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Prediction of EPB tunnelling performance for various grounds in Korea using discrete event simulation

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Abstract. This study investigates Tunnel Boring Machine (TBM) performance prediction by employing discrete event simulation technique, which is a potential remedy highlighting its stochastic adaptability to the complex nature of TBM tunnelling activities. The new discrete event simulation model using AnyLogic software was developed and validated by comparing its results with actual performance data for Daegok–Sosa railway project that Earth Pressure Balance (EPB) TBM machine was used in Korea. The results showed the successful implementation of predicting TBM performance. However, it necessitates high-quality database establishment including geological formations, machine specifications, and operation settings. Additionally, this paper introduces a novel methodology for daily performance updates during construction, using automated data processing techniques. This approach enables daily updates and predictions for the ongoing projects, offering valuable insights for construction management. Overall, this study underlines the potential of discrete event simulation in predicting TBM performance, its applicability to other tunneling projects, and the importance of continual database expansion for future model enhancements.

Keywords: discrete event simulation; EPB; TBM

1. Introduction

Tunnel Boring Machine (TBM) tunnelling is widely recognized as an efficient method for underground construction in urban areas due to its numerous advantages in terms of safety, speed, quality, and environmental friendliness. In TBM tunnelling, the prediction of TBM performance at the construction site is ambiguous area with many unknown variables. As a rule of thumb, utilization factor (U) and rate of penetration (ROP) are used to predict TBM performance, which are influenced by unknown variables and unpredictable circumstances, including geological conditions, machine characteristics, and operational considerations. Some relationships of operational and geological data were recently analyzed by machine learning (Zhang *et al*. 2020, Kim *et al*. 2021, Mahmoodzadeh *et al.* 2022, Benemaran and Esmaeili-Falak 2023, Chen and Seo 2023, Esmaeili-Falak and Benemaran 2023, Fereidooni and Karimi 2023, Mahmoodzadeh *et al*. 2023). However, the complex interdependencies among these variables and circumstances, along with unexpected downtime events, make performance evaluation challenging and often inaccurate.

Several performance prediction models were developed based on mostly empirical observations and experiences from completed tunnelling projects due to the complex interdependencies. The Colorado School of Mines (CSM) (Rostami and Ozdemir 1993) and the Norwegian University of Science and Technology (NTNU) (Bruland 1998) are the most widely recognized models for the prediction of TBM performance. The CSM model can be defined as a semi-theoretical model based on the Cerchar Abrasivity Index (CAI). The model calculates individual cutter forces using the laboratory index, and estimates the overall thrust, torque, and power requirements of the entire cutterhead together with penetration rate prediction. On the other hand, the NTNU model has a more practical background based on a large amount of field data from various case histories. Time and cost curves for various tunnelling operations were developed by collecting and analyzing a significant amount of data. However, the prediction results using either the utilization factor or the prediction models do not provide reliable references because the limited information is available considering unknown variables and unpredictable construction circumstances.

To address these complications, simulation techniques was introduced to reasonably estimate TBM performance (Rahm *et al.* 2012, Rahm *et al.* 2016, Frough *et al.* 2019, Khetwal *et al.* 2020, Khetwal 2021, Khetwal *et al.* 2021, Khetwal *et al.* 2022, Khetwal *et al.* 2023). A simulation is considered to be a very powerful tool for understanding the complexity of the design and operation of a TBM system. Considering a TBM as a tunnelling plant, the simulation methodology effectively mitigates the inherent limitations in conventional approaches, thus contributing to more

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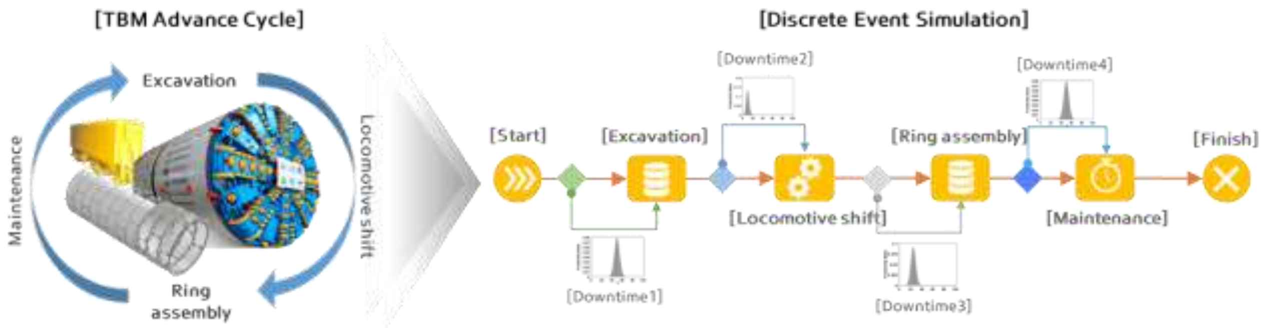


Fig. 1 Concept diagram of discrete event simulation in TBM tunnelling

accurate performance estimation. Simulating the TBM operation necessitates the integration of a vast database encompassing various tunnel- related activities and their interdependencies, incorporating unexpected downtimes. Rahm *et al.* (2012) simulated the process and logistics in Earth Pressure Balance (EPB) TBM tunnelling using hybrid approach: discrete event modelling for the process and system dynamics for the material flow using AnyLogic software. Rahm *et al.* (2016) analyzed the influence of downtimes in slurry TBM tunnelling and then evaluated the performance considering the downtimes. Frough *et al.* (2019) examined the discrete event simulation using Arena software in predicting the utilization for double shield TBM, and concluded that discrete event simulation is a promising method considering its accuracy but applicable for similar projects in terms of geology, TBM specification, site set up and components, logistics and experiences. Khetwal *et al.* (2020) investigated the impact on TBM performance regarding the specification of the TBM and system components using discrete event simulation approach. Khetwal *et al*. (2021) compared the discrete event simulation to various existing empirically-based models based on a statistical analysis of available TBM project database and suggested that the discrete event simulation model showed comparable results with actual site data. With those outcomes, Khetwal *et al*. (2022) developed and proposed a stochastic simulation model CSM2020 for utilization prediction and Khetwal *et al.* (2023) combined the CSM 2020 with Decision Aid in Tunnelling (DAT), which is a decision-making process regarding the uncertainties in project aspects proposed by Einstein (1996), for estimating the completion time for TBM tunnels. Their works suggested that the discrete event simulation is a relevant means for predicting TBM performance in terms of applicability and accuracy. However, the model still has limitations that the prediction results depend on available database, necessitating to build as much localized and detailed information as possible

In this study, a database was developed considering EPB TBM tunnelling in Korea to generate probability distributions for various activities as input for the simulation model through geologic units including mixed face, hard rock, and soft soil sections. Based on that, tunnelling activities were simulated in detailed manner using discrete event model approach and the completion period was predicted. The prediction results were compared to actual data to see their applicability. Furthermore, the TBM performance prediction for on-going project using daily updated database was introduced.

2. Discrete event simulation

The discrete event simulation is defined as a method that can simulate events occurring in sequences making it possible to include the influence of one event on other events as shown in Fig. 1. The major advantage of this approach is its capability to represent a variety of events or processes and their complexities and interdependencies, and therefore discrete event simulation approach is well fit for TBM tunnelling considering stochastic nature of tunnelling activities. The various TBM construction activities including excavation, locomotive shift, and segment ring assembly, are allocated in the simulation model. In this study, the discrete event simulation model of EPB tunnelling was developed using AnyLogic simulation software, a commercial simulation program supporting three simulation methods: discrete event, agent-based, and system dynamics. Each of these methods offers varying levels of abstraction. In this study, the discrete event approach was chosen to utilize data of independent continuous events observed at the site.

3. Database establishment

3.1 Project overview

To develop and evaluate the effectiveness of simulation model, the database from Daegok–Sosa TBM tunnel project was used. The Daegok–Sosa project in Korea spans a total length of 3,049 meters, connecting the Sosa–Wonsi railway to the western coastline. It comprises two distinct sections: New Austrian Tunnelling Method (NATM) section covering 290 meters and TBM section spanning 2,702 meters as seen in Fig. 2. Additionally, the tunnel includes five cross passages and two ventilation shafts to ensure safety of passengers and efficient operation. The TBM section's excavation commenced at Shaft #2, located south of the Han River, and extended to Shaft #1, positioned north of the Han River. The excavation process involved the use of two

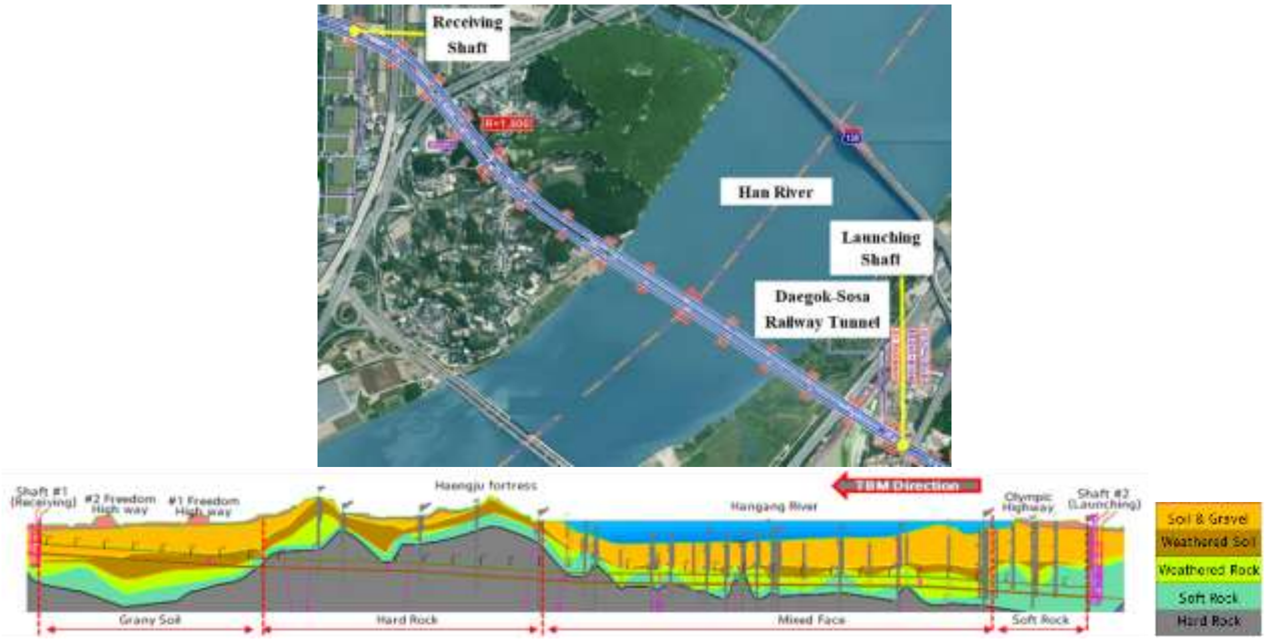


Fig. 2 Plain view and profile of Daegok-Sosa railway tunnel

EPB TBMs, resulting in a double-line parallel tunnel configuration. The design of EPB TBM machine was meticulously planned to accommodate various geological conditions, encompassing soft rock, mixed ground, hard rock, and sand ground. A significant geological challenge was encountered in the 1.2-kilometer-long section beneath the Han River, where mixed ground conditions prevailed. The site investigation revealed a diverse composition of geological formations, including Loose Sand, Silty Sand, Gravel, Weathered Soil, Weathered Rock, Soft Rock, and Hard Rock. The types of rock encountered were primarily Granite and Gneiss, exhibiting varying degrees of weathering. Both gneiss and granite are highly abrasive, with 4–6 Cerchar abrasivity index (CAI) values. As the tunnel undercrossed the river, it transitioned into full face hard rock sections, followed by a mix of soil with sandy gravel (Shin 2022). Table 1 lists the engineering parameters of the rock mass.

The application of EPB TBM in the project was decided after a thorough assessment of site constraints, water pressure, and geological conditions. The presence of high-water pressure and mixed ground along the tunnel alignment raised concerns about the feasibility of using EPB TBM. Nevertheless, due to land acquisition challenges during the detailed design stage, a decision was made to utilize the EPB type machine manufactured by Herrenknecht. To address the specific geological complexities and ensure successful tunnelling, several technical measures were introduced, supporting the suitability of the chosen TBM (Shin 2021). Table 2 and Fig. 3 provides detailed specifications of the EPB TBM machine. The cutter head of the machine is dressed with disc cutters and cutter bits, strategically arranged at suitable intervals, mostly 90 mm. This arrangement considers the mixed composition of soil and rock sections encountered along the excavation.

Table 1 Engineering parameters for rock mass.

Parameter	Specification
Rock type	Gneiss/granite
Unit weight	26–27 kN/m3
UCS	30–140 MPa
RQD	60–100%
RMR	30–85%
P-wave	750–2000 m/sec
Quartz	30–40%
Permeability	8.1 x 10-7–9.7 x 10-8 m/s

Table 2 Specification of TBM.

Item	Specification
TBM Type	EPB
Cutting diameter	8.1m
Opening ratio	31%
Cutter	Disc Cutter 50pcs Scarper 106pcs Bucket 56pcs
Torque	7,510 kN·m
RPM	0~3.7
Thrust force	66,523 kN(350bar)
Power	2,080 kW(13x160 kW)

3.2 Actual performance

The tunnelling process for the railway tunnel took a total of 710 days, approximately 24 months, commencing from the launching shaft on June 16, 2019 and concluding at the sheet pile of the receiving shaft on May 25, 2021. Throughout the construction period, the advance rate of the TBM was closely monitored and recorded, resulting in an

Fig. 3 Earth Pressure Balance Tunnel Boring Machine (EPB TBM).

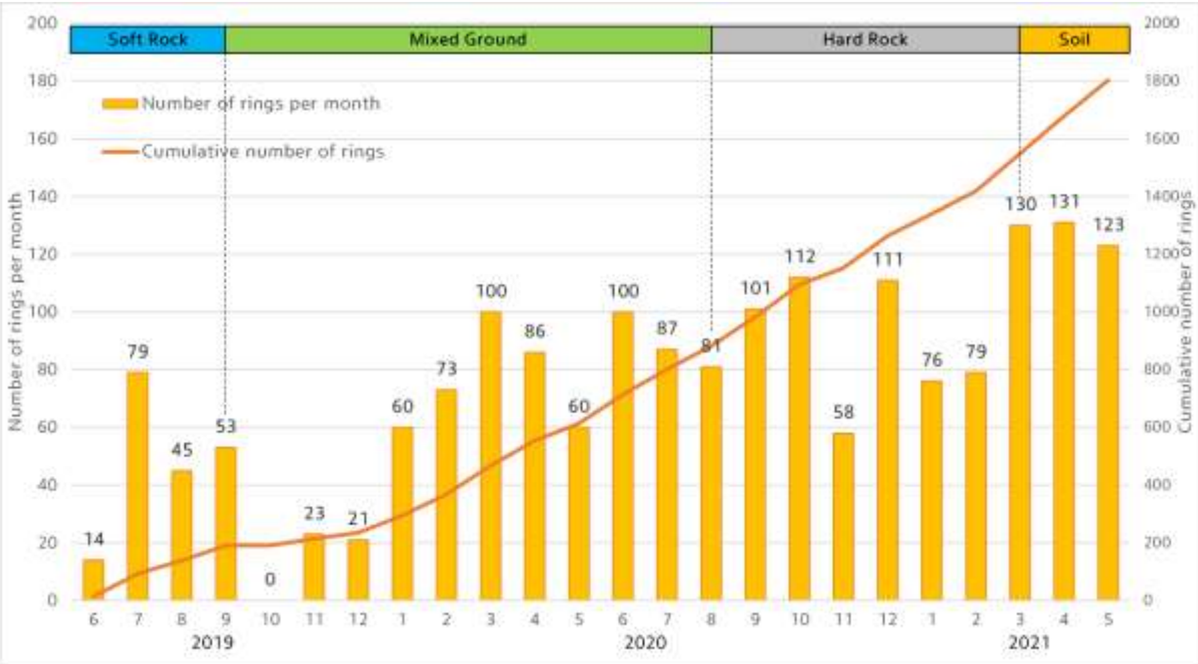


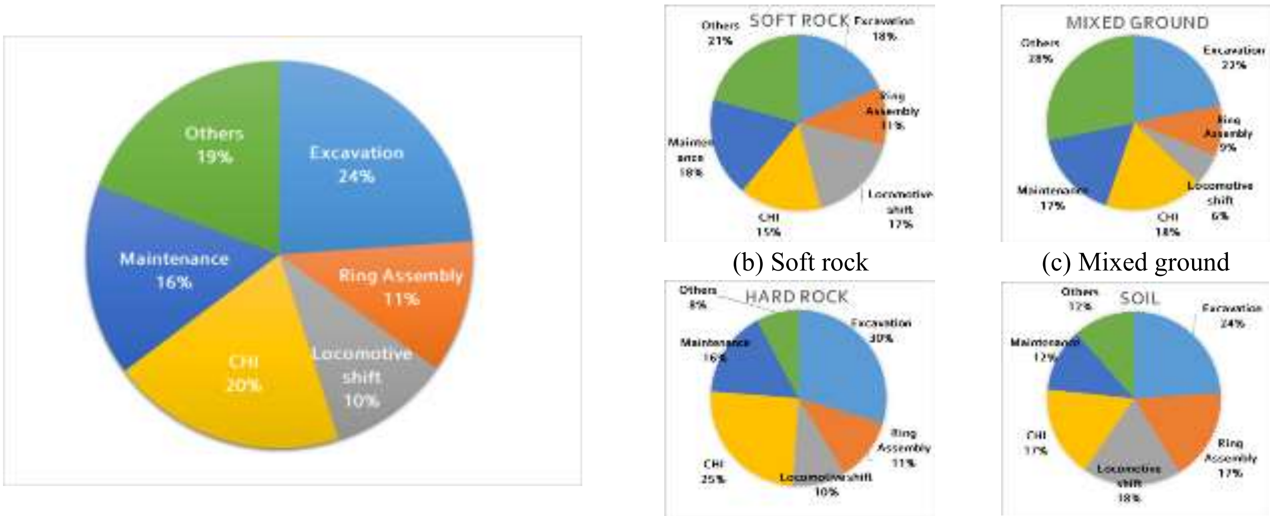
Fig. 4 Monthly progress of tunnelling

Table 3 Average performance by tunnelling section

Section	Length (m)	Period (month)	Advance rate (m/month)
Soft rock	270	3.2	83.7
Mixed ground	965	10.7	89.8
Hard rock	918	7.0	131.6
Soil	549	2.7	201.0
Total	2,702	23.7	114.1

average rate of 114.1 meters per month as summarized in Table 3. The monthly excavation performance, as depicted in Fig. 4, illustrates the progress made during each month. Initially, the advance rate was relatively low, reflecting the challenges faced at the beginning of the project including learning curve. However, as the TBM encountered hard rock and soil sections, the productivity gradually improved, and therefore the advance rate of tunnel improved. As a matter of course, the mixed ground with high water pressure under the Han River proved to be problematic. This section caused various troubles, including clogging, wear of augers in screw conveyor, and the need for ground improvement. These complications led to a decrease in TBM performance in the mixed ground section.

To better understand the performance of the project, the 24-hour shift report for TBM operation along the alignment was compiled and analyzed as cycle time in pie chart format as shown in Fig. 5. The “Advance” event took up 24% and “Ring Assembly and Locomotive Shifting” events accounted for 21%, so the work required for actual advance work took 45% in the project. It should be noted that the “Locomotive Shift” 10% was caused by logistics of locomotive and California switch, which was specific issue in this project such that it must be considered otherwise when applying to other projects. “Cutterhead Intervention (CHI)”, “Maintenance”, and “Others” events, namely downtimes, are rated at 55%. Here, "Maintenance" is a



(a) Whole section (b) Soft rock (c) Mixed ground (d) Hard rock (e) Soil

Fig. 5 Pie chart of cycle time.

preparation event for excavation work, including equipment checks and repairs (9.3%), pipe extensions (1.4%), and equipment cleaning (3.6%). “Others” event in the chart means unclassified downtimes including probe drilling, ground improvement, screw conveyor jamming, and muck car derailment. The cycle time analysis for each geological unit was also presented respectively in Fig. 5.

In the soft rock section, "Maintenance" was evaluated at a similar rate to "Excavation". This is because it reflects the initial excavation process and the process of dismantling the temporary segment lining and installing the rail branches. In the mixed ground section, the proportion of "Others" was the highest due to frequent problems such as cutterhead clogging and groundwater eruption. The excavation was relatively stable in the hard rock and soil sections. The portion of CHI was high due to disc cutter wear. In the soil section, the proportion of locomotive shifts is higher due to the increase in the distance traveled by the muck car as the TBM advances. The outcomes correspond to the performance in Table 3 and Fig. 4.

3.3 Tunnelling activities and probability distribution

Based on data in the pie chart, the tunnelling activities were categorized in five events: advance, ring assembly, locomotive shift, CHI, and maintenance and others. Each event had associated downtimes as shown in Table 4. The downtimes included extension of piping and cables, backfill system problems, muck out system (screw conveyor and belt conveyor) problems, supplementation of additives and hydraulic oil, delay in shifting of locomotive, and cleaning in the back- up system. For the described events and associated downtimes, the raw data was compiled and sorted out to generate stochastic probability distributions as input parameter in terms of frequency of occurrence and its duration. The advance, ring assembly, and locomotive shift are unconditionally occurring tasks with a probability of 1, and only the duration was applied as a probability distribution. For other activities, both the probability of occurrence and the probability of duration were applied because it is not certain whether it occurs during the 1-ring cycle. After extracting the occurrence interval of each activity, the probability of occurrence per ring was calculated and expressed as the frequency by probability distribution. Fig. 6 exhibits examples of probability distribution as best fitting curve. This data processing aimed to ensure that the discrete model accurately captured the probabilistic nature of the activities and their occurrences during the excavation process.

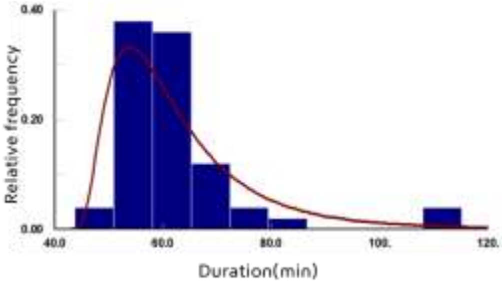
Table 4 Classification on EPB TBM activities

Event	Associated downtime	Detailed description of downtime
Advance	Inspection Muck out system trouble Safety set fault	Periodic & urgent Inspection, Broken, etc. Screw conveyor and belt fault
Ring assembly	Ring install system trouble Transfer system fault Soil cleaning	Erector and ring adjustor fault Feeder fault Soil cleaning
Locomotive shift	Machine trouble Working delay	Gantry crane fault Dumping and loading delay
CHI	Wear inspection Replacement	Measuring & logging Drainage & cutter replacement
Maintenance	Extension work Supplement Back fill system inspection	Rail, pie, fan tube and cable Additives and oils Hardware(Port, pipe) and software

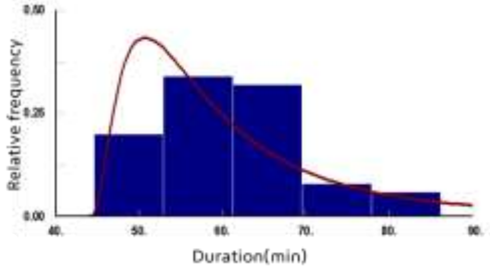
4. Model Implementation

4.1 Discrete event modeling

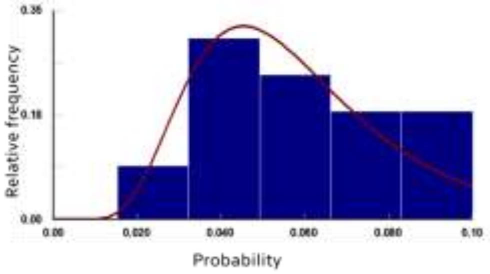
Using the tunnelling activities and their connections, a simulation model of the EPB TBM tunnelling was built with discrete event approach as shown in Fig. 7. The 1-ring tunnelling process was arranged in sequences: the first half



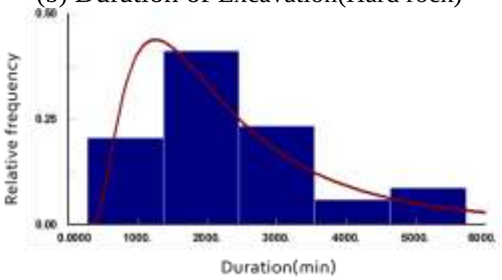
(a) Duration of Ring assembly(Hard rock)



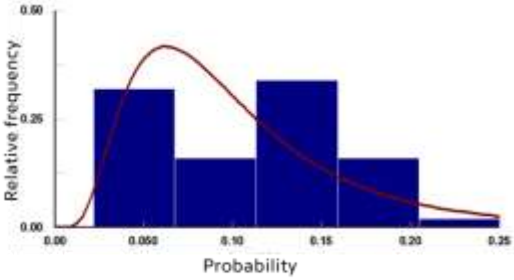
(b) Duration of Excavation(Hard rock)



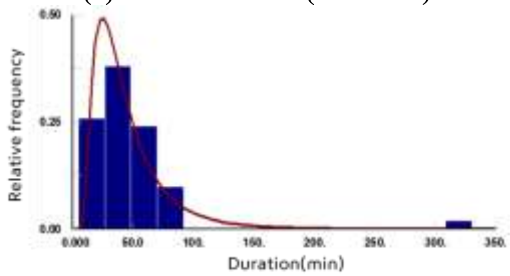
(c) Occurrence for CHI(Hard rock)



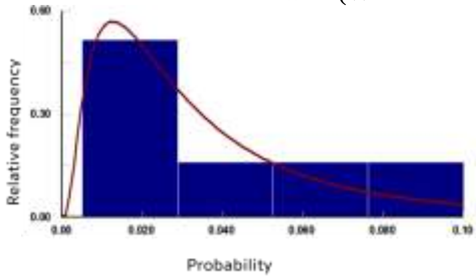
(d) Duration for CHI(Hard rock)



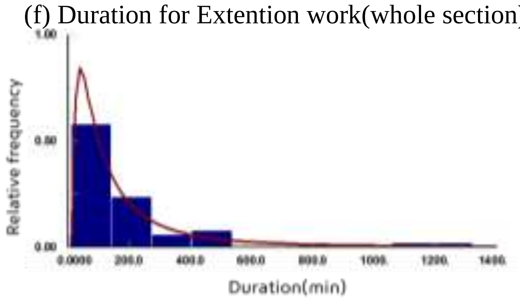
(e) Occurrence for Extention work(Whole section)



(f) Duration for Extention work(whole section)



(g) Occurrence for Backfill system inspection(Whole section)



(h) Duration for Backfill system inspection(Whole section)

Fig. 6 Probability distribution of activities

excavation, the first locomotive out, the second locomotive in, the second half excavation, the second locomotive out, ring assembly and the completion of a ring. Associated downtimes that may occur at each stage are added to complete the modelling. As categorized in Table 4, there is an associated downtime before and after each task corresponding to the event, and the downtime occurrence (rhombus) and duration (square) are determined by probability data.

4.2 Validation of simulation

The discrete event simulation model calculated the completion time for the Daegok–Sosa EPB TBM tunnel by aggregating the probabilistic distributions in database, subsequently comparing the simulation result with the actual construction period of the project for the validation purpose. Table 5 presents a comparison between the actual construction data and the simulation results. To increase reliability, the simulation results are based on the average of 10 runs. Overall, the total construction period exhibited a difference of only 1% between the model and the actual value, indicating the simulation's close approximation to the real-world scenario. However, in the categories of Downtime and CHI, differences of 8.1% and 13.9% were observed. These discrepancies are attributed to the occurrence of abnormal troubles during the excavation of mixed ground, which are challenging to predict accurately. Despite these variations in specific categories, the developed simulation model showed promising potential for performance prediction.

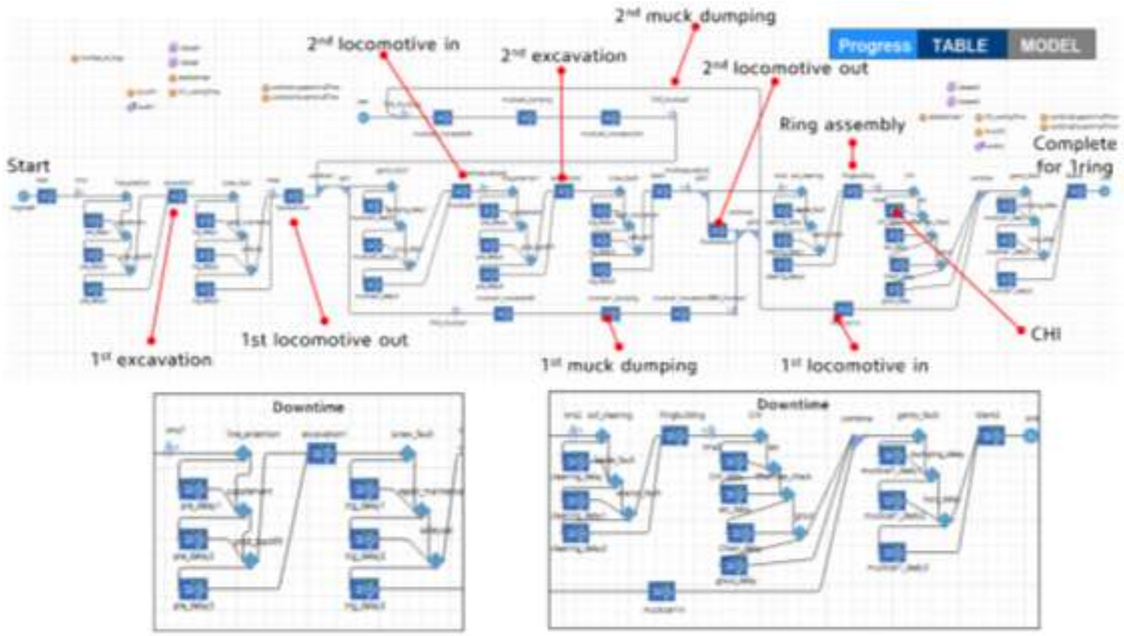


Fig. 7 Discrete Model for EPB TBM simulation

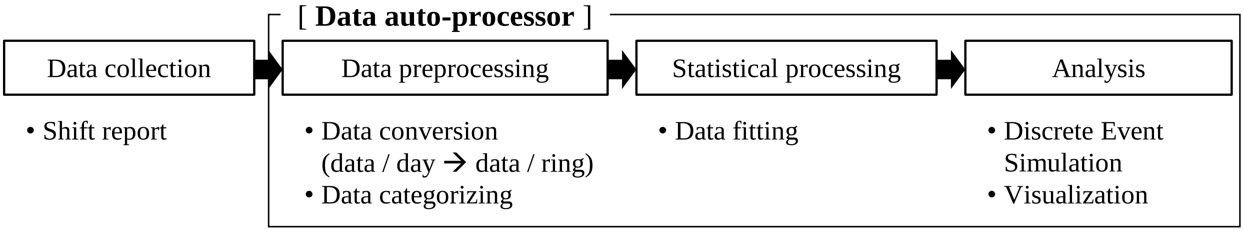


Fig. 8 The flowchart of data auto-processor

Table 5 Comparison between model and actual value

Category	Model value (days)	Actual value (days)	Difference (%)
Excavation	177.2	171.0	3.7
Ring Assembly	82.2	79.8	3.0
CHI	159.0	139.5	13.9
Locomotive shift	61.3	62.6	2.1
Downtime	223.6	243.3	8.1
Total(month)	23.4	23.2	1.0

5. Performance update during construction

5.1 Automation of data processing

To update the performance during construction, the data processing was automated by Python. The daily shift report can be processed and transmitted to the discrete event simulation as shown in Fig. 8. It makes the simulation more efficient and enables daily updated database, which was not previously available due to the manual management of massive amounts of data or partial automation (Khetwal, 2021).

Initially, the data auto-processor converts the daily-based event time data into ring-based data. Table 6 lists the categories of activities and the corresponding best-fitting probability distributions for the entire period of Daegok Sosa project. The event time data of “Advance” and “Ring Assembly” were distributed following a T distribution, and “CHI” data followed a Gamma distribution. A generalized extreme value distribution was adequate to describe the event time data of “Downtime Regular”, involving supplements and extension of pipes and cables, and “Locomotive shift” while the data categorized as “Downtime Others” was fitted by a Pareto distribution. “Downtime Fixed” was regarded as constant without undergoing statistical analysis, as these events occurred within a specific amount of time for the given project. As an example of analysis by data auto-processor, Fig. 9 illustrates how to monitor changes in the distribution of event time data. The data for 300 rings was analyzed to collect a sufficient amount of data for statistical analysis. Over the time, the average time for "Ring Assembly" and "Downtime_Regular", drawn by red dashed line in Fig. 9, decreases and eventually converges, predominantly influenced by the proficiency of workers. Conversely, the average time for "Locomotive shift" increases due to two factors: the elongation of the distance between the TBM and the muck disposal place as excavation progresses, and the increased muck volume resulting from excessive water inflow. In addition, the duration of "Advance" is contingent upon the strength of the rock mass.

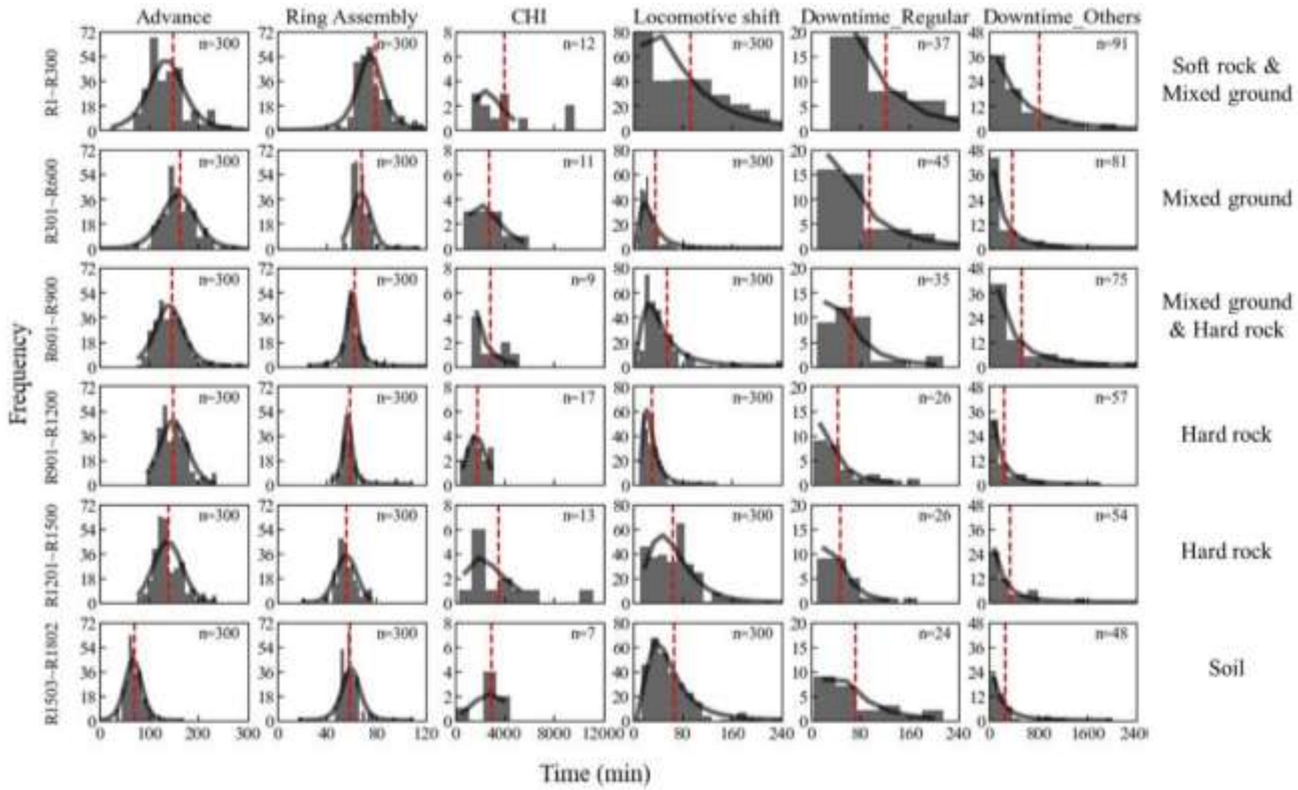


Fig. 9 The histogram of time spent for 300 rings

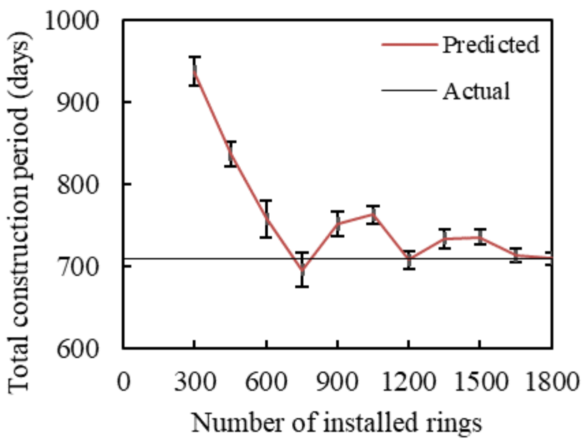


Fig. 10 The construction period predicted during operation

Table 6 Best-fitting probability distributions in data auto-processor

Category	Best-fitting probability distribution
Advance	T
Ring Assembly	T
CHI	Gamma
Locomotive shift	Generalized extreme value
Downtime_Regular	Generalized extreme value
Downtime_Fixed	Constant
Downtime_Others	Pareto

5.2 Prediction update during construction

The total construction period can be updated based on the data auto-processing of shift report. Specifically, during construction, the remaining time required to build the remaining rings can be predicted using the probability distribution derived from the daily-updated database. As an example, the total construction period can be estimated using the event time data of the most recent 300 rings built in the same section with the same TBM(Red line in Fig. 10). This prediction assumes that the type of best-fitting probability distribution identified in Table 6 remains consistent (refer to Fig. 9). The event time in “Downtime_Fixed” is simply added to the predicted construction period. According to Fig. 10, the total construction period is predicted with fair accuracy as tunnel progresses, and the relative error after the 600th ring reached less than 10% using only the data obtained from the current project. Hence, the simulation using daily-updated database can offer valuable insights for remaining construction period, risk management, therefore construction schedule management during construction.

6. Conclusions

In this study, the discrete event simulation was implemented based on an EPB TBM tunnel project in Korea. Data obtained from Daegok-Sosa project was used to generated relevant probability distributions for various tunnelling activities, which were used as input parameters for simulation modelling. A thorough comparison demonstrated a good correlation between the simulation results and the actual performance of TBM construction process. The results demonstrate the potential of predicting TBM performance based on high-quality input parameters. Furthermore, updating the performance prediction during construction was introduced. The key conclusions of this study are as follows:

- The discrete event simulation model serves as a valuable tool, offering a comprehensive and realistic means of assessing TBM performance. It accounts for the inherent uncertainties and interdependencies present in tunneling projects. It can provide insights for the project in advance and allow relevant measures for potential risks. Nevertheless, the model still has limitations as the prediction results rely on the accessible database reflecting ground conditions, operational settings, and tunnelling activities.
- By introducing automated data processing technique, the simulation can be updated on daily basis during construction. It can help better understanding for tunnelling progression throughout construction and therefore, allow engineers to make informed decisions in the construction management.
- For the future development of discrete event simulation for TBM, it is required to build extensive database spanning a diverse array of TBM projects and to establish efficient data management protocols. By doing so, the accuracy and applicability of simulation can be improved.

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