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TECHNOLOGICAL ADVANCEMENTS IN THE RISK MITIGATION OF UNCERTAIN GROUND CONDITIONSINSINGAPORE METRO PROJECTS

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Singapore is rapidly expanding its urban metro network, which involves underground construction. The deep excavation and tunnelling works bring constructionrisks due to uncertain ground conditions and dense urban surroundings. The Land Transport Authority, as the governmental body overseeing these works, thus seeks to improve construction risk identification and mitigation through research and development. This paper provides an overview of two recent projects where technological advancements have enhanced risk managementin the mitigation of ground condition uncertainties: (1) machine learning to enhance ground profile predictions, and (2) geophysical look-ahead system to detect obstacles in tunnel boring machine (TBM) drives.

Keywords: underground construction; tunnelling; ground investigation; machine learning; geophysics; seismic detection.

1.Introduction

The Land Transport Authority (LTA) is the governmental agency responsible for overseeing Singapore's Mass Rapid Transit (MRT) development. LTA is currently driving the expansion of the MRT network, from 200 km in 2024 to a target of 360 km by the 2030s. These projects, including the most recent 50km long fully underground Cross Island Line, involve significant risks due to deep excavation and tunnelling (Eskesen et al. 2004).

To avoid adverse impact to construction safety and the surrounding urban environment, it is thus essential for appropriate measures to be taken to identify and mitigate risks in these major civil engineering projects. Traditional methods include careful impact assessment and extensive instrumentation and monitoring during construction.

Recent technological advancements have provided opportunities to further enhance risk mitigation measures, aiding in the prevention of negative impacts to cost, time, and safety. LTA has been actively developing its risk management capabilities through research into these new technologies. This paper presents an overview of two promising initiatives in this field.

2. Project 1: Machine Learning To Enhance Ground Profile Interpretation

2.1.*Rationale*

Accurate ground condition determination is crucial for undergroundconstruction projects. Soil properties consequentlyimpact geotechnical requirements of earth retaining and stabilization structures (ERSS), deep foundations, and tunnelling works. Site investigation (SI) is thus essential for establishing ground conditions, but it is restricted to discrete locations and usually constrained by programme, budget and access limitations.

To develop an interpretative continuous ground profile for design, additional methods are thus necessary. Currently, methods to generate this continuous ground profile involve two main families: interpolation and machine learning (ML) algorithms.

2.2. *Results*

This project developed a novel Multi-scale Meta-learning Method (M^3) for predicting geological interfaces from existing borehole data (Fig.1). The M^3 framework puts together three main aspects.

(i) Different location-specific predictions are first generated from up to 15 existing interpolation/regression techniques across three families: Kriging, Multivariate Adaptive Regression Spline (MARS), and Radial Basis Function (RBF).

(ii) A stacked ensemble learning framework integrates the different predictions. Generally, this involves using a further method, or “meta-learner”, to learn from the outputs of the individual models, or “base learners”.

(iii) ML algorithms act as the meta-learner. These algorithms correlate the location-specific predictions as inputs to give an overall prediction as the output.

Hence, compared to traditional methods, the M^3framework is different as both interpolation and ML methods are used. This may generate better predictions since the ML algorithm can learn from the range of interpolation predictions to give a best overall prediction.

For validation, the model was used to predict rock head levels using data from 1512 boreholes in Singapore's Bukit Timah Granite Formation. The dataset was split into training (70%) and testing (30%) groups, with performance quantified using the coefficient of determination (r^2) and root-mean-squared error (RMSE).

Fig.2 shows the results of the M^3 model using Random Forest (RF) as the ML algorithm. The M^3 model produced more accurate results than the 15 individual regression predictions, with higher r^2 and lower RMSE values. This is because the individual learners use different regression techniques that givevarying resultsfor different input scenarios. Comparatively, the M^3 framework can intelligently learn from the range of results from all the individual models to derive the overall prediction with the least errors. Similar learning may be achieved in Bayesian Model Averaging and Conventional Stacking Ensemble Learning, which thus also see lower errors compared to the individual learners. This performance enhancement is not observed in simple averaging, which does not possess the ability to optimize the contribution weightages of the individual learners to the final output. Additional studies ondifferences among aggregation techniques andmachine learning algorithm types were conducted but are not further elaborated in this paper.

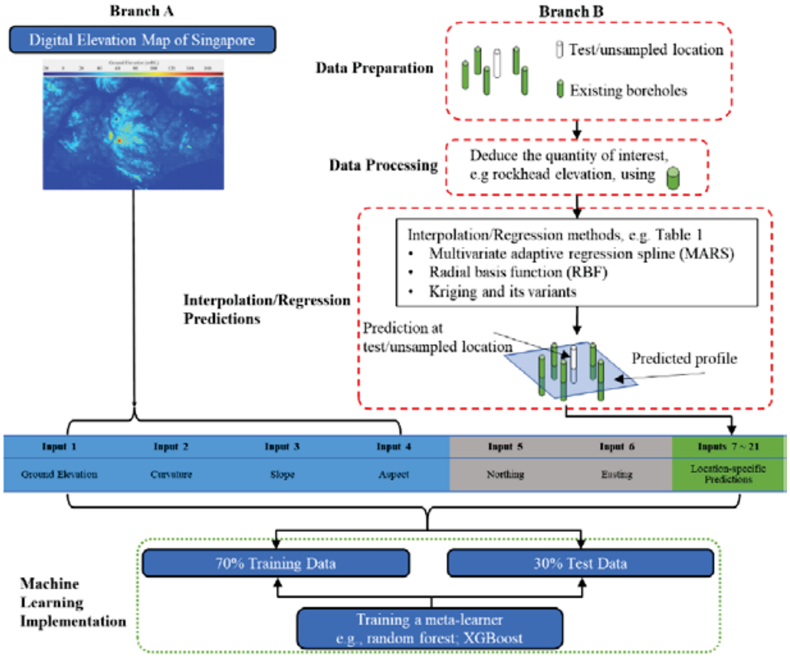

Fig. 1.Schematic overview of the M^3 methodology process (taken from Goh et al. 2024).

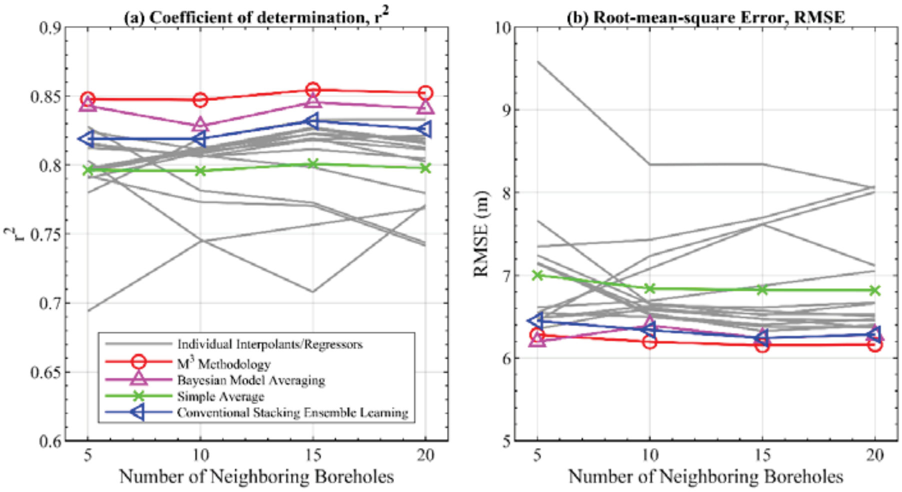

Fig. 2.Coefficient of determination and root-mean-squared-error of predictions using various methodologies (taken from Goh et al. 2024).

Overall, the novel M^3 model demonstrates noticeable improvements in ground profile interpretation, particularly in determining rock head levels. These enhancements are likely to bolster risk management in LTA's MRT projects by providing a better understanding of ground conditions to be encountered during construction. Additionally, the method can aid in identifying optimal locations for additional site investigation, such as in areas with highly spatially variable predictions.

3. Project 2: Geophysical Look Ahead System In Tunnelling

3.1.*Rationale*

Due to land scarcity, most new MRT lines in Singapore are constructed underground. Tunnelling through varied soil and rock layers in a dense urban environment necessitates the use of tunnel boring machines (TBMs). TBM operation carries significant risks dependent on ground conditions. Abandoned piles may obstruct tunnelling and damage equipment, while mixed face or fractured rock conditions lead to challenging face stability and seepage control. Therefore, forward detection of oncoming obstacles is crucial for effective risk management in TBM tunnelling.

3.2. *Results*

This project developed a tunnel look-ahead system which uses seismic waves to detect ground conditions up to 40m ahead of the TBM, with ±2m accuracy. The method utilizes the generation and detection of Rayleigh seismic waves and their reflections. Since interfaces between different materials cause wave reflections, obstacles can be identified through signal detection and analysis. Ground penetrating radar (GPR) and electrical resistivity tomography (ERT) methods were explored in this project, but seismic method was shown to outperform in detection range and accuracy.Seismic waves are generated in two modes:

(i) Passive mode: During TBM operation, from cutting action.
(ii) Active mode: During TBM downtime, by impacting a sledgehammer on the tunnel lining.

Field acquisition is done with 24 geophones attached to each side of the TBM (Fig.3). A semblance method is used for processing.Generally, geophone data is transformed from a time-geophone offsetdomain to time-slowness domainthrough scanning the data with a range of assumed wave velocities (as velocities vary depending on the ground material medium). Signal peaks across the geophones correlating to the velocities would indicate the detection of a wave or its reflections from obstacles ahead.

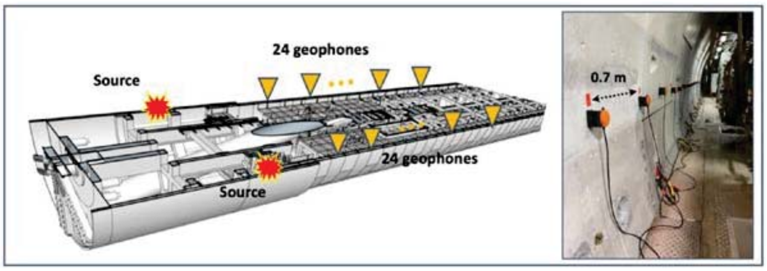

Fig. 3.Schematic overview of geophone and active source (sledgehammer) layout (taken from Chian et al. 2024).

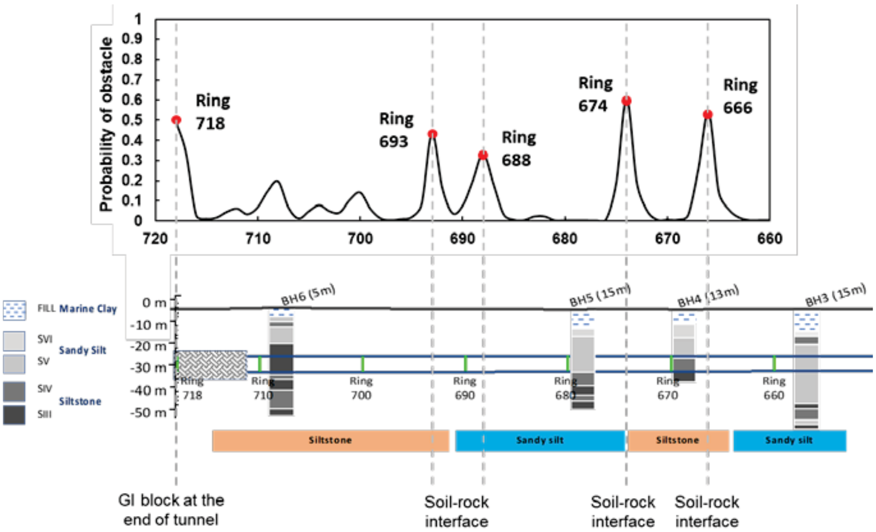

Fig. 4.Seismic predictions plotted with soil investigation data from selected LTA tunnelling project (adapted from Chian etal. 2024).

Table 1. Analysis corresponding to the five probability peaks identified by seismic detection technology (taken from Chian et al.2024).

Reflection Ring	Validation
666	Supported by sudden decline of muck density data and borehole information.
674	Supported by sudden surge of muck density data and borehole information.
688	Supported by sudden decline of muck density data and borehole information.
693	Supported by sudden surge of muck density data and borehole information.
718	Location of final ring.

To further enhance predictive capabilities and reduce false alarms caused by noise or detection errors, a novel probabilistic approach was implemented. Multiple readings during TBM advance are combined using Bayesian inference to produce overall obstacle encounter probabilities. Reflections detected consistently at given locations would raise the probability of an obstacle.

This approach was tested in an Earth Pressure Balance TBM of an ongoing LTA tunnelling project in Singapore's Jurong Formation of various weathering grades. Prediction validation was conducted using TBM operation parameters (Penetration Index = Torque / Average Penetration), muck density, and SI borehole data as ground truth.

Fig.4 shows results from a selected stretch. Elevated obstacle encounter probabilities are identified in five ring locations. These peaks likely correspond to changes in soil conditions from soil to rock and vice versa at the TBM excavation face. Table 1 corroborates these findings with changes in muck density and ground changes from SI boreholes. With a better understanding of the location of ground condition interfaces which may lead to more challenging face stability control or abnormal cutter head wear, appropriate measures can be taken, such as timely cutter head replacement or more stringent monitoring levels.

Overall, this project demonstrated an enhanced approach to forward detection in TBM operation, combining seismic wave signal processing with Bayesian inference for probabilistic prediction. A better understanding of tunnelling conditions may then inform TBM operating decisions to mitigate unknown risks.

4. Conclusion

This paper presented two LTA initiatives to improve underground metro line construction in Singapore:

(i) Machine learning for enhanced ground profile predictions: A novel M^3 methodology, incorporating multiple regression models with machine learning algorithms via stacked ensemble learning, demonstrated improved prediction accuracy.

(ii) Geophysical look-ahead system: Combining seismic wave analysis within a probabilistic framework using Bayesian inference allowed for the accurate quantification of the likelihood of obstacles ahead of TBMs during operation.

Both initiatives provide examples of how technology may be leveraged to establish an understanding of the ground profile more accurately and quickly, with lower operational requirements unlike traditional methods of additional ground investigation. These aregreatly valuable forSingapore's metro projects. Thus,LTA continues to explore cutting-edge technologies to drive further innovative improvements to its civil construction works.

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