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# Microtunneling decision support system (MDS) using Neural-Autoregressive Hidden Markov Model

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ABSTRACT

Microtunneling is a trenchless technology method used for installing new pipelines. The inherent advantages of this method over open-cut trenching have led to its increasing use. This paper presents a general model for microtunneling decision support system (MDS) that can be used as a basis for developing more effective microtunneling design and construction. The model objectives are to: (1) develop a description of local geology that reflects the uncertainty of the information on which it is based and (2) provide the input data necessary for other decision support systems. MDS is composed of two main modules: (1) geology prediction model (GPM) module which is based on Neural-Autoregressive Hidden Markov Model and (2) excavation method selection module to select appropriate excavation method based on GPM result. In order to validate the proposed model, a microtunneling project: Zhong-he drainage water tunnel in Taiwan, was used as a case study. The result shows that the MDS model achieves these objectives to a satisfactory degree.



## 1. Introduction

Tunnels are vital options for modern transportation system. At the same time, tunnels are expensive underground structures where a variety of risks are encounters in every phase of the project delivery process. Comprehensive and realistic tunneling plans must strive for optimal decision that minimize time and cost while addressing important tunneling risks (Likhtruangsilp & Ioannou, 2004). One of the most important decisions in tunneling is to determine the optimal sequence of excavation method and support system along the tunnel profile (see Fig. 1), so that the time and cost of tunnel construction can be optimized. However, these decisions are greatly influenced by geologic uncertainty and variability. Generally soil conditions are unknown because soil samples taken from vertical boreholes show only the soil present in the discrete borehole location. Therefore, it contributes the project uncertainty (Riwanpura, AbouRizk, & Allouche, 2003).

Uncertainty behavior of ground condition is inevitably in tunneling construction process. Many studies have been conducted to build decision support system (DSS) for tunneling projects. Chung, Abraham, and Gokhale (2004) build DSS for micro-tunneling. It is used to evaluate whether micro-tunneling will be economically feasible and suggest appropriate micro-tunneling methods. A concept for decision support in the selection of a type of shield tunneling machine and of an appropriate construction technology is presented by Kakoto and Skibniewski (1991). Likhtruangsilp and Ioannou (2004) and Karam, Karam, and Einstein (2007) build DSS based on three interrelated models: probabilistic geologic prediction, probabilistic tunnel cost estimates and risk sensitive dynamic decision model. The decision support system proposed in this paper is focused on probabilistic geologic prediction model (GPM). However, the result of the prediction model can be used as input data for other decision support systems such as equipment and support selection and scheduling support system.

Several geological prediction models have been developed. Chan (1981), Ioannou (1987) and Sutanto (2008) used Discrete-state Markov process and Bayesian updating for modeling uncertainty of geological parameters along the tunnel line. Adi and Leu (2009) using Hidden Markov Model (HMM) to predict the geology parameters in the microtunneling project; however in their model, the relationship among soil parameters are assumed independence. Hu and Huang (2007) used 2D conditional Markov process to predict the soil transition and get the probabilistic risk index by Monte Carlo simulation. Neural Network approaches is also used by several researchers to predict geological condition in the tunnel construction, such as: geological hazards at the tunnel face (Alimoradi, Ali, Reza, Mojtaba, & Fshin, 2008) and prediction of tunnel settlement (Santos & Celestino, 2008). Neural Networks are suitable for use in the prediction of geological parameters

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**Fig. 1.** Optimal sequence of tunneling system.

because it can analyze non-linear patterns and trends common to geology. The geological prediction model which is proposed in this paper was designed using Hybrid Neural-Autoregression Hidden Markov Model (Neural-ARHMM). This model is a refinement of an earlier model that used Bayesian updating (Ioannou, 1987) and the Hidden Markov Model (HMM) (Adi & Leu, 2009). Its architecture is a combination of the Autoregressive Hidden Markov Model (AR-HMM) and iterative Back Propagation Neural Network (BPNN), and expectedly produces more accurate predictions of geological profiles.

## 2. Methodology

### 2.1. Framework

Microtunneling decision support system (MDS) is divided into 3 main parts: (1) GPM Model, (2) Database subsystem, and (3) User Interface (I/O). Fig. 2 describes data flow diagram of the program.

GPM model received input data from user by using both manual input or import the information provided by GIS database. GPM model processes the information and produce Ground class prediction for the current tunnel. Then, this information is combined by equipment and support database to produce optimal excavation method. The final result data can be exported to other decision support system such as MS Project ™ to calculate optimal tunneling construction time and cost.

### 2.2. Neural-ARHMM module architecture

A Hidden Markov Model (HMM) is a statistical model in which the system being modeled is assumed to be a Markov process with unknown parameters. The challenge is to determine the hidden parameters from the observable data. In a regular Markov model, the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. Autoregressive Hidden Markov Model is a combination of autoregressive time series and hidden Markov chains (Xuan, 2004). The autoregressive structure admits the existence of dependency amongst time series observations while the hidden Markov chain could capture the probability characteristics of the transitions amongst the underlying states. The hybrid model – Neural-Autoregressive HMM – proposed in this paper is described in Fig. 3.

In this model, the autoregressive time series model – to predict observed geologic parameters – is represented by an iterative Back Propagation Neural Network (BPNN). As mentioned in the previous part, the reason of using Neural Network in this model is its capability in analyzing non-linear pattern of soil parameters. The main advantage of this model is the calculation of posterior states. Probability not only

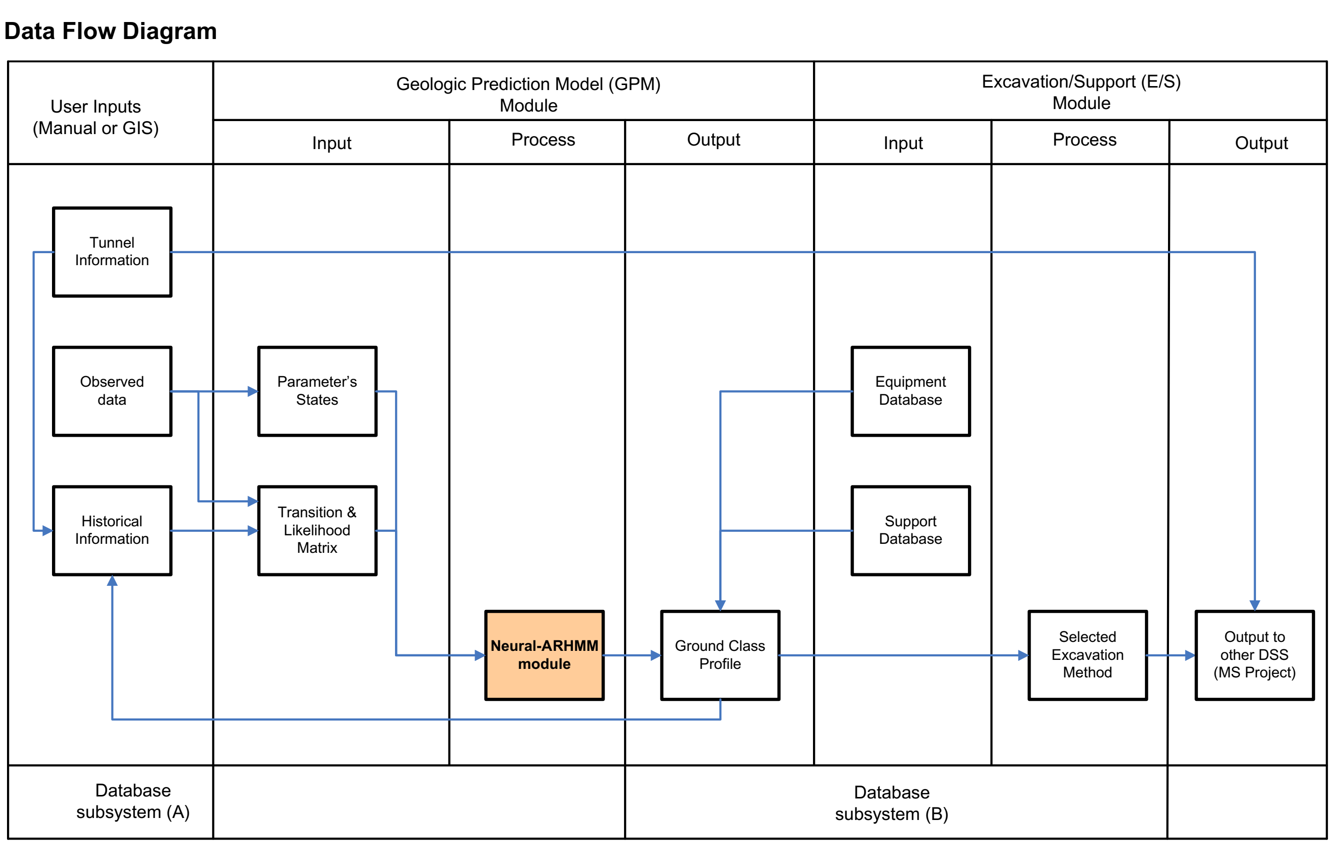


**Fig. 2.** MDS data flow diagram.