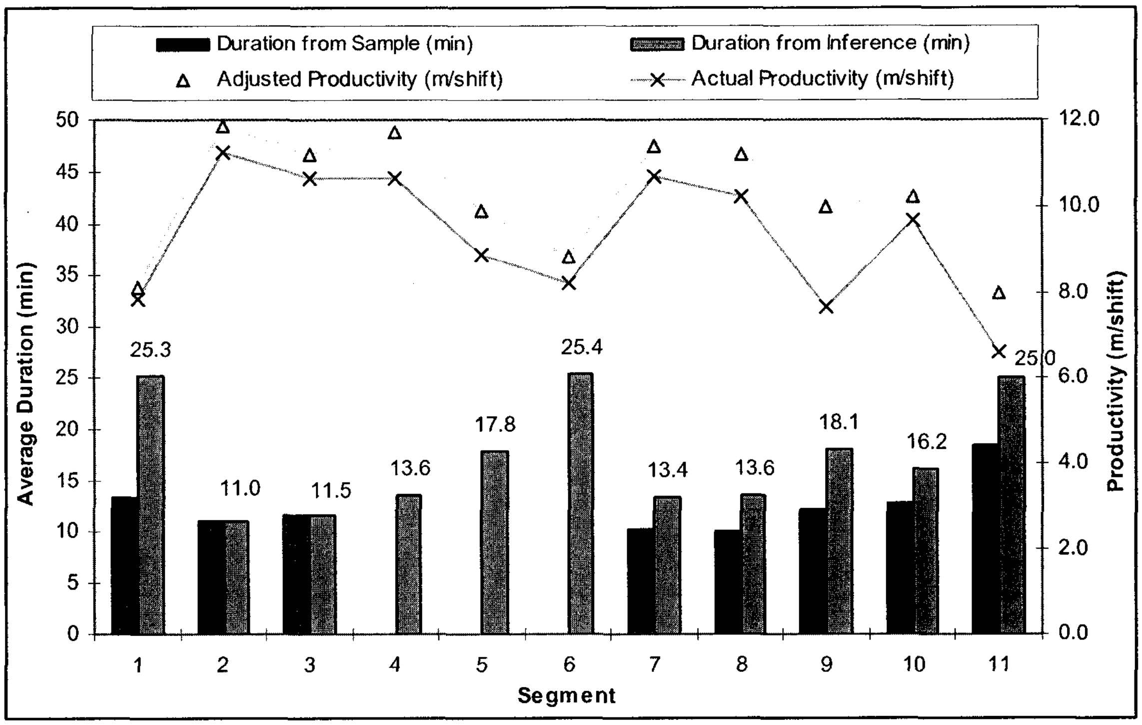


Figure 7-7: Comparison of TBM Advance Durations and Productivities

7.3.4 Effects of Rock Drilling on the TBM Penetration Rates

In order to see how the rock drilling affects the TBM penetration rates, it was decided that an actual example of samples on the specific date is given. Figure 7-8 illustrates a sample of the recorded data on January 23, 2002, which plots the advancing distance on the time of day. The inclined portions of the plot indicate the times when the TBM was advancing, whereas the flat portions indicate the time when the TBM was not advancing due to the installation of segmental linings or disruptions such as rock drilling, TBM maintenance/breakdown, and surveying times. A visual inspection of the plot indicates 9–m-long segmental linings were installed. A major disruption occurred for the TBM advancement required for the installation of the second, third, and fourth segmental lining. The review of the project progress report shows a total of one hour was spent on the rock drilling and there were no major delays occurred on that date. It was thus assumed that rock drilling was an only major factor causing the delays for the TBM advancement on these segmental liners.

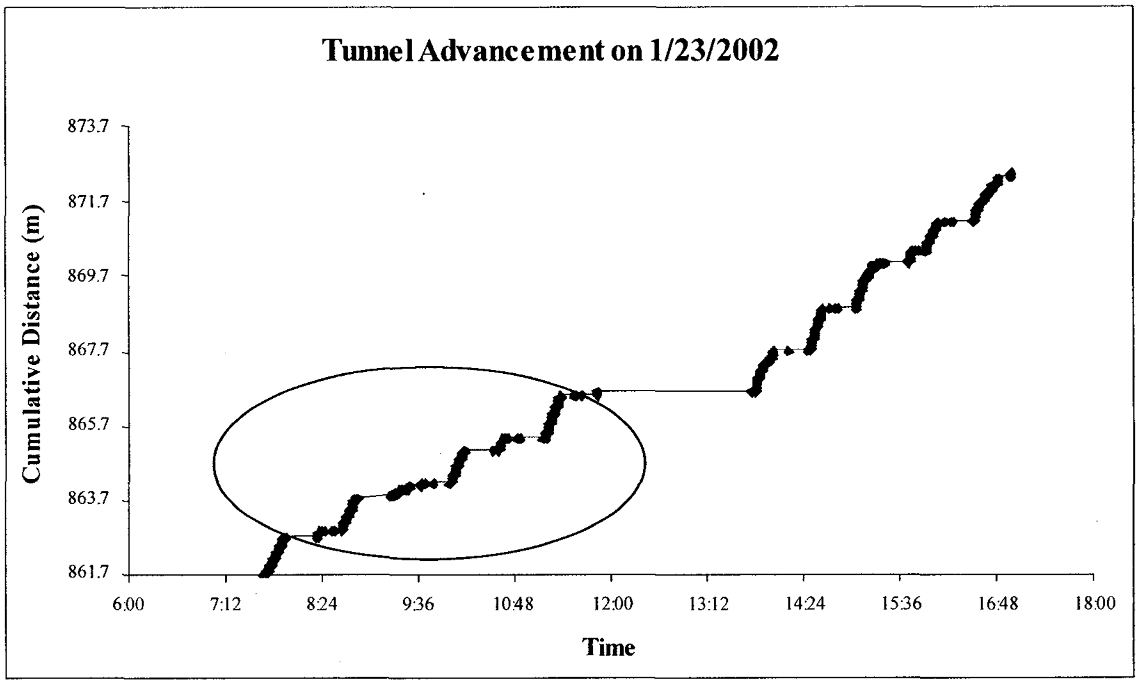


Figure 7-8: Tunnel Advancement on January 23, 2002

Figure 7-9 illustrates the tunnel advancement on the second, third, and fourth segmental lining, which was disrupted by rock drilling. A disruption due to rock drilling results in three portions for the TBM advancement for each segmental lining: the first inclined, second somewhat flat, and third inclined portion. It was assumed that the second flat portion is the times when the TBM was not advancing at the normal speed due to rock drilling.

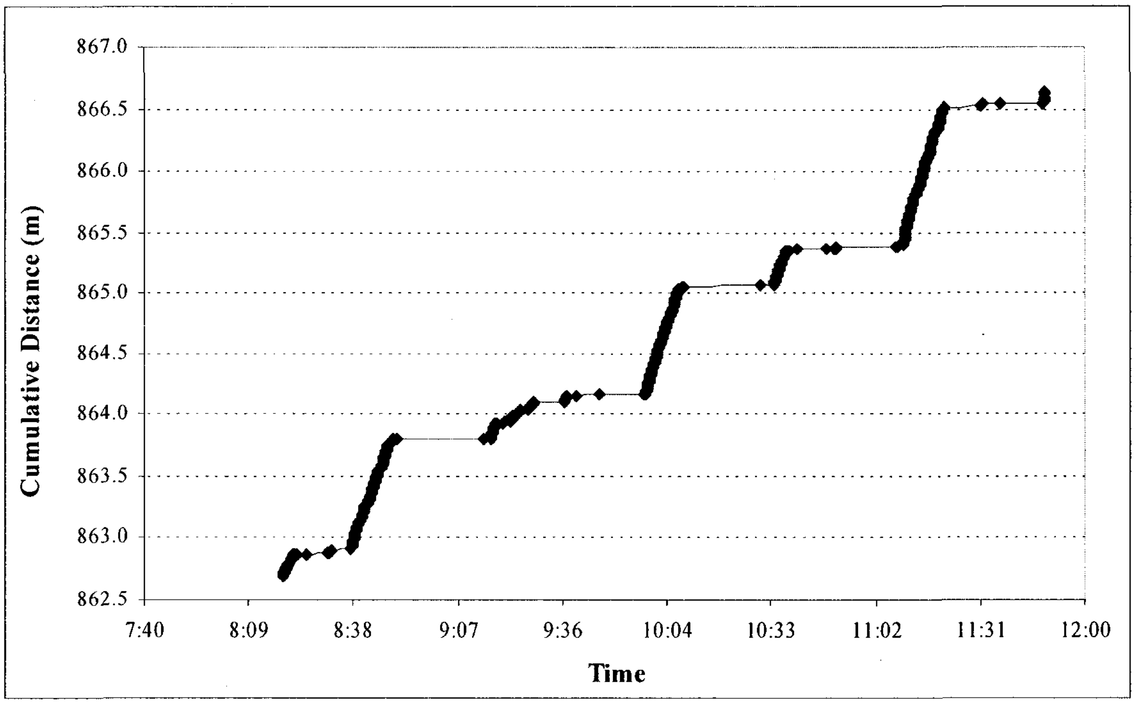


Figure 7-9: TBM Advancement from the 2nd to 4th Segmental Liner on Jan. 23, 2002

Table 7-12: TBM Advancement from the 2nd to 4th Segmental Liner on Jan. 23, 2002

Segmental Liner	Status	Distance (m)	Time (hr)	Advance Rate (m/h)
2nd	Advancing	0.178	0.066	2.699
	Rock Drilling	0.041	0.250	0.164
	Advancing	0.886	0.207	4.270
	Lining	NA	0.405	NA
3rd	Advancing	0.294	0.195	1.507
	Rock Drilling	0.059	0.510	0.116
	Advancing	0.897	0.188	4.786
	Lining	NA	0.353	NA
4th	Advancing	0.289	0.074	3.930
	Rock Drilling	0.020	0.449	0.046
	Advancing	1.130	0.224	5.046

Table 7-12 summarizes the distance, time, and TBM advance rates for the second, third, and fourth segmental liner. On the second segmental liner, for instance, the TBM advanced for the first portion of 0.178 m with a rate of 2.699 m/h, which is significantly lower than the one of 4.270 m/h for the last portion of 0.886 m. The flat portion indicates that the TBM was very slowly advancing at a rate of 0.164 m/h, which seems to be times spent on drilling and splitting rocks. The similar trends that the TBM was slowly advancing on the first and second portion were also found on the third and fourth segmental liner.

During the data collection and cleaning process, the TBM penetration rates on the sample was calculated with only inclined portions to obtain the rate at which the TBM actually advances. It was believed that the inclusion of the flat portion may result in the underestimation or miscalculation of the true TBM penetration rates since the sample data for the TBM penetration rates obtained from the data recorder had many outliers and inadequate data points. It was also hard to determine the exact causes for the disruptions for the flat portions since the total times spent on each TBM delay were only recorded on a daily basis on the project progress report.

If the rock drilling is included for the calculation of the TBM penetration rate, the mean is significantly lowered as compared in Table 7-13. For instance, the mean of 2.112 m/h for the TBM advancement for the second segmental liner was obtained with the inclusion of rock drilling time while the one of 3.891 m/h could be achieved if the time for rock drilling was removed. Based on both methods for calculating the mean TBM penetration rates for the installation of 9–m-long segmental linings on January 23, 2002, the mean of 3.572 m/h was obtained in case of the inclusion of the rock drilling time.

However, the exclusion of the rock drilling time results in the higher mean of 4.490 m/h. The analysis of actual samples in this section leads to a conclusion that the mean TBM penetration rates inferred from the productivity model for this study are close to the ones affected by the hard rocks. From these results, the obtained rates are determined as reliable results and can be used for the soil transitions along the entire tunnel path to relate the TBM rates to the tunnel productivity.

Table 7-13: Comparison of TBM Rates from the 2nd to 4th Segmental Liner on Jan. 23, 2002

	Segmental Liner		
	2nd	3rd	4th
Excluding Rock Drilling	3.891	3.114	4.770
Including Rock Drilling	2.112	1.401	1.929

7.4 Soil Transitions Modeling along the Tunnel Length

TBM penetration rates obtained from the inference and sample are compared on each segment as shown in Figure 7-10. Actual and adjusted productivities are also compared. The comparison of TBM penetration rates and productivities illustrates that some correlations exist for those variables. It should be noted that TBM penetration rates on the fourth, fifth, and sixth segment are available only from the inference. It is believed that these inferred rates can play important roles in establishing relations between TBM advance rates and tunnel productivity when the sample data do not exist.

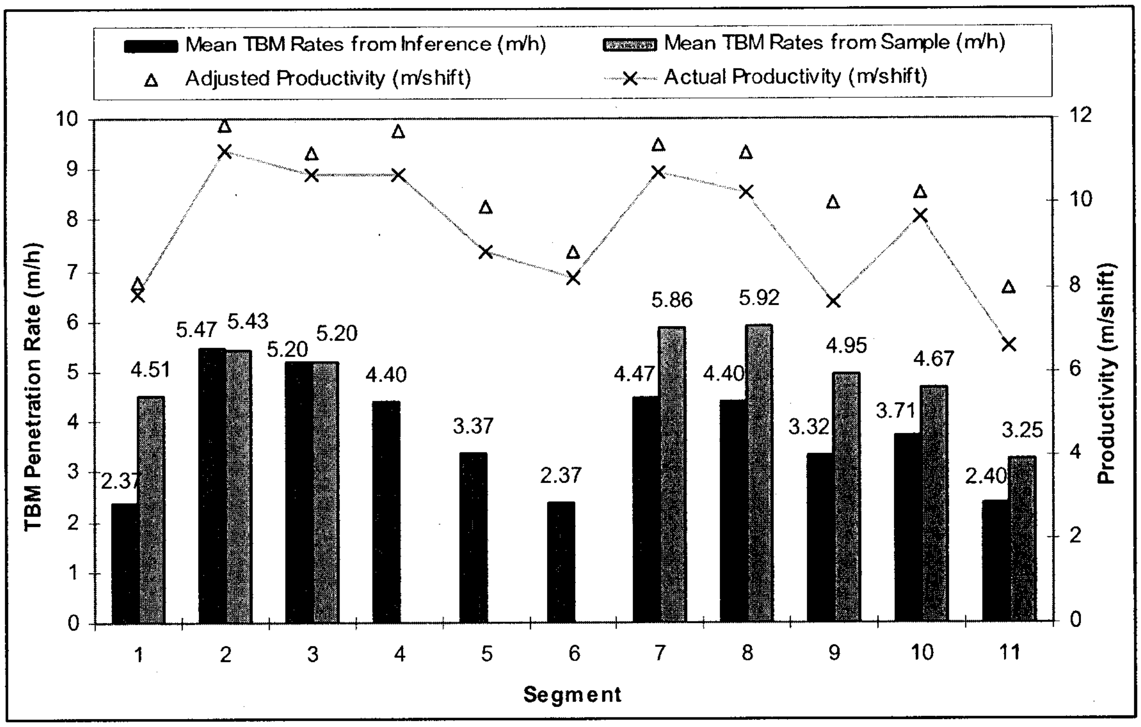


Figure 7-10: Comparison of TBM Penetration Rates and Productivities

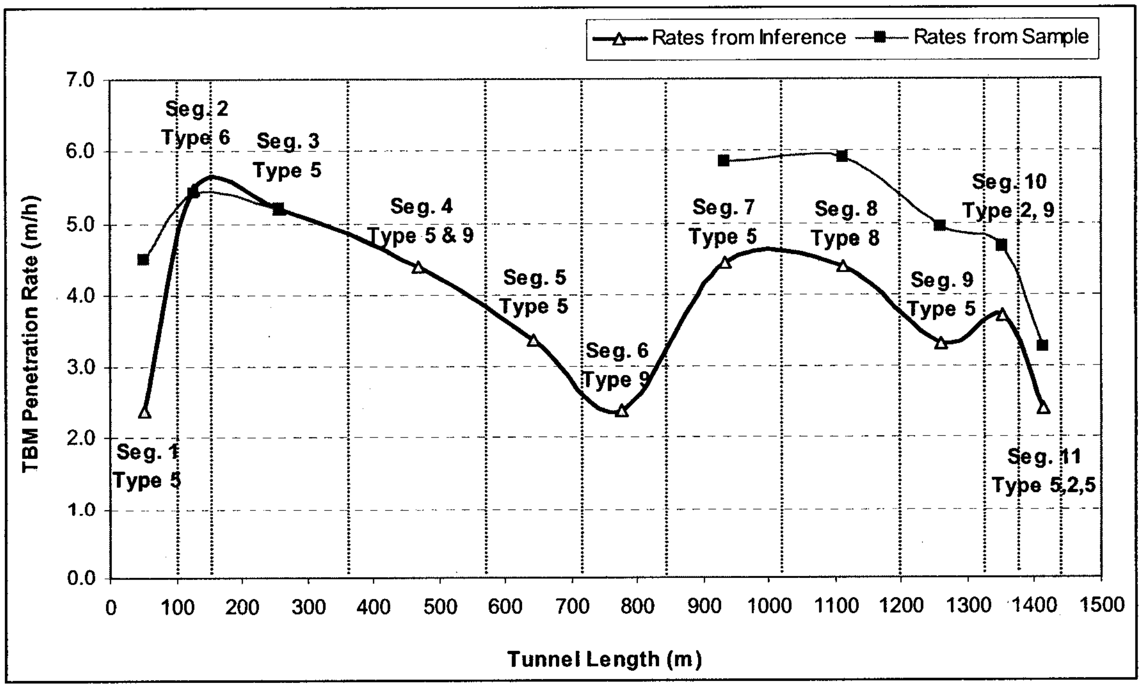


Figure 7-11: TBM Penetrations for Soil Transitions along the Tunnel Path

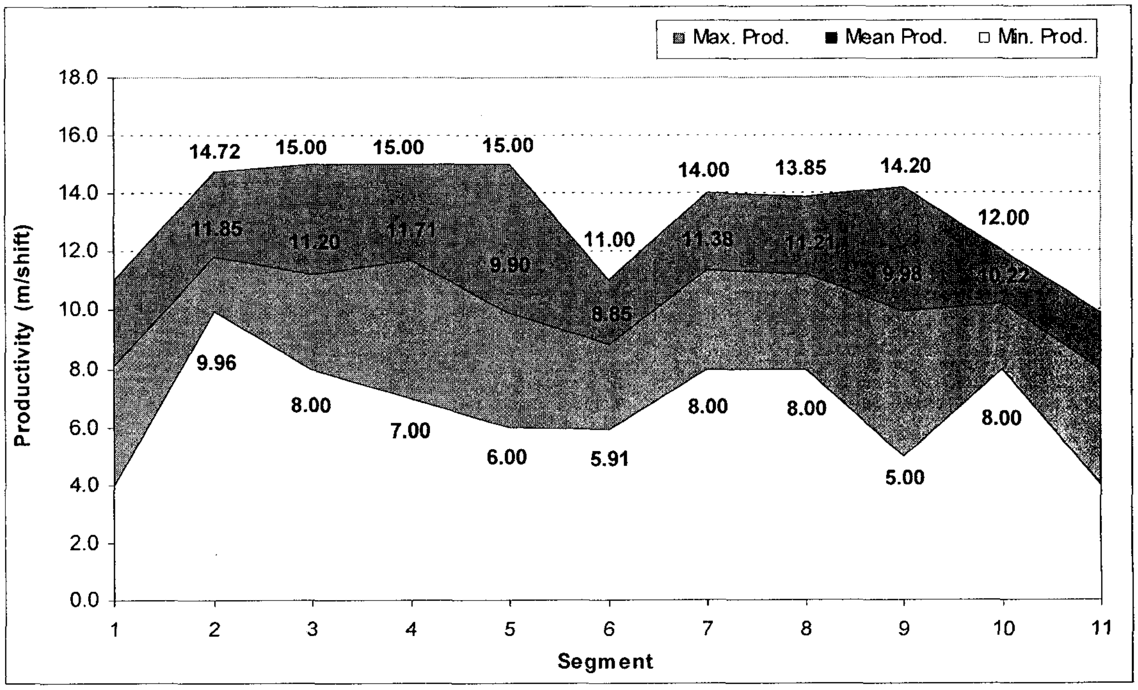


Figure 7-12: Adjusted Productivity Transitions for Tunnel Sections

Figure 7-11 plots the mean TBM penetration rates for the soil transitions along the tunnel path. The rates from inference tend to demonstrate clearer trends of the soil transitions than ones from sample. Both rates from the inference and sample on the segments from the 7th to 11th show the similar trend that overall rates gradually decreased although there were some consistent differences. The productivities are also compared on each segment as the minimum, maximum, and the mean productivities are shown in Figure 7-12. Similar patterns are also detected in the productivity transitions on the segments. The mean and minimum productivities seem to be strongly related to the TBM penetration rates as the visual inspection illustrates the similarity in transition patterns in both variables. It is thus believed that the proposed methodology to make inferences of

TBM penetration rates using the tunnel productivity models is successful. Inferred TBM rates for the various geological conditions can be utilized as a guideline for major simulation inputs for the future tunnel projects. The adjusted productivity based on the methodology considering the productivity loss can be also a useful reference for planning the future projects.

7.5 Summary and Conclusions

This chapter discussed the method using the developed tunnel productivity model to make inferences of the TBM penetration rates for 11 segments, which were mainly divided by the soil types. Since the sample for TBM penetration rates only consist 36% of data for the entire 1,446 m tunnel length, some tunnel sections have limited number of the data or even no data available.

The TBM penetration rate is the single most important factor for determining the tunnel productivity for the simulation application. It is commonly believed the TBM penetration rate for that purpose should represent the characteristics of soil layers being excavated. However, the effects of other factors such as surveying time, TBM maintenance/breakdown, and rock drilling should not be neglected as their influences on the productivity were identified and quantified through the productivity model in Chapter 6. The direct use of actual productivity without considering the effects of those factors on it thus may lead to erroneous interpretation and application for the future projects.

In this chapter, the effects of the TBM delays and rock drilling were first identified from the use of the multiple regression technique on the daily production recording from the project progress report. The adjusted productivity excluding the effects of those factors was attainable from actual daily productivity by compensating the productivity loss occurred due to the corresponding factor. It is thus believed that the adjusted productivity should be more clearly related to the soil characteristics than the actual productivity influenced by the various factors. For this project, it turns out that the adjusted overall productivity of 10.32 m/shift instead of the actual one of 9.36 m/shift would be achieved if there were no major disruptions due to the TBM breakdown and rock drilling. The comparison of both production rates indicates that the total loss of about 14 shifts incurred from those delay factors.

Using the developed productivity model, the mean TBM penetration rates were first inferred for the fourth, fifth, and sixth segment where no sample data were available. With the obtained rates, simulation was conducted for each segment and the simulation results successfully validated the rates inferred from the productivity model.

In a similar way, the rates for the remaining segments were also inferred and compared with the sample. For the second and third segment with the actual sample of 100% and 82.2%, respectively, the mean rates inferred for both segment were almost identical with ones from the sample. For the segments where the TBM advancement was somewhat or considerably disrupted by rock drilling, there were some differences in the mean rates between inference and sample. However, the review of actual sample on the specific date indicates that the TBM penetration rates can be significantly affected by the inclusion of time interrupted by rock drilling.

Among the total 11 segments, the highest mean TBM penetration rate of 5.47 m/h was achieved on the second segment containing soil type 6 while the lowest rate of 2.37 m/h was recorded on the first and sixth segment. The major reasons for the slowest TBM advance on the first and sixth segment were learning curve effects and soil conditions, respectively. The results also indicate that rock soil conditions were also major reasons for lower TBM rates on the ninth, tenth, and eleventh segment resulting in the lower production rates.

From the results of this study, it was concluded that the proposed method of the TBM penetration rates inference using the tunnel productivity model was successful and this framework using simulation and statistical models can be applied for similar tunnel construction projects. Since the data collection procedures for the TBM penetration rates may be tedious and considerable efforts for data cleaning process need to be made for the collected data, the proposed method can be utilized as a very effective, beneficial, and accurate approach to predict soil characteristics for various soil types.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

8.1 Research Summary

This thesis proposed techniques to develop a construction productivity and soil penetration model for the tunnel construction operations using a special purpose simulation and analytical approach. One of the tunneling projects recently completed by the City of Edmonton Public Works Department, NEST was selected as a major case study for this research study. The project was fully instrumented and continuously monitored to obtain continuous feedback on progress, causes for delay, production loss, production increase, and other relevant information. A special purpose simulation template for tunneling developed under *Simphony* was utilized. The simulation tool was developed under the successful collaborative research work between the City of Edmonton Asset Management and Public Works Department and the NSERC/Alberta Construction Industry Research Chair in Construction Engineering and Management (Ruwanpura 2001). The research presented in the thesis can be divided into three phases.

During the first phase, a special purpose simulation tool for tunneling was utilized with Bayesian input modeling approach to update an original schedule planned prior to construction as the project progressed. In order to obtain and update the TBM penetration rates, which are considered one of the critical factors influencing the tunnel productivity, a wheel anchored to the conveyor traveling on the segmental liner behind the TBM was connected to a data recorder which monitored the advancement of the wheel. Due to many outliers and inadequate data points, considerable efforts were expended to identify and remove the outlier points. After the data cleaning process, the cleaned logger data consisting of 140,772 data points for 521 meter tunnel sections were believed to be reliable and were used in further analysis. A regression analysis based on the data extracted from the project progress report successfully identified the critical factors affecting the productivity. The results showed that factors such as rock drilling and TBM breakdown significantly affect productivity. The use of Bayesian techniques to update the distributions of input parameters for tunnel simulation demonstrated a formal approach for combining original assumptions with sample data obtained during construction. The simulation results showed that even early updates during construction (for instance, about 9% completion of the total tunnel section) can significantly improve the prediction of a project's performance by eliminating the uncertainty contained in the original assumption. A sampling-based Bayesian inference approach was further utilized for estimation of major input parameters for a tunnel simulation template. Those parameters included TBM penetration rates for five different soil types (Type 2, 5, 6, 8, and 9), rock encountering, and surveying activities. While the study successfully identified and obtained the soil characteristics based on the TBM penetration rates, it showed that TBM penetration rates for even same soil type significantly vary depending on the location of soil. It is believed that the variation in means for each soil may be related to the soil state and properties such as plasticity, moisture, and granularity.

During the second phase of the research, a tunnel productivity model using simulation and analytical techniques was successfully developed to identify the effects of uncertainty factors and predict the productivity under various project circumstances related to the geological uncertainty and machine performance. As with the TBM penetration rates, other major factors such as survey interval, a percent of rock encountering, an average duration of rock drilling, and TBM breakdown occurrence were considered critical factors exerting a significant influence on the overall productivity. After simulation model and its inputs were validated with actual results, the multiple regression technique with data sets generated from the simulation was utilized to develop the productivity model. The developed model allows industry practitioners to predict the tunnel productivity and plan their future projects in a more effective and systematic manner.

During the third phase of the research, the use of the developed tunnel productivity model successfully predicted TBM penetration rates for various soil conditions. The predicted mean TBM penetration rates were also utilized to identify soil transitions along the entire tunnel path. This approach provided a way to make inferences of the TBM penetration rates for some tunnel sections containing limited or no sample data. The comparison of the predicted and sample rates for sections containing relatively large number of sample successfully validated this analytical approach. Among the total 11 segments mainly divided by soil types, the highest mean TBM penetration rate of 5.47 m/h was achieved on the second segment having soil type 6 while the lowest rate of 2.37 m/h was recorded on the first and sixth segment. The main reasons for the slowest TBM advance on the first and sixth segment were learning curve effects and rock soil conditions, respectively. Rock soil conditions also resulted in a relatively low TBM penetration rates for some segments including the ninth, tenth, and eleventh segment. The soil transition model was successfully validated with the patterns from the plots of actual productivity. The soil transition model based on the TBM penetration rates showed a clearer trend of soil characteristics for various soil conditions and can be used as valuable guidelines for predicting the TBM penetration rates and the overall tunnel productivity for planning future projects.

8.2 Summary of Research Contributions

This thesis research had led to significant contributions to construction simulation, the prediction of soil characteristics and tunnel productivity for tunnel construction operations, and the plan and management of tunneling projects.

The successful application of Bayesian statistical approach into the actual tunnel construction project for updating the schedule is a major contribution to construction simulation application as project control techniques. The use of the proposed methodology with simulation techniques demonstrates a remarkable enhancement to planning prediction and opened various avenues for the industry practitioners to use the developed framework as a means of project control over schedule and cost. The obtained results from the sampling-based Bayesian inference method not only provide valuable inputs for tunnel simulation, but also provide useful guidelines for the planning of future tunnel projects.

This research study attempted to identify uncertainly factors in tunnel construction operations related to geological conditions and machine performances. As a result, the tunnel productivity model was developed with advanced methods such as simulation and statistical techniques. The modeling approach allows its users first to identify the uncertainty quantitatively and then to obtain the prediction of tunnel productivity in systematic and scientific manners. The developed tunnel productivity model motivated the further research opportunities to develop the practical models in various construction operations using simulation and advanced analytical techniques.

As with results of the sampling-based Bayesian inference, the soil transitions based on the TBM penetration rates along the tunnel length was modeled with the use of the developed productivity model. This approach allows to identify the soil characteristics for various soil conditions and to thoroughly recognize the soil transition pattern along the tunnel path. The soil transition model from the use of tunnel productivity model leads to the motivation for the further collaborative research to develop more extensive soil transition and tunnel productivity models using historical project data, which enables industry practitioners to obtain practical sources of data for planning the future projects.

8.3 Limitations

The developed productivity model from this research was built on a single tunnel project, the NEST, which is a 1538-meter tunnel having a 2.94-meter finished diameter lined with pre-cast concrete segment. Since TBM penetration rates and tunnel productivity are influenced by many factors such as the depth of tunnel, TBM diameter, and quality of equipment and crew, the developed model's applicability to the actual industry practice is only limited to future tunneling projects with similar scopes.

This research identified and quantified the effects of the TBM delays and rock drilling on the productivity from the NEST project. However, those uncertainty factors may vary depending on the equipment and geological condition of each project. Thus, assumptions on modeling unforeseen events during tunnel still need to be made for its application.

8.4 Recommendations for Future Research and Development

During this research study, the following have been noted as recommendations for further research and development to improve construction simulation modeling, tunnel construction operation, and tunnel project control over schedule and cost.

1. The input modeling and output validation are fundamental part of successful simulation. Repetitive processes of tunnel construction operations will give many benefits with the use of simulation experiment. Major efforts need to be made to collect data of its process and make a well-established database for tunneling projects. As this study demonstrated the importance of input modeling, more advanced level of input modeling based on the data with a good quality can produce outstanding simulation results. Simulation results also should be cautiously validated with actual performance.
2. This study recognized uncertainty factors including encountering of rocks and equipment breakdown. The study identified their effects on the overall productivity and trends of occurrence from the case study. In order to develop more robust models considering these events for the prediction of tunnel productivity, further analysis applying the proposed framework into various project data is recommended.
3. Soils having various properties such as plasticity, moisture content, and granularity would result in different TBM penetration rates. It is recommended to

identify those properties for various soil types and develop a thorough analytical model to relate those properties to the TBM penetration rates, which could be used as input for simulation for accurate prediction of tunnel productivity.

4. The prediction of soil characteristics and machine performances is crucial part of tunnel productivity modeling. The study also demonstrated that a tunnel simulation template is best suited for modeling these uncertainties in order to obtain the practical and realistic prediction of tunnel productivity. It is recommended to enhance the uncertainty modeling using advanced analytical techniques to make the tunnel template more accurate and reliable.

The use of simulation and advanced analytical techniques can be efficient and beneficial method for the project plan and control.

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APPENDIX "A": TBM Penetration Rate Calculation

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
7/30/2001	1	0.9316	0.2761	3.3739	Type 5
	2	0.9999	0.3733	2.6783	
	3	0.8154	0.3142	2.5954	
	4	0.7175	0.2117	3.3896	
	5	1.0044	0.4083	2.4599	
	6	1.0637	0.3236	3.2869	
	7	0.9999	0.3614	2.7668	
7/31/2001	8	1.0022	0.2714	3.6927	Type 5
	9	0.9042	0.2533	3.5693	
	10	0.9953	0.1989	5.0045	
	11	0.9931	0.2478	4.0079	
	12	0.9999	0.1842	5.4293	
	13	0.9976	0.1503	6.6385	
	14	1.0022	0.1553	6.4540	
	15	0.9748	0.1886	5.1685	
	16	1.0067	0.3633	2.7708	
	17	1.0295	0.2450	4.2020	
8/1/2001	18	1.0409	0.1739	5.9859	Type 5
	19	1.2368	0.1825	6.7768	
	20	1.1684	0.1572	7.4318	
	21	1.2185	0.1931	6.3119	
	22	1.1548	0.2550	4.5285	
	23	1.1821	0.1708	6.9196	
	24	1.1570	0.1606	7.2065	
	25	1.2345	0.2906	4.2487	
	26	1.0113	0.4806	2.1044	
8/3/2001	27	1.2641	0.1922	6.5762	Type 5
8/9/2001	28	0.9999	0.2506	3.9907	Type 5
	29	1.0022	0.2803	3.5756	
	30	1.0022	0.2494	4.0176	
	31	1.0022	0.1817	5.5165	
	32	0.9976	0.1700	5.8683	
	33	0.9908	0.2206	4.4922	
	34	0.9384	0.2103	4.4626	
	35	0.9338	0.2150	4.3434	
	36	0.9999	0.3297	3.0325	
8/13/2001	37	1.0181	0.3850	2.6444	Type 5
	38	1.0568	0.2236	4.7262	
	39	1.1047	0.1931	5.7220	
	40	1.0181	0.1847	5.5116	
	41	0.9931	0.1819	5.4580	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
8/13/2001	42	0.9726	0.3672	2.6484	Type 5
	43	1.0136	0.2289	4.4282	
	44	1.0113	0.1992	5.0775	
	45	1.0363	0.3203	3.2357	
	46	1.0887	0.2700	4.0323	
	47	1.1138	0.2953	3.7720	
8/14/2001	48	1.0204	0.2878	3.5458	Type 6
	49	1.0477	0.2269	4.6166	
	50	1.0454	0.3708	2.8192	
	51	1.0227	0.1894	5.3982	
	52	1.0341	0.2203	4.6943	
	53	1.0067	0.1842	5.4664	
	54	0.9885	0.2069	4.7767	
	55	1.0044	0.1642	6.1185	
	56	1.0227	0.3119	3.2784	
	57	1.0477	0.2272	4.6110	
8/15/2001	58	1.1274	0.2089	5.3973	Type 6
	59	1.0386	0.2169	4.7874	
	60	1.0363	0.2008	5.1602	
	61	1.0363	0.2058	5.0348	
	62	1.0181	0.2389	4.2619	
	63	1.4736	0.1797	8.1996	
	64	1.0022	0.1547	6.4772	
	65	1.1639	0.1703	6.8352	
	66	1.1092	0.1869	5.9334	
	67	1.0591	0.2028	5.2230	
	68	1.2459	0.2242	5.5578	
	69	0.9817	0.1828	5.3708	
	70	1.0204	0.1808	5.6427	
	71	1.0409	0.1950	5.3379	
8/16/2001	72	1.1161	0.1958	5.6990	Type 6
	73	1.0181	0.2156	4.7232	
	74	1.1001	0.2225	4.9443	
	75	1.0432	0.1422	7.3348	
	76	1.0204	0.1644	6.2051	
	77	1.0682	0.2022	5.2824	
	78	1.1206	0.1731	6.4754	
	79	1.0249	0.1447	7.0822	
	80	1.1297	0.1942	5.8183	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
8/17/2001	81	0.9931	0.1692	5.8703	Type 6
	82	1.1411	0.2192	5.2066	
	83	1.1935	0.4175	2.8587	
	84	1.0090	0.1953	5.1670	
	85	1.0454	0.1667	6.2727	
	86	1.1047	0.2056	5.3740	
	87	1.0044	0.1742	5.7672	
	88	1.0318	0.1417	7.2831	
	89	1.1001	0.2003	5.4929	
	90	1.0022	0.1661	6.0331	
	91	1.0386	0.1947	5.3338	
	92	1.0204	0.1842	5.5406	
8/18/2001	93	1.0409	0.3514	2.9622	Type 5
	94	1.0136	0.2489	4.0723	
	95	1.0887	0.2261	4.8150	
	96	1.4440	0.1972	7.3219	
	97	0.9726	0.1758	5.5311	
	98	1.1274	0.2258	4.9924	
	99	1.0386	0.1419	7.3170	
	100	1.0044	0.1497	6.7087	
8/20/2001	101	0.7972	0.1511	5.2755	Type 5
	102	1.0318	0.1825	5.6536	
	103	0.9976	0.1711	5.8302	
	104	1.0978	0.1686	6.5110	
	105	1.0136	0.1592	6.3679	
	106	1.1502	0.1819	6.3218	
	107	1.1001	0.2294	4.7947	
	108	1.0591	0.2231	4.7482	
	109	1.1183	0.2156	5.1881	
	110	1.0568	0.2303	4.5894	
	111	1.1001	0.1992	5.5236	
	112	1.1411	0.2575	4.4315	
8/21/2001	113	0.6719	0.1389	4.8377	Type 5
	114	1.1001	0.1925	5.7148	
	115	0.9111	0.1378	6.6125	
	116	1.0933	0.1564	6.9907	
	117	1.0249	0.1617	6.3399	
	118	1.0249	0.1656	6.1909	
	119	1.1252	0.2061	5.4590	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
8/21/2001	120	1.0751	0.1458	7.3718	Type 5
	121	1.0022	0.1406	7.1300	
	122	1.0227	0.1419	7.2047	
	123	1.1707	0.2075	5.6420	
	124	1.0500	0.1531	6.8602	
	125	1.1206	0.1792	6.2545	
	126	1.1252	0.1964	5.7293	
	127	1.0910	0.2336	4.6701	
8/22/2001	128	1.1047	0.2411	4.5815	Type 5
	129	1.0751	0.2033	5.2871	
	130	1.1092	0.2006	5.5307	
	131	1.0454	0.1503	6.9567	
	132	1.1252	0.1953	5.7619	
	133	1.0318	0.1892	5.4543	
	134	1.0181	0.1664	6.1189	
	135	1.0067	0.1597	6.3030	
8/23/2001	136	1.0090	0.1983	5.0874	Type 5
	137	1.0044	0.2028	4.9534	
	138	0.9931	0.2231	4.4521	
	139	0.9999	0.1978	5.0556	
	140	1.0523	0.2217	4.7471	
	141	1.1593	0.3289	3.5250	
	142	1.0409	0.2269	4.5865	
	143	1.0318	0.1914	5.3910	
	144	1.0341	0.2147	4.8158	
	145	1.0090	0.2139	4.7174	
	146	0.9703	0.2225	4.3608	
8/24/2001	147	1.0523	0.2086	5.0442	Type 5
	148	1.0637	0.2008	5.2963	
	149	1.0591	0.2169	4.8819	
	150	1.1365	0.2214	5.1337	
	151	1.0249	0.1961	5.2263	
	152	1.0842	0.2083	5.2040	
	153	1.1844	0.1897	6.2427	
	154	1.1229	0.2064	5.4406	
	155	1.0454	0.3031	3.4497	
	156	1.0022	0.1664	6.0230	
8/25/2001	157	1.0432	0.2189	4.7657	Type 5
	158	0.9543	0.2747	3.4738	
	159	0.9156	0.2028	4.5154	
	160	0.8382	0.2172	3.8586	
	161	1.0067	0.1808	5.5671	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
8/25/2001	162	1.0204	0.2156	4.7338	Type 5
	163	1.1069	0.2042	5.4217	
	164	1.0090	0.1869	5.3973	
8/27/2001	165	0.9908	0.2750	3.6028	Type 5
	166	1.0067	0.2283	4.4090	
	167	1.0454	0.1692	6.1800	
	168	1.1343	0.2406	4.7152	
	169	1.1297	0.1972	5.7281	
	170	1.0887	0.2153	5.0573	
	171	1.2687	0.2869	4.4213	
	172	1.0819	0.2036	5.3135	
	173	1.0659	0.1881	5.6682	
	174	1.0956	0.2019	5.4250	
	175	1.0363	0.1847	5.6102	
8/28/2001	176	1.0956	0.2297	4.7690	Type 5
	177	1.2550	0.2436	5.1516	
	178	0.9953	0.1800	5.5296	
	179	1.1024	0.2217	4.9732	
	180	1.0386	0.1833	5.6651	
	181	1.0090	0.1531	6.5924	
	182	1.0136	0.2575	3.9361	
	183	1.1229	0.2086	5.3827	
8/29/2001	184	0.5307	0.1383	3.8363	Type 5
	185	1.1365	0.2564	4.4329	
	186	1.1115	0.2175	5.1103	
	187	1.0773	0.2358	4.5682	
	188	1.1411	0.2167	5.2666	
	189	1.1092	0.2017	5.5003	
	190	1.0978	0.1922	5.7113	
	191	1.1889	0.3739	3.1799	
	192	1.2527	0.2694	4.6492	
	193	1.0659	0.2019	5.2784	
	194	1.0887	0.2344	4.6438	
	195	1.1092	0.2206	5.0292	
	196	1.1365	0.2214	5.1337	
8/30/2001	197	1.0363	0.2397	4.3231	Type 5
	198	1.0090	0.1839	5.4870	
	199	1.0249	0.1889	5.4262	
	200	1.0044	0.2108	4.7642	
	201	1.0249	0.1950	5.2561	
	202	0.9976	0.2319	4.3011	
	203	1.0409	0.2458	4.2341	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
8/30/2001	204	0.9748	0.2400	4.0618	Type 5
	205	0.9156	0.2092	4.3775	
	206	0.8701	0.3342	2.6037	
	207	1.1411	0.2297	4.9673	
8/31/2001	208	1.0956	0.2225	4.9238	Type 5
	209	1.0796	0.2361	4.5725	
	210	1.0864	0.2200	4.9384	
	211	1.1047	0.2314	4.7741	
	212	1.0341	0.1922	5.3795	
	213	1.0568	0.1847	5.7212	
	214	1.0523	0.1767	5.9563	
	215	0.9817	0.2086	4.7057	
	216	1.0044	0.1989	5.0503	
9/4/2001	217	0.9726	0.2197	4.4263	Type 5
	218	0.9771	0.2164	4.5155	
	219	0.9202	0.1800	5.1121	
	220	0.9156	0.1931	4.7428	
	221	1.1069	0.1986	5.5734	
	222	1.1092	0.1997	5.5538	
	223	1.1161	0.1728	6.4595	
	224	1.1069	0.1808	6.1213	
	225	1.0659	0.1667	6.3957	
9/5/2001	226	1.0978	0.2042	5.3771	Type 5
	227	1.1115	0.1850	6.0081	
	228	1.0842	0.1797	6.0324	
	229	1.0728	0.1764	6.0819	
	230	1.1252	0.2067	5.4443	
	231	1.0272	0.1772	5.7962	
	232	1.1388	0.2058	5.5328	
	233	1.0022	0.1556	6.4425	
	234	1.1161	0.2325	4.8002	
	235	1.0910	0.1628	6.7024	
	236	0.9931	0.2092	4.7477	
	237	1.0637	0.2003	5.3109	
	238	1.1001	0.2353	4.6758	
9/6/2001	239	1.0454	0.2175	4.8066	Type 5
	240	0.9862	0.1767	5.5824	
	241	1.1138	0.2239	4.9747	
	242	1.0796	0.2331	4.6324	
	243	1.0500	0.2014	5.2138	
	244	1.0363	0.2133	4.8578	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
9/7/2001	245	1.0386	0.2256	4.6047	Type 5
	246	0.9931	0.1786	5.5599	
	247	0.9817	0.1989	4.9358	
	248	1.0272	0.1753	5.8605	
	249	1.0158	0.1778	5.7141	
	250	0.9999	0.1767	5.6598	
	251	0.9612	0.1814	5.2989	
	252	0.9429	0.1511	6.2401	
	253	0.9384	0.2031	4.6214	
	254	1.0796	0.2172	4.9701	
	255	0.9703	0.1803	5.3821	
9/10/2001	256	0.9338	0.2142	4.3603	Type 5
	257	0.9680	0.2206	4.3889	
	258	0.8291	0.1853	4.4747	
	259	0.8427	0.2286	3.6863	
	260	0.7926	0.2167	3.6583	
	261	1.0113	0.2122	4.7652	
	262	1.0341	0.2503	4.1316	
	263	0.8974	0.1944	4.6152	
	264	0.9680	0.2028	4.7737	
	265	0.9316	0.1753	5.3148	
	266	0.9885	0.2447	4.0393	
	267	1.0659	0.2211	4.8208	
11/5/2001	268	0.8177	0.2339	3.4960	Type 5
	269	1.1092	0.1594	6.9568	
	270	1.1138	0.1650	6.7501	
	271	0.5466	0.1578	3.4646	
	272	1.0568	0.2208	4.7857	
	273	1.0659	0.2167	4.9197	
	274	1.1889	0.2178	5.4594	
11/6/2001	275	1.1753	0.1817	6.4694	Type 5
	276	1.0272	0.1517	6.7729	
	277	1.0181	0.1608	6.3302	
	278	1.0067	0.1597	6.3030	
	279	1.0751	0.1953	5.5053	
	280	1.1912	0.1711	6.9616	
	281	1.0272	0.1981	5.1865	
	282	1.0477	0.2167	4.8356	
	283	1.0637	0.1547	6.8747	
	284	1.0637	0.2022	5.2599	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
11/6/2007	285	0.3735	0.1456	2.5663	Type 5
	286	1.0637	0.2428	4.3812	
	287	0.8473	0.1856	4.5662	
11/15/2001	288	1.1229	0.1706	6.5837	Type 5
	289	1.0318	0.1517	6.8029	
11/22/2001	290	1.0044	0.1389	7.2320	Type 5
	291	0.8336	0.1114	7.4839	
	292	0.9202	0.1242	7.4108	
	293	1.0432	0.1292	8.0761	
	294	1.0022	0.1336	7.5006	
	295	1.1252	0.1806	6.2317	
	296	1.0705	0.1442	7.4254	
	297	1.1069	0.3128	3.5391	
	298	1.0090	0.1867	5.4054	
11/26/2001	299	1.0591	0.2036	5.2016	Type 8
	300	0.8336	0.2067	4.0337	
	301	0.9589	0.1869	5.1293	
	302	1.0728	0.2092	5.1288	
	303	1.1297	0.2381	4.7456	
	304	1.1024	0.2364	4.6634	
	305	1.1047	0.1978	5.5854	
	306	1.1047	0.1764	6.2627	
11/27/2001	307	1.0773	0.2019	5.3348	Type 8
	308	1.1434	0.1747	6.5440	
	309	1.0773	0.1939	5.5564	
	310	0.8746	0.1281	6.8300	
	311	1.1297	0.1853	6.0974	
	312	0.8017	0.1458	5.4976	
	313	0.8541	0.2192	3.8971	
	314	1.0910	0.1600	6.8187	
	315	1.0409	0.1711	6.0831	
11/28/2001	316	0.9908	0.1789	5.5385	Type 8
	317	0.8974	0.2506	3.5816	
	318	1.0910	0.1475	7.3966	
	319	0.9839	0.1172	8.3939	
	320	1.0751	0.1603	6.7074	
	321	1.1115	0.1731	6.4228	
	322	1.0819	0.1536	7.0430	
	323	1.1115	0.1792	6.2037	
	324	0.9680	0.1328	7.2904	
	325	0.7835	0.1431	5.4770	
	326	0.9771	0.1217	8.0311	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
12/3/2001	327	0.9020	0.2006	4.4973	Type 8
	328	1.1024	0.1692	6.5166	
	329	0.9475	0.1233	7.6825	
	330	1.0773	0.1394	7.7259	
	331	1.0136	0.1292	7.8469	
	332	1.1024	0.2011	5.4815	
	333	1.0432	0.1244	8.3826	
	334	0.6423	0.1561	4.1144	
	335	1.0682	0.1564	6.8305	
12/6/2001	336	0.7539	0.1536	4.9079	Type 8
	337	1.0386	0.1581	6.5712	
	338	1.0454	0.1975	5.2934	
	339	1.1138	0.2192	5.0819	
	340	1.1001	0.1947	5.6496	
12/7/2001	341	1.0295	0.1986	5.1835	Type 8
	342	1.0295	0.1508	6.8254	
	343	1.0751	0.1839	5.8462	
	344	1.3484	0.3444	3.9146	
	345	1.0477	0.2572	4.0732	
	346	0.7812	0.1769	4.4151	
12/10/2001	347	1.0318	0.2397	4.3041	Type 8
	348	1.0842	0.1850	5.8603	
	349	1.0363	0.1672	6.1973	
	350	1.1320	0.1625	6.9661	
	351	1.0933	0.1361	8.0322	
	352	1.0113	0.1122	9.0114	
	353	1.1229	0.1453	7.7292	
	354	1.1365	0.1856	6.1251	
	355	1.0978	0.2231	4.9218	
	356	0.9407	0.1508	6.2365	
12/11/2001	357	1.1138	0.2447	4.5512	Type 8
	358	0.8997	0.1614	5.5746	
	359	0.9748	0.2408	4.0478	
	360	0.8313	0.2881	2.8861	
	361	0.9908	0.1422	6.9664	
	362	0.9771	0.1394	7.0072	
	363	1.0022	0.1681	5.9633	
	364	0.9498	0.1642	5.7855	
12/18/2001	365	1.0044	0.1814	5.5375	Type 5
	366	0.6947	0.1614	4.3044	
	367	0.8815	0.2461	3.5815	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
12/18/2001	368	0.7084	0.1978	3.5815	Type 5
	369	0.8382	0.1558	5.3787	
	370	0.5717	0.1772	3.2258	
	371	1.0204	0.2950	3.4589	
	372	1.0295	0.2858	3.6017	
	373	1.2208	0.3014	4.0507	
12/19/2001	374	1.2254	0.2111	5.8044	Type 5
	375	0.6013	0.1100	5.4664	
12/21/2001	376	1.1229	0.3072	3.6550	Type 5
	377	0.8564	0.1506	5.6883	
	378	1.1525	0.2269	5.0783	
1/4/2002	379	0.5808	0.2050	2.8332	Type 5
	380	0.9293	0.3242	2.8667	
	381	1.0933	0.2131	5.1314	
	382	1.1502	0.2189	5.2548	
	383	1.1297	0.1786	6.3250	
	384	0.7266	0.1247	5.8255	
	385	0.6765	0.1200	5.6372	
	386	1.1320	0.1806	6.2695	
1/7/2002	387	0.8746	0.2153	4.0627	Type 5
	388	1.1069	0.2631	4.2080	
	389	0.9361	0.1689	5.5428	
	390	0.9020	0.1417	6.3667	
	391	1.0477	0.1661	6.3074	
	392	1.0842	0.2169	4.9974	
	393	1.1092	0.1772	6.2589	
	394	1.2277	0.2297	5.3441	
1/8/2002	395	0.8450	0.1292	6.5420	Type 5
	396	1.2345	0.2358	5.2346	
	397	1.2117	0.3878	3.1248	
1/9/2001	398	0.9543	0.2908	3.2814	Type 5
	399	1.0249	0.2961	3.4614	
1/10/2002	400	0.7311	0.1975	3.7019	Type 5
	401	1.1069	0.1622	6.8236	
	402	0.9566	0.2044	4.6791	
	403	0.8723	0.1839	4.7439	
1/15/2002	404	1.0933	0.2628	4.1605	Type 5
	405	1.2527	0.3447	3.6340	
	406	1.1115	0.3694	3.0086	
	407	1.0591	0.2083	5.0837	
	408	0.9931	0.1956	5.0781	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
1/16/2002	409	1.1479	0.2206	5.2048	Type 5
	410	1.1183	0.2169	5.1549	
	411	1.0249	0.2044	5.0133	
1/17/2002	412	1.1775	0.2628	4.4812	Type 5
	413	1.0705	0.1750	6.1171	
	414	1.0363	0.1442	7.1884	
	415	1.0978	0.1744	6.2933	
	416	1.1115	0.2033	5.4664	
	417	1.0819	0.1778	6.0856	
	418	1.0591	0.1997	5.3029	
	419	1.0842	0.2292	4.7309	
	420	1.0272	0.2458	4.1785	
	421	0.7903	0.1381	5.7248	
	422	1.1069	0.1847	5.9925	
	423	1.1229	0.1981	5.6695	
	424	1.0796	0.1939	5.5682	
	425	1.0044	0.1739	5.7764	
1/18/2002	426	1.0523	0.2100	5.0108	Type 2
	427	1.0136	0.3103	3.2666	
	428	1.0591	0.2744	3.8591	
	429	1.1138	0.2475	4.5001	
	430	1.0773	0.2047	5.2624	
	431	1.0978	0.2344	4.6827	
	432	1.0864	0.2414	4.5008	
	433	1.0705	0.2206	4.8536	
	434	1.0773	0.2394	4.4993	
	435	1.0477	0.2367	4.4270	
1/21/2002	436	1.1047	0.3189	3.4641	Type 2
	437	1.0318	0.3489	2.9573	
	438	1.0864	0.2186	4.9697	
	439	1.0751	0.2281	4.7140	
	440	1.0637	0.2392	4.4474	
	441	1.0887	0.2314	4.7051	
	442	1.0659	0.1911	5.5776	
	443	1.0523	0.2517	4.1812	
	444	1.0432	0.2497	4.1773	
	445	1.0432	0.2083	5.0072	
	446	1.1183	0.2489	4.4933	
1/22/2002	447	1.1343	0.3097	3.6622	Type 2
	448	1.0318	0.3414	3.0223	
	449	1.1274	0.2067	5.4554	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
1/22/2002	450	1.1297	0.2714	4.1627	Type 2
	451	1.0682	0.2600	4.1085	
	452	1.0409	0.1850	5.6264	
	453	0.9953	0.2025	4.9152	
1/23/2002	454	0.9794	0.2772	3.5329	Type 9
	455	1.0637	0.2733	3.8915	
	456	1.1912	0.3825	3.1143	
	457	1.1297	0.2239	5.0459	
	458	1.0568	0.2339	4.5185	
	459	1.0887	0.1600	6.8045	
	460	1.1365	0.2064	5.5068	
	461	1.0682	0.2203	4.8494	
	462	1.1548	0.3375	3.4215	
1/24/2002	463	1.1069	0.3131	3.5359	Type 9
	464	0.9953	0.1867	5.3322	
	465	1.0295	0.2103	4.8959	
	466	1.0181	0.1531	6.6519	
	467	0.9680	0.1925	5.0286	
	468	1.1502	0.1997	5.7591	
	469	0.8291	0.1928	4.3006	
	470	0.7698	0.2961	2.5999	
1/25/2002	471	1.0887	0.1997	5.4512	Type 9
	472	1.1001	0.1900	5.7900	
	473	1.1229	0.1861	6.0334	
	474	1.0454	0.1822	5.7372	
	475	1.0819	0.2125	5.0912	
	476	1.1069	0.1989	5.5656	
	477	1.0933	0.1967	5.5590	
	478	0.9338	0.1972	4.7350	
1/28/2002	479	0.9202	0.3631	2.5345	Type 5
	480	1.1001	0.2275	4.8356	
	481	1.0409	0.3500	2.9740	
	482	0.9748	0.2233	4.3649	
	483	0.9657	0.4242	2.2768	
	484	0.6491	0.2242	2.8958	
	485	0.6491	0.2808	2.3114	
1/29/2002	486	0.9976	0.3606	2.7669	Type 5
	487	0.7311	0.2467	2.9640	
	488	1.0090	0.2878	3.5062	
	489	0.7881	0.4253	1.8531	
	490	0.8336	0.3258	2.5584	

Date	Segment #	Distance (m)	Time (hr)	Rate (m/hr)	Soil Type
1/29/2002	491	0.7402	0.2267	3.2658	Type 5
	492	0.7995	0.2672	2.9917	
	493	0.8131	0.2675	3.0397	
	494	0.7471	0.1908	3.9148	
1/31/2002	495	1.2072	0.4144	2.9127	Type 2
	496	1.0044	0.5028	1.9978	
	497	0.8746	0.2600	3.3639	
	498	1.1274	0.3836	2.9390	
	499	1.0113	0.4617	2.1905	
	500	1.0659	0.2878	3.7040	
	501	0.9612	0.2506	3.8362	
2/1/2002	502	1.1297	0.3783	2.9860	Type 2
	503	0.7812	0.3300	2.3674	
	504	0.9111	0.4200	2.1692	
	505	0.9293	0.2283	4.0699	
2/4/2002	506	1.0113	0.4081	2.4783	Type 2
	507	1.2163	0.4333	2.8068	
	508	1.0682	0.4900	2.1800	
	509	0.9908	0.3244	3.0538	
	510	1.0796	0.2856	3.7807	
2/5/2002	511	1.0546	0.3269	3.2255	Type 5
	512	0.9953	0.2869	3.4687	
	513	1.0728	0.3197	3.3553	
	514	1.1753	0.2972	3.9542	
	515	1.4554	0.4161	3.4977	
2/6/2002	516	1.5442	0.3672	4.2052	Type 5
	517	1.3689	0.4106	3.3342	
	518	1.2413	0.2892	4.2928	
	519	1.4213	0.3094	4.5929	
	520	1.0796	0.2331	4.6324	
	521	1.0705	0.1986	5.3899	