

INTRODUCTION

Geological modeling is a vital step in tunneling projects that improves the understanding of the geological settings and structure, leading to a more efficient design, construction process, and management of tunneling projects [1]–[4]. Three-dimensional visualization tools have become a favorable means because of the intuitive experience it creates for owners, engineers, construction managers, and contractors [5]. In most tunneling projects, underground uncertainty is a major factor in cost and time over run of the project.

To address this issue, Random Forest (RF) and Neural Network (NN) techniques are used to predict lithology of ground associated with a section of the Hudson Tunnel Project [3]. Data sources for developing the model include 65 excavated boreholes along the proposed tunnel path. Lithology of the ground along these boreholes and three-dimensional associated coordinates are input features used for developing these models. Also, a software called Decision Aids for Tunneling (DAT) is utilized to investigate effect of uncertainties and risk events on time and cost of the Hudson tunnel project.

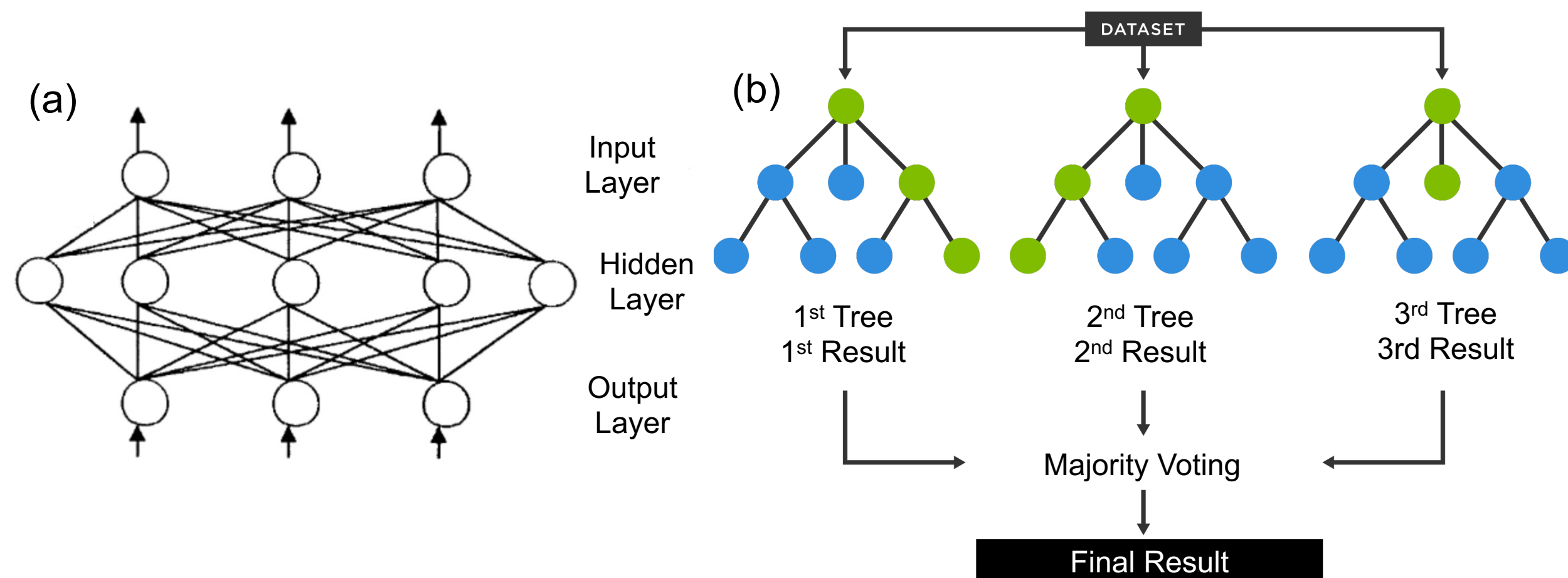


Fig. 1: Schematic view of a (a) Neural Network [6], (b) Random Forest [7]

Decision Aid for Tunneling

The DAT consist of four modules: the Geology Module, Construction Module, Resource Module and Updating Module. In the Geology Module, the user defines geology and its uncertainties. The geological information and related probabilities are obtained through a combination of objective information and subjective estimates by engineers [6, 7] who provide geological profiles, which relate the geological conditions along the tunnel profile to tunneling methods. The construction process can be described in as much

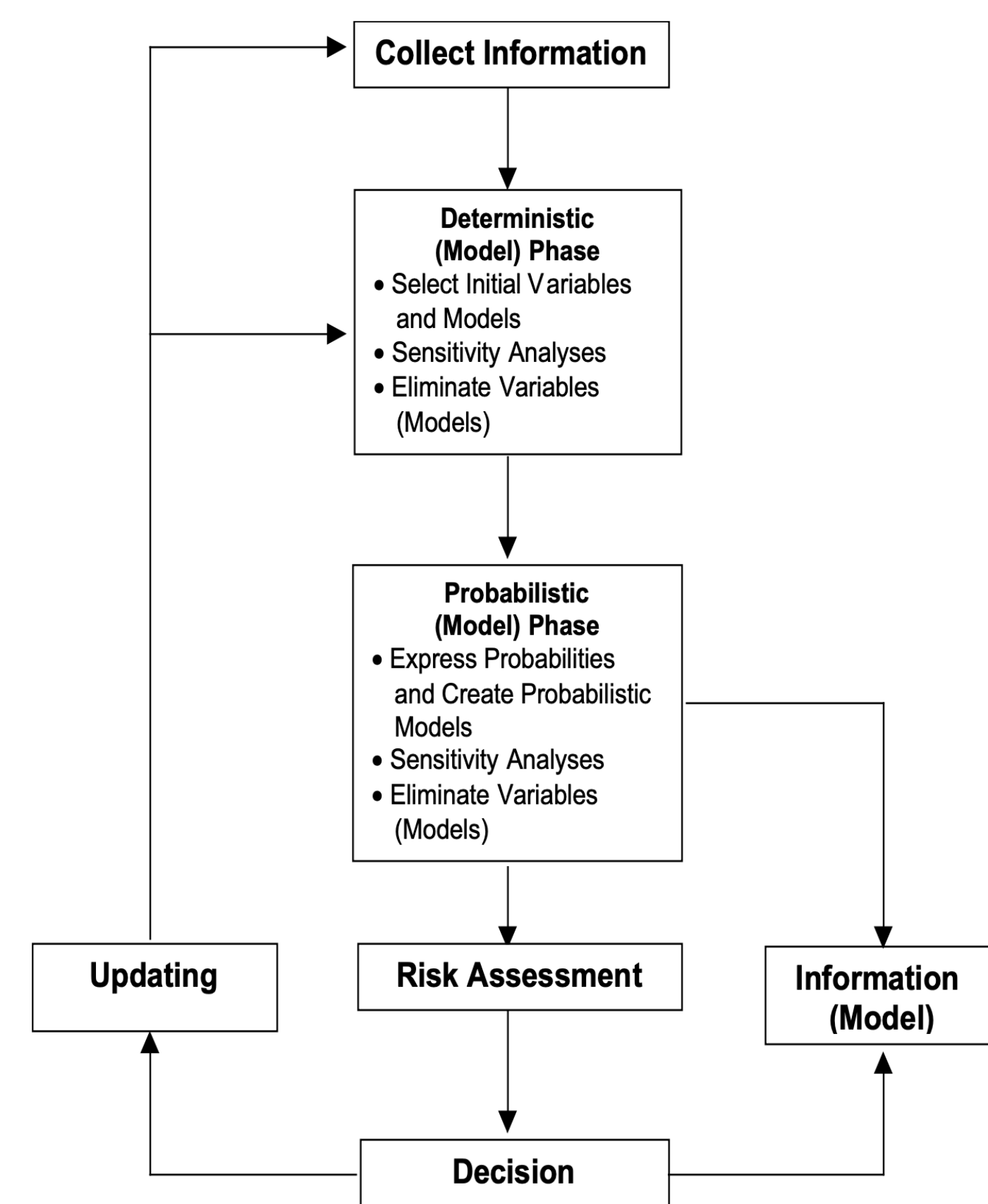


Fig. 2: Decision cycle - basis for the DAT algorithm [8]

detail as desired, ranging from simple to advance rates and costs per unit length for each construction method. The Resource Module is the third component of the DAT and allows one to consider the scheduling and assessment of resources required in tunnel construction. The fourth DAT module allows one to update the cost, time and resource estimates [8].

RESULTS

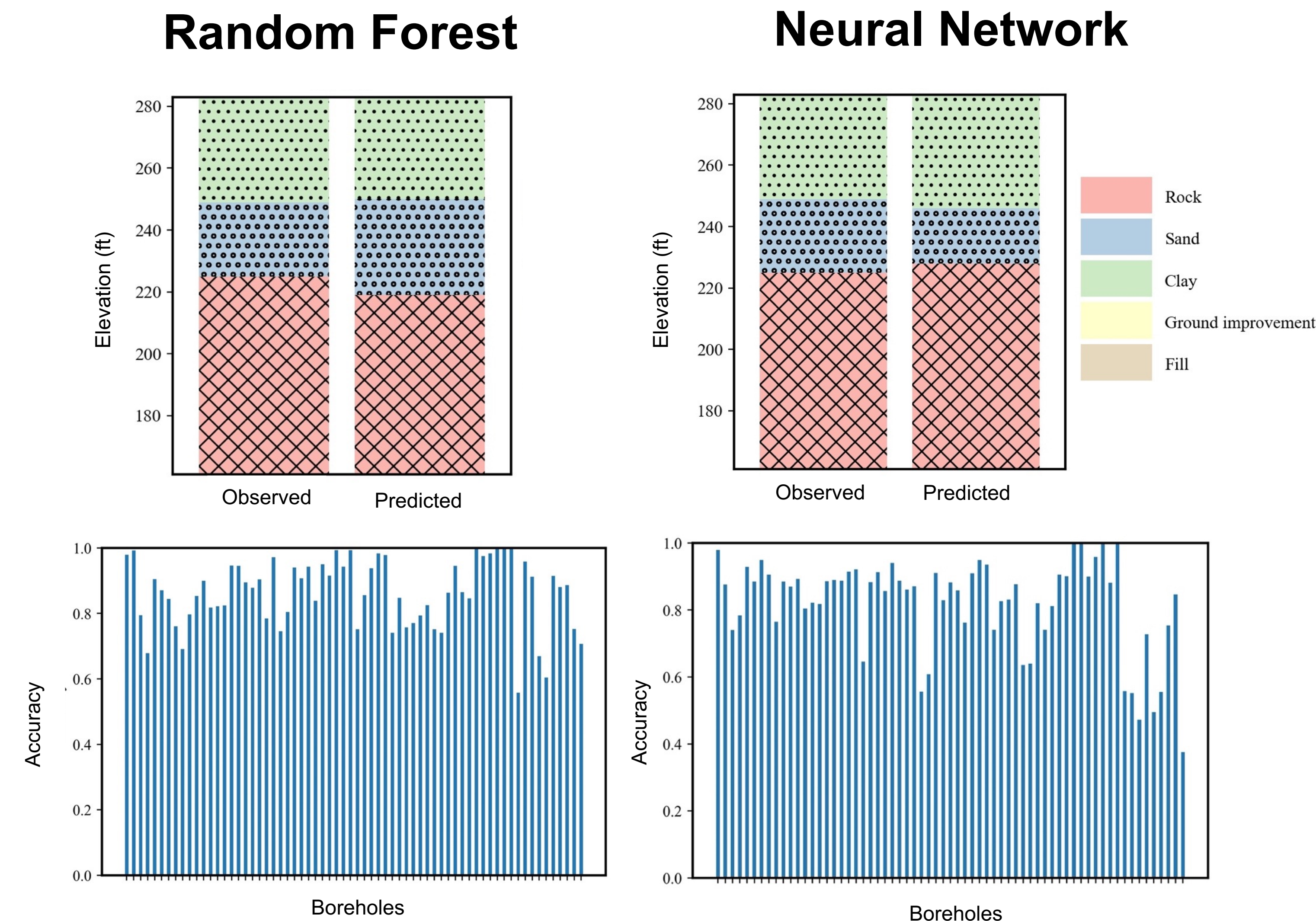


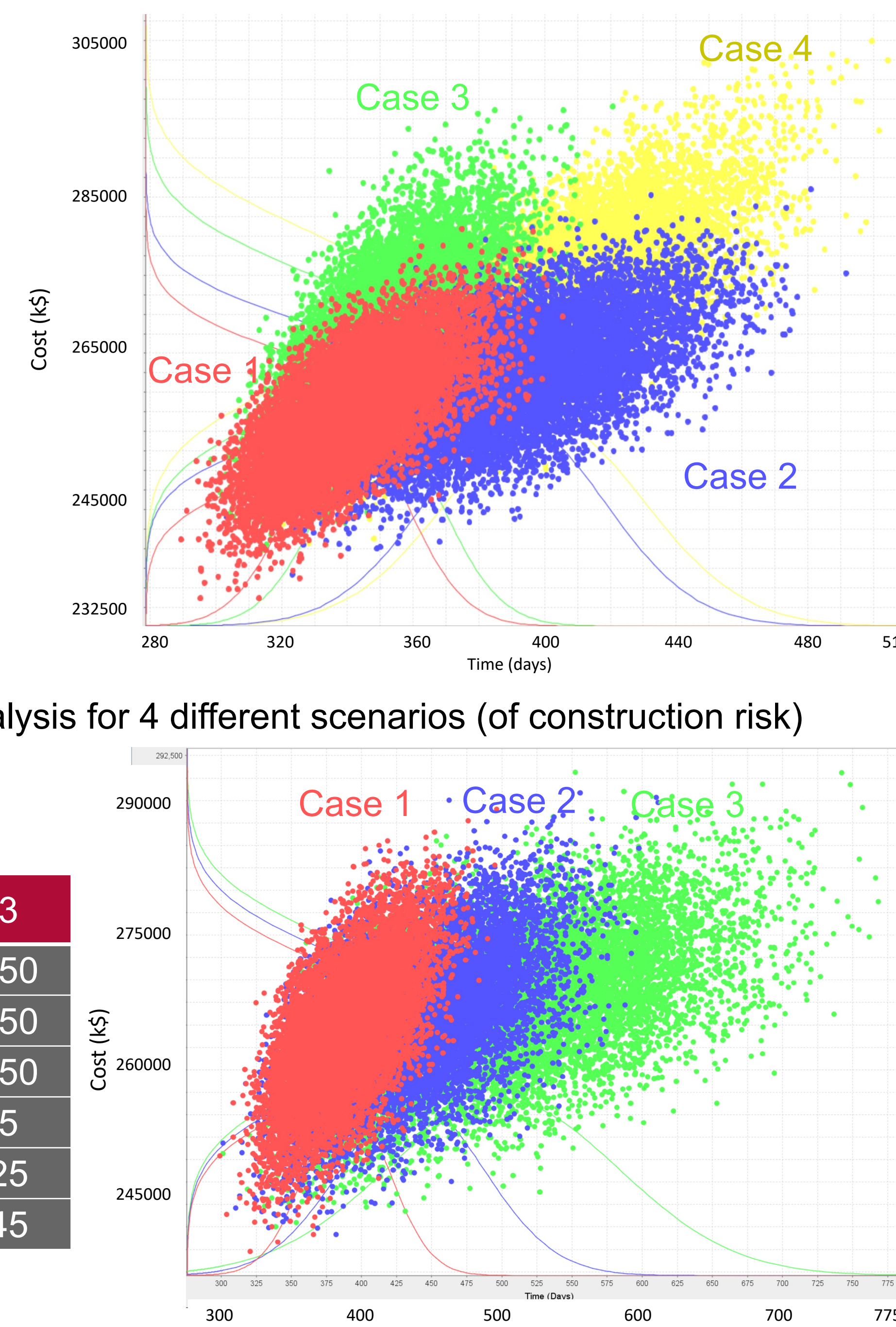
Fig. 1: Performance of Random Forest and Neural Network Model in geological prediction

Case	Methods
1	Without water inflow
2	Method change (major water inflow)
3	Increase cost but decrease advance rate (nuisance water inflow)
4	Combined (2+3)

Fig. 2: Result of time and cost analysis for 4 different scenarios (of construction risk)

Case	1	2	3
Additional cost (k\$)	Min	250	250
	Mode	340	450
	Max	460	650
Delay (day)	Min	5	5
	Mode	8	15
	Max	10	25

Fig. 3: Sensitivity of DAT prediction to cost and time estimation variability



DISCUSSION

Preliminary insights:

- By changing the data extraction intervals, the Neural Network model showed a slight increase in performance, however, its effect on the Random Forest model was negligible.
- Performance of the neural network model in the middle vertical section of each borehole was better than at the two vertical ends of the boreholes. The Random Forest model showed a uniform performance along the borehole height.
- A higher variability in additional cost and delay increase the variance of the assessed cost and time. Using equal minimum value for time and cost leads to having similar projected cost and time prediction (left edge in graph Figure 3).
- Four different scenarios of construction risk (water inflow) were utilized for time and cost analysis of the Hudson tunnel project. Large inflow has a greater effect on time of construction while nuisance seems to affect the overall cost of construction more.

FUTURE RESEARCH

Based on this study, AI models can be integrated into the DAT system to offer alternative geologic prediction methods. Since both of the proposed AI models provide probability of occurrence of each category of geology at any location, the certainty of occurrence of each of these categories at any location can be calculated. Using these certainty values, the optimal location of new boreholes can be found as the locations with highest uncertainty in prediction. Also, models that consider specific risk events affecting the tunneling process, such as water inflow can be developed on the same proposed framework. Using probabilistic prediction of these factors can provide a stochastic prediction of time and cost of tunneling projects. Furthermore, using this predicted parameters, cost and time analysis and tunneling construction management tools can be developed.

RELATED PUBLICATIONS

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