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Prediction of frictional jacking forces using Bayesian inference

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Abstract Application of pipe-jacking method in the form of microtunneling has become more popular over the conventional open cut method for the installation of underground infrastructure such as buried sewer pipelines in urban setting in recent years. This is due to the advantages offered by trenchless technology such as reduced disruptions to traffic and the surrounding environment as well as minimized ground settlements. Prediction of frictional jacking forces is a crucial component of the design of pipe-jacking works. In view of the challenges faced in calculating pipe-jacking forces in highly weathered and highly fractured geological formations, this paper proposes the use of Bayesian inference method to predict the frictional jacking forces developed from traversing the weathered rock formations. A probabilistic framework based on Bayesian approach is proposed using a well-established pipe-jacking force model, which considers arching effect from the surrounding ground. The main advantages of Bayesian inference include (i) consideration of uncertainty in deriving the soil parameters and (ii) ability to incorporate prior information and expert judgement from previous research studies into the model in the form of prior distribution. The model uncertainty is expected to be significantly reduced through the sequential updating process when more data become available.

Keywords: Bayesian inference, pipe-jacking, uncertainty, friction, probabilistic model

1 Introduction

Trenchless technology in the form of microtunneling by pipe-jacking method has become increasingly popular over the conventional open cut method for the installation of underground utilities such as pipes and cables in urban environment in recent years. Trenchless excavation offers minimum surface disturbance and reduces disruption to local traffic during the works, thus minimizing the costs that result from conflicts with existing utilities and surface obstacles that need to be mitigated prior to project commencement (Hemphill, 2013).

The calculation of frictional jacking forces is one of the most crucial components in the design of any pipe-jacking works. Since the invention of trenchless technology, the assessment of frictional jacking forces is an area of strong interest in research as it is a key aspect that overlaps the concerns of designers, contractors and equipment manufacturers (Sterling, 2018).

Choo and Ong (2017) mentioned that many empirical models have been developed for the calculation of jacking forces for pipe-jacking drives traversing soils (Bennett, 1998; Chapman and Ichioka, 1999; Staheli, 2006; Olson et al., 2016), with very limited considerations for drives through rock. Due to the challenges faced in assessing jacking forces in highly weathered and highly fractured geology, a Bayesian probabilistic framework has been proposed to predict the jacking forces developed in traversing such geological formations, by integrating existing knowledge with field observations collected during construction.

2 Bayesian Inference

The empirical models that have been established for the assessment of jacking forces are unable to consider various uncertainties that are associated with the models, such as inherent variability (i.e. uncertainty of soil and rock properties due to their inherent random characteristics) and knowledge uncertainty (e.g., measurement errors, statistical uncertainty and transformation uncertainty) (Wang et al., 2016). By adopting a probabilistic framework, the uncertainties of soil and rock properties can be quantified in a reasonable manner.

The proposed Bayesian approach can incorporate existing knowledge from previous studies into the model, and with in-situ field observations available, the model parameters of interest can be estimated by integrating the two aspects in the analysis. The existing knowledge that is available prior to the project is known as "prior knowledge" under the Bayesian framework. The prior knowledge includes, but are not limited to, published reports and studies, engineering judgment, local experience, visual observations, maps and surveys (Wang and Cao, 2013). By integrating the prior knowledge and in-situ field observations probabilistically, information from different sources can be combined rationally (Wang and Cao, 2013).

There have been many successful applications of Bayesian method in geotechnical engineering, such as study on unified soil compression model (Jung et al., 2009), prediction of Young's moduli of rocks (Feng, 2015), study on soil parameters for braced excavations (Juang et al., 2013; Jin et al., 2018), characterization of model uncertainty (Zhang et al., 2012), and site characterization (Ching and Wang, 2016).

2.1 Bayes' rule

The probability distribution of parameters of interest, $\boldsymbol{\theta}$ given the observed data, $\mathbf{D}$ can be described as $p(\boldsymbol{\theta}|\mathbf{D})$. The probability distribution $p(\boldsymbol{\theta}|\mathbf{D})$ is known as posterior distribution of the parameters and can be calculated using Bayes' rule in Eq. (1).

$$p(\boldsymbol{\theta}|\mathbf{D}) = \frac{p(\boldsymbol{\theta})p(\mathbf{D}|\boldsymbol{\theta})}{p(\mathbf{D})} \tag{1}$$

Eq. (1) consists of three components for the calculation of posterior distribution of the parameter: (i) the prior distribution $p(\boldsymbol{\theta})$, which represents the knowledge of the parameters prior to the observation of data; (ii) the likelihood function $p(\mathbf{D}|\boldsymbol{\theta})$, which represents how likely the observed data are, given the parameters; and (iii) the model evidence $p(\mathbf{D})$, which is the normalizing constant for the posterior distribution in Eq. (1). The model evidence $p(\mathbf{D})$ can be calculated by integrating the likelihood function over all possible parameters as expressed in Eq. (2).

$$p(\mathbf{D}) = \int p(\boldsymbol{\theta})p(\mathbf{D}|\boldsymbol{\theta})d\boldsymbol{\theta} \tag{2}$$

Computing the integral in Eq. (2) can be difficult, therefore, sampling method such as Markov chain Monte Carlo (MCMC) can be employed to estimate the integral (Jin et al., 2018).

3 Markov chain Monte Carlo (MCMC) Simulation

MCMC simulation is a sampling method that generates a sequence of samples of a random variable (i.e. parameter of interest) by constructing a Markov chain with the target density of interest (i.e. the posterior distribution of the parameter) as the stationary distribution of the chain. MCMC simulation is employed as the sampling method for the Bayesian approach proposed in this study to produce accurate approximations of the posterior distribution of the parameters so that the statistics of the parameters such as mean, standard deviation, probability density function (PDF) and credible intervals can be obtained from the analysis. Wang and Cao (2013) stated that integrating MCMC simulation with the Bayesian approach can mitigate the difficulty in generating samples from complicated posterior distribution.

MCMC simulation has been applied successfully to geotechnical engineering, such as characterization of model uncertainty (Zhang et al., 2012), determination of site-specific soil-water characteristic curve (Wang et al., 2018), and characterization of Young's modulus of soil (Wang and Cao, 2013).

3.1 Metropolis-Hastings (MH) algorithm

The Metropolis-Hastings (MH) algorithm (Metropolis et al., 1953; Hastings, 1970) is adopted for the MCMC simulation that is used in this study. It is the most common

MCMC method used for sampling from a probability distribution that is difficult to sample from directly (Zuev and Katafygiotis, 2011). The steps for the MH algorithm are as follows:

1) Choose an arbitrary value as the initial state of the sample $\boldsymbol{\theta}^0$ at time step, $t = 0$.
2) Draw a candidate sample $\boldsymbol{\theta}^*$ from the proposal distribution q of the Markov chain based on the current state $\boldsymbol{\theta}^0$ (i.e. $q(\boldsymbol{\theta}^*|\boldsymbol{\theta}^0)$). The proposal distribution is set as a Gaussian distribution centered at $\boldsymbol{\theta}^0$.
3) Compute the acceptance probability, r:

$$r = min\left(\frac{p(\boldsymbol{\theta}^*)q(\boldsymbol{\theta}^0|\boldsymbol{\theta}^*)}{p(\boldsymbol{\theta}^0)q(\boldsymbol{\theta}^*|\boldsymbol{\theta}^0)}, 1\right) \tag{3}$$

4) Generate a random number u from a uniform distribution with the range of [0,1].
5) Accept or reject $\boldsymbol{\theta}^*$ by setting:

$$\boldsymbol{\theta}^1 = \begin{cases} \boldsymbol{\theta}^*, & if\ u < r \\ \boldsymbol{\theta}^0, & if\ u \geq r \end{cases} \tag{4}$$

6) Repeat steps 2 to 5 for $t = 1, 2, \ldots, n$ to obtain $\boldsymbol{\theta}^1$, $\boldsymbol{\theta}^2$, ..., $\boldsymbol{\theta}^n$ samples.

The Markov chain constructed will reach a stationary state when t is sufficiently large, with its stationary distribution converged to the posterior distribution in Eq. (1).

4 Proposed Bayesian Framework

4.1 Empirical jacking force model

In this study, a well-established empirical jacking force equation is used for constructing the probabilistic model that will be applied for Bayesian inference. Pellet-Beaucour and Kastner (2002) developed a jacking force model that considers arching effect from the surrounding ground, with the equation expressed as follows:

$$F = \mu L D_e \frac{\pi}{2}\left[\left(\sigma_{EV} + \frac{\gamma D_e}{2}\right) + K_2\left(\sigma_{EV} + \frac{\gamma D_e}{2}\right)\right] \tag{5}$$

where F is the total frictional jacking force; μ is the coefficient of soil-pipe friction; L is the pipe span; D_e is the outer pipe diameter; γ is soil unit weight; K_2 is the thrust coefficient of soil acting on the pipe; and σ_{EV} is the vertical soil stress at the pipe crown, which is further expressed as Eq. (6).

$$\sigma_{EV} = \frac{b\left(\gamma - \frac{2C}{b}\right)}{2K \tan\varphi}\left(1 - e^{-2K\frac{h}{b}\tan\varphi}\right) \tag{6}$$

where h is the soil cover from the ground level to the pipe crown; K is lateral earth pressure coefficient; C is soil cohesion; φ is soil internal friction angle; and b is the influencing soil width above the pipe, which is further expressed as Eq. (7).

$$b = D_e\left(1 + 2\tan\left[\frac{\pi}{4} - \frac{\varphi}{2}\right]\right) \tag{7}$$

4.2 Probabilistic model for Bayesian inference

Following Jin et al. (2018), a probabilistic predictive jacking force model can be developed as follows:

$$F(\boldsymbol{\theta}, \boldsymbol{\emptyset}) = \hat{f}(\boldsymbol{\theta}, \boldsymbol{\emptyset}) + \sigma\varepsilon \tag{8}$$

where $\hat{f}(\boldsymbol{\theta})$ is the deterministic model used for predicting jacking forces, which is taken as the Pellet-Beaucour and Kastner jacking force model as expressed in Eq. (5); $\boldsymbol{\theta}$ is the set of unknown soil parameters; $\boldsymbol{\emptyset}$ is the set of known parameters; σ is the standard deviation for the deterministic model; and ε is a random variable with zero mean and unit variance.

Eqs. (5), (6) and (7) show that the empirical model consists of known project-specific parameters $\boldsymbol{\emptyset} = \{L, D_e, \gamma, K_2, h, K\}$ and unknown soil parameters $\boldsymbol{\theta} = \{\mu, C, \varphi\}$. The unknown soil parameters $\boldsymbol{\theta}$ will be modelled as random variables and inferred using the proposed Bayesian approach. The estimates of the parameters from the inference will then be used to predict the frictional jacking forces for pipe-jacking projects in similar soil conditions.

5 Implementation Procedure

The implementation procedure for the proposed Bayesian framework is shown schematically in Fig. 1. In general, there are five steps in implementing the proposed approach. The steps are summarized as follows:

1) Obtain a set of measured jacking forces from the project site (i.e. observed data **D** to form the likelihood function $p(\mathbf{D}|\boldsymbol{\theta})$ of the model).
2) Obtain a set of prior knowledge on the unknown model parameters $\boldsymbol{\theta} = \{\mu, C, \varphi\}$ (i.e. the typical ranges of values used in the design that are available in published literature to form the prior distribution $p(\boldsymbol{\theta})$ of the model).
3) Run the MCMC simulation using MH algorithm as explained in Section 3.1 to generate large number of samples $\boldsymbol{\theta}$ to approximate the posterior distribution of $\boldsymbol{\theta}$ after observing the data (i.e. $p(\boldsymbol{\theta}|\mathbf{D})$).
4) Obtain the posterior statistics of $\boldsymbol{\theta}$, such as mean, standard deviation, PDF and credible intervals based on the large number of samples generated.

5) Predict the frictional jacking forces F using the estimates of parameters obtained from the simulation, as expressed in Eq. (8).

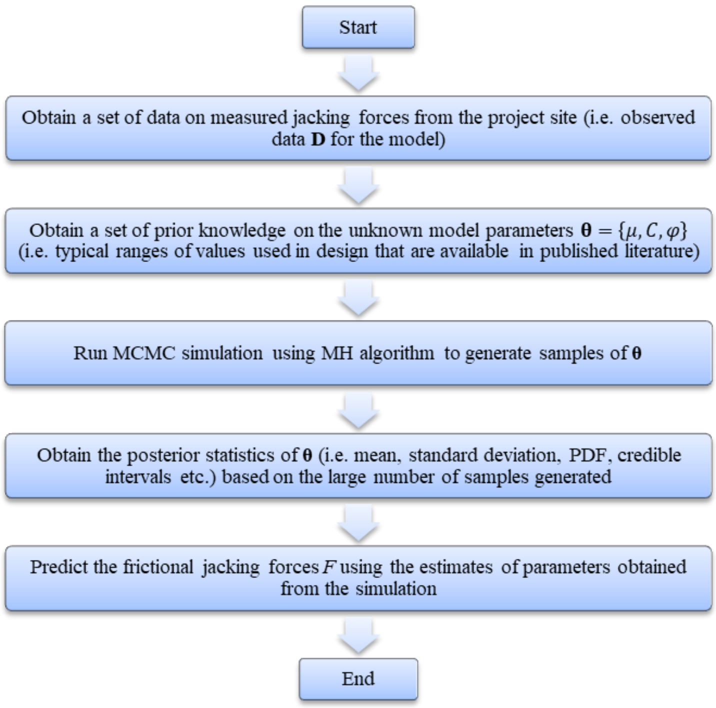

Fig. 1 Schematic flow chart for the implementation of the proposed Bayesian approach

By inferring the unknown soil parameters using Bayesian approach, the uncertainty that is inherent in the soil properties can be reasonably quantified by expressing the estimates of the parameters as a range of plausible values using credible intervals.

6 Application to Case Study

The proposed Bayesian framework will be applied to a microtunneling project in Malaysia, whereby 7.7km of trunk sewer lines were constructed for the Kuching Wastewater Management System Phase 1 project by pipe-jacking method (Choo and Ong, 2017). It was also reported by Choo and Ong (2017) that 1.2 m and 1.5 m diameter reinforced concrete sewerage pipelines were installed at depths of up to 25 m from the existing ground level beneath the central business district of Kuching City, Malaysia, with the pipelines buried well within the upper carboniferous Tuang Formation. The Tuang Formation is characterized by highly fractured lithological units of phyllite, shale, metagraywacke and sandstone (Tan, 1993).

The extraction of intact rock cores for rock strength testing became a challenge due to the highly weathered and highly fractured geological formation (Choo and Ong, 2017; Ong and Choo, 2018). As rock strength testing is required for measuring the in-situ rock strength parameters that are crucial for the assessment of jacking forces, an alternative method is necessary to obtain the rock parameters so that the jacking forces can be estimated reasonably for the project in the future. Therefore, the proposed Bayesian approach will be used to infer the rock parameters $\boldsymbol{\theta} = \{\mu, C, \varphi\}$ by using the site record of measured jacking forces that is available. Then, the jacking forces can be predicted using the parameters estimated for future phases of the project.

7 Conclusions

A Bayesian framework has been proposed to predict the frictional jacking forces for microtunneling works in highly weathered and highly fractured geological formations. This is due to the challenges faced in extracting intact rock cores in such geological setting for rock strength tests that are necessary for the assessment of jacking forces based on the in-situ rock properties.

The published literature mentioned in Sections 2 and 3 have shown that there are many successful applications of Bayesian method and MCMC simulation in geotechnical engineering. This shows that the proposed Bayesian framework integrated with MCMC simulation using MH algorithm is a feasible approach in inferring unknown soil/rock parameters that will be useful for the prediction of jacking forces in similar geology in the future. By using Bayesian approach, the inherent variability in soil parameters can be quantified reasonably using credible intervals, implying a range of plausible values for the parameters of interest with certain confidence level.

The framework will be applied to a microtunneling project in Malaysia to infer in-situ rock parameters by using the site data available and to predict the jacking forces for the future phases of the project subsequently. The application of the proposed framework will be part of the future work for this study.

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