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AI-augmented project controls: Enhancing predictability in complex tunnel construction environments

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Abstract

Construction of tunnels is one of the most complicated and risky tasks of civil engineering, and it is not predictable due to uncertainties of geological conditions and logistical difficulties. It analyzes the need for more predictive and controllable tunnel projects using artificial intelligence (AI) in project management. The conventional venture control techniques were found lacking, as they are receptive and for the most part, utilize obsolete or siloed information. In any case, AI-controlled, extended control is based on aggressive decisions using real-time information, machine learning and careful analysis. Analyzing tunnel excavators (TBMS) and location sensors to analyze the sum of AI's vast data, designs can be observed and estimated before potential future problems become devastating. Teams can resolve issues before they stop and become expensive. Success Stories for Using AI Predict TBM Performance and Optimize Maintenance and Communication Between All Stakeholders Presented in the Form of Case Studies. In addition, real-time monitoring systems are used with artificial intelligence, which is equipped to analyze data obtained by sensors, monitor the operation, and continuously analyze sensor data to improve security by recognizing inconsistencies that an administrator might otherwise miss. In addition to simplifying activities, this method promotes data -based culture, allowing project managers to manage their resources more effectively and, to a certain extent, to predict risks. Ultimately, AI does not replace human operators; it transforms conventional project management into a more dynamic and responsive.

Keywords: Tunnel Construction; Artificial Intelligence; Machine Learning; Predictive Maintenance; Project Controls; Real-Time Monitoring

1. Introduction

1.1. The Complexity of Tunnel Construction Projects

Tunnel construction is one of the most complex and challenging works in civil engineering. These projects begin from significant underground courses underneath bustling cities up to long areas to pass through the mountains. They are uncommonly complex in organizing and execution, while grasping appropriate measures to oversee with unexpected circumstances. An area of civil building is basic to supply the much-needed transport, water supply, and communication system. Unlike surface construction, tunnel construction has constraints such as lack of accessibility through limited points, differences in ground conditions, and a higher risk of equipment malfunction because of harsh conditions underground.

The topography itself is one of the first complex issues. With the most advanced geological surveys, you can only predict so much as to what's below ground. Construction groups can tunnel through insecure shake courses of action,

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groundwater entrances, or unexpectedly troublesome shake zones. Not only are these surprises safety risks, but they can stop the work cold or require massive redesign after it is already underway.

Then there's the machinery. Operate continuously under extreme conditions, such as tunnel boring machines (TBMs), several meters in diameter and hundreds of tons in weight. Project victory depends on their execution, but their administration could be a science in itself. Disruption to a TBM's performance can cascade into a project delay.

Apart from the topography and machinery, calculated imperatives also complicate tunnel construction. The tunnels are confined, and personnel and materials cannot move freely; thus, complex scheduling and coordination are needed to deliver resources on time. Add stringent health, safety, and environmental regulations, and it becomes apparent why tunnel projects are so demanding to manage.

Given the range of factors at work, tunnel construction may be a high-stakes operation with consistency uncommon and ever so profitable. In the tough environment, enhanced project controls – including those fostered with artificial intelligence (AI) – are becoming game changers.

1.2. The Need for Enhanced Predictability and Control

With such stakes in tunnel construction, predictability isn't an extravagance but a need. In any of these projects, delays or cost overruns, which can span several years and bills, can be a disaster. Tunneling environments involve complex and ever-changing environments, and traditional project management methods find it challenging to catch up. In an unpredictable context, having enhanced project controls is essential to ensure that projects stay on track.

The main point is that it all boils down to foreseeing the disruptions in advance before they occur. It may foresee TBM lull due to overheating or shake collapse due to extend plans identified in genuine time. The conventional venture control frameworks tend to depend on intermittent detailing and post hoc examination, and in this way, by the time the nature of the issue is analyzed, it is tossed into a few harms.

In expansion, a few partners as a rule embrace burrow development, counting engineers, geologists, extend supervisors, temporary workers, and administrative bodies. It is a logistical challenge to coordinate all these groups. Better project controls simplify communication so that the right information is sent to the right people at the right time. Here, you need to make the actual time choice, especially for tunnel projects where soil conditions or equipment conditions change rapidly. Moreover, technical predictability is no different from financial predictability. Many tunnel projects are hampered by overriding costs caused by delays and changes in the plans themselves. Project managers can apply better forecasting tools and scenario analysis to allocate budgets more accurately while also finding out financial risks at the early stage.

Thus, well-known traditional "reactive" approaches to expand management are insensitive to these complex tunnel environments. We require a proactive approach, showing a data-organic demeanor and proactively expecting change rather than responding to change. Here, Ai augmented Project Controls helps to provide a more intelligent approach to dealing with unknown.

1.3. Role of AI in Transforming Construction Management

In tunnel construction, where there are few or no guarantees of how a tunnel will go, AI is a powerful toolkit that allows us to increase efficiency, safety, and predictability.

Whatever AI contributes to tunnel construction, its contribution to prediction is the most impactful. Given that daily TBMs, sensors, and site activity generate vast amounts of data, AI systems can discover patterns and correlations on things that would be impossible for humans to find while performing manual investigations. Through these insights, teams of projects can anticipate the specter of malfunctions in machines, geological surprises, and any other problems before they proliferate.

From globalization to support, workers, and deviations in requirements and joint fees, it creates an ideal storm that increases development costs from both offers and requests. It's no longer about replacing human intelligence with machines; it's about improving it. In particular, a subset of AI, machine learning models, is good at making these predictions. For example, they can extrapolate wear and tear of wearing parts (e.g., cutter heads) from TBM historical performance data and predict machine overheating during operating conditions. Predictive insights allow maintenance to be planned ahead of time instead of playing a game of 'firefighter' reacting only after an unexpected breakdown, which can be costly, running to millions.

AI also helps in dynamic simulations to schedule its projects. AI schedules differ from the static, predetermined schedules formed at the beginning of the project, as they change throughout the project based on new data coming in. This makes all the difference in tunneling, where a slight deviation from progress can set all your planning astray.

The second transformational aspect of AI comes from its use in decision-making. With AI-powered Dashboards & decision support systems, project managers can see real-time insights on their KPIs, risk forecasts, and scenario building. By doing this, their decision-making ability is elevated, which is very important when working underground, where changes can happen quickly.

2. Project Controls in Tunnel Construction

2.1. Definition and Scope of Project Controls

Systems, processes, and practices are known as project controls used for planning, monitoring, and managing the performance of a construction project. Project controls promote the work to run optimally, timeously, reasonably, and according to a project objective. Tunnel construction can be biased and have very high risk coupled with dramatic shifts in conditions. Thus, robust project control mechanisms are essential to the overall success of a project.

Project controls are encompassing. It comprises cost management, schedule planning, risk identification, change management, progress tracking, and reporting. They make up a picture of how a project performs at any time. Imagine it would be the control tower in an airport—or rather, managing the traffic flow of flights, spotting possible disruptions, and ensuring that the operations are still running as intended. Project Controls also synchronize and direct (right) a tunnel construction project in moving all its parts with control.

In tunnel projects, this scope extends into highly specialized areas like equipment monitoring, geological forecasting, ventilation planning, and compliance with environmental regulations. Project controls include TBM performance metrics, ground settlement data, and shift scheduling. All of these must be combined into a single framework, which involves using technology, experience, and strategic foresight.

In addition, the project controls serve as the communication backbone of the project. It lets them create an issue, a change, or learn performance trends in a structured way. Well configured, they provide transparency and accountability and keep all the parties, engineers, investors, etc., on the same page.

2.2. Traditional Methods and Their Limitations

Conventional project control methods for tunnel construction have included manual reporting, static Gantt charts, and post facto performance reviews for decades. These approaches have been successfully used to deliver many tunnels worldwide, and while they are no longer being phased out, they are quickly being outpaced by the complexities of today's infrastructure programs. In the cyber world, we seek traditional methods and cannot understand the software's behavior in real-time and adapt to it, which is necessary for today's projects.

One major limitation is their reactive nature. Traditional controls usually identify problems only after they've occurred. A delay in excavation, for instance, may only be flagged in a weekly meeting or once the timeline is skewed. By then, the domino effect of that delay—impacting subsequent work phases, labor allocation, and equipment logistics—may already be in motion.

The second drawback is that data is treated in a siloed manner. On the other hand, it is common to have information about a particular project in different formats in different departments, such as engineering, procurement, and operations, which makes it hard to see the project's health in a unified view. This slowness in the process results in slow decision-making and leaves blind spots, especially in tunnel environments where coordinated and quick decisions are required.

Accuracy is another concern. Humans can manually enter and interpret data, which has an error rate. Poor decisions and expensive setbacks are possible because of misreporting of equipment performance or underestimated geological risks. In addition, static tools such as spreadsheets and standalone scheduling tools have very low scalability. Since the size and complexity of the tunnel projects are growing, these tools have difficulty dealing with the volume of data and dynamic variables involved.

Also, traditional methods do not have predictive power. They are expert at telling history but not the future. Project managers must depend on experience and intuition because they usually have no forecasts or risk simulations, which can be helpful but do not suffice when the high stakes and timelines are tight.

2.3. Impact of Delays and Cost Overruns in Tunneling

Delays and cost overruns are the most dreaded outcomes in tunnel construction. They don't just strain budgets—they can derail entire projects, damage reputations, and trigger legal or contractual consequences. In complex tunneling environments, the consequences of poor project control are magnified, making the stakes exceptionally high.

One of the biggest issues is the cascading nature of delays. A seemingly minor hold-up in rock excavation can cause a domino effect, delaying the installation of support structures, electrical systems, and waterproofing. Since tunnel work is linear—one section must be completed before the next begins—every delay pushes the entire schedule further out. In urban environments, this can disrupt traffic systems, delay transit expansions, or halt connecting infrastructure projects, creating a ripple effect across a city's development timeline.

Cost overruns are just as devastating. The tunneling projects start with a multi-billion-dollar budget; even a small percentage of enormity leads to enormous financial losses. These overruns often result from unforeseen geological conditions, equipment breakdowns, labor inefficiencies, and design changes, all improving with better foresight and control.

Nor can the effects of human impact be ignored. Inevitably, any extended timelines raise the pressure on the workers and the management and increase the risk of burnout and accidents. Speaking too are reputational costs; contractors who continually underestimate the time and resources they need to conduct a job risk losing future jobs and funding.

In practice, delay costs public agencies, contractors, and private investors from the stakeholder perspective due to loss of trust and tension between them. However, public infrastructure projects, in particular, are very political. One of the biggest foes for anyone is that if a project is not delivered on time and budget, this can have a huge backlash.

3. Machine Learning in Tunnel Boring Machine Operations

3.1. Predicting TBM Performance and Anomalies

Tunnel Boring Machines (TBM) are used to perform rock-tunneling excavation by mechanical means. A TBM's main bearing is the colossal machine's mechanical core. It enables the cutter head to be turned and transmits the machine's torque to the terrain. At all times, it is critical to keep the bearing properly lubricated, often to the tune of 5000 liters of oil. One of the ways to monitor TBM performance is to analyze the physical and chemical properties of the lubricant oil at regular intervals. This is where machine learning (ML) truly earns its stripes.

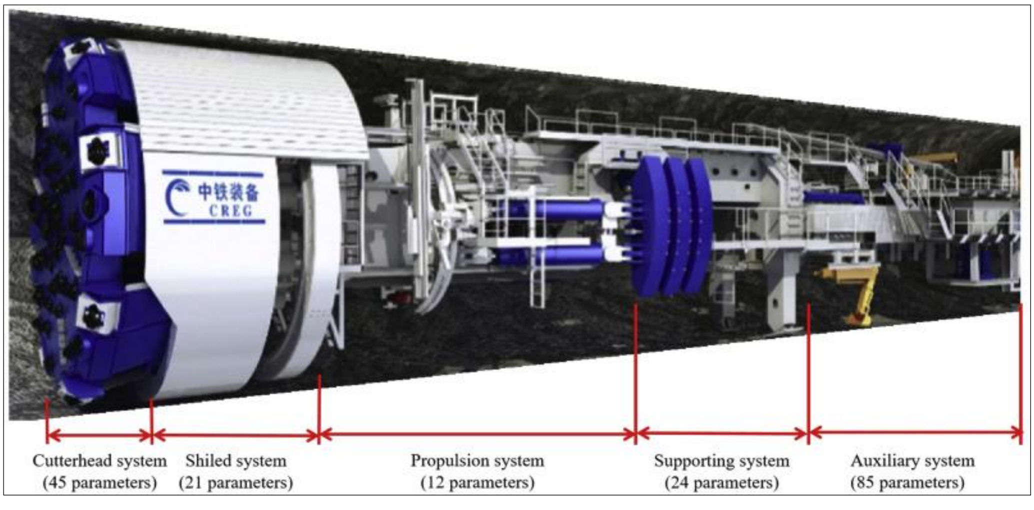

Figure 1 (A) Tunnel Boring Machine

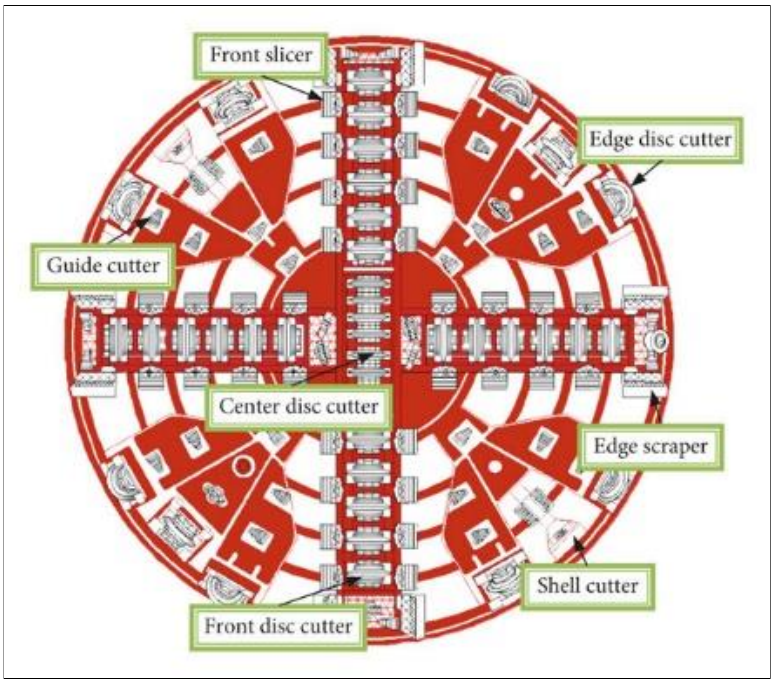

Figure 1 (B) Overview of the Cutterhead

ML provides a way to predict how TBMs behave based on past and real-time data. Sensors embedded in the TBM continuously feed temperature, torque, rotation speed, penetration rate, pressure, and more data. When processed using ML algorithms, this firehose of data turns into actionable insights. The model can learn from previous tunneling conditions and performance to recognize normal operating ranges and flag anomalies when deviations occur.

For example, if a TBM starts to drill slower than usual while maintaining the same torque and pressure, the ML model might predict that a mechanical part—like a cutter head or thrust system—is starting to fail. These predictions allow maintenance teams to intervene early, preventing full-scale breakdowns that could halt a project for days or weeks.

In addition to mechanical predictions, ML also helps forecast interactions between the TBM and the geology ahead. Based on the power draw or vibrations of its cutterhead, it could guess when it was transitioning from soft soil to hard rock and give crews a chance to set adjustments or swap other tools. That level of foresight is extremely valuable for keeping downtime to a minimum and equipment from damage.

This provides the operational paradigm with a shift from reactive to proactive. Instead of responding to failures, teams prevent them. Instead of adjusting after inefficiencies show up, they optimize performance in advance. With ML in the driver's seat, TBM operations become smarter, safer, and significantly more cost-effective.

3.2. Case Study 1: Predicting Oil Temperature Anomalies in Tunnel Boring Machine (TBM)

One very interesting real-world use case event was that of Guillem Ràfales from SENER. Founded in 1956 in Spain, SENER is a multi-national private engineering and technology group active in diverse industrial activities such as construction, energy, environment, aerospace, infrastructure and transport, renewables, power, oil & gas, and marine.

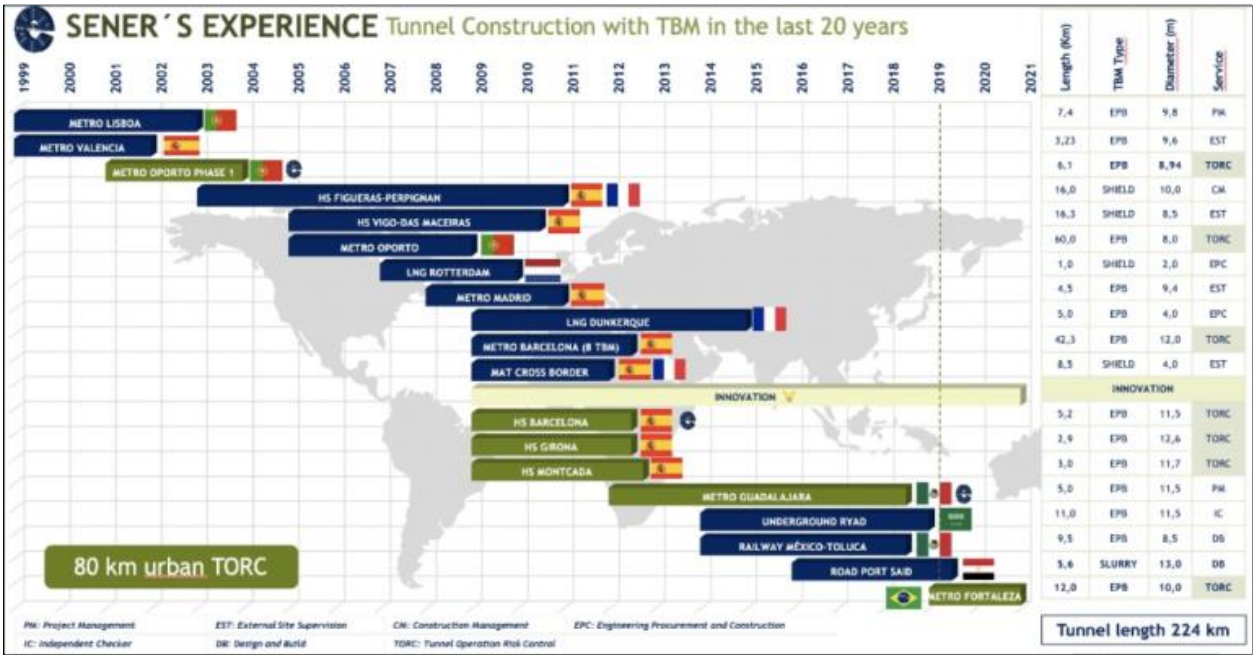

Figure 2 SENER's Tunnel Construction Projects

Under its construction activities, SENER has completed 19 large-scale tunnel boring projects amounting to 80 kilometers of urban tunnels and a total of 224 kilometers of tunnels in the last 20 years. A great example is the high-speed railway service project in Barcelona. SENER delivered the 5.25 km segment near Gaudi's architectural masterpiece Basílica de la Sagrada Família, a UNESCO World Heritage site.

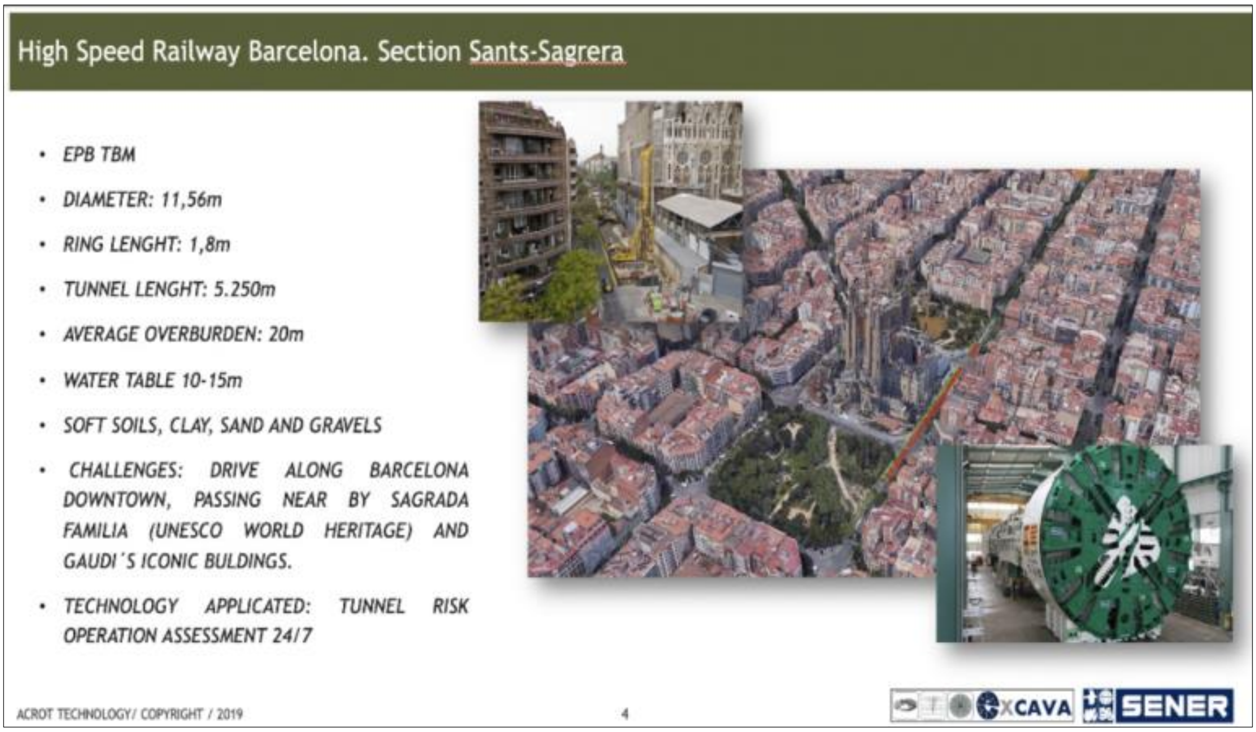

Figure 3 SENER's project in Barcelona, Spain

In this instance, machine learning was used to analyze oil temperature data in the hydraulic systems of a TBM to detect early signs of mechanical failure. What they found was eye-opening.

The TBM in question was used in a big tunneling project where downtime was very expensive—the cost of not using the machine (longer downtime due to lack of spare parts, etc.) was about thousands per hour of machine unavailability. The team used historical data regarding these oil variables, such as temperature, pressure, and flow rates. By feeding this information into a supervised ML model, they aimed to predict when anomalies might signal deeper mechanical issues.

The model uncovered a subtle but significant correlation: oil temperature spikes, especially in specific operational conditions (like high torque or low penetration rates), tended to precede mechanical failures by several days. Traditional monitoring systems had missed these warning signs because the individual values stayed within “acceptable” thresholds. But the ML model looked deeper—at combinations of data points and their patterns over time.

With these insights, project managers could take early action. On occasion, the team could schedule maintenance or replace parts before a breakdown would occur. The result? Fewer unplanned stops, better TBM health, and a smoother overall project timeline.

3.3. Case study 2: Italian tunnels

Data for TBM performance analysis have been obtained from two tunnels (Maen, Pieve) excavated in metamorphic rocks in the Italian Alps. The combined tunnel length is approximately 11.5 km, while data records exist for the 8.5 km. In the Maen tunnel, the recordings were made at a 5 m interval, whereas at the Pieve tunnel, data relating to the geotechnical conditions was gathered daily. Details on the specific tunnel projects and the TBMs used are given in Table 1, while in Table 2, data relating to the characteristics of the geological formations encountered is presented.

Regarding the lithological types (categorical target variables) that were introduced in the ANN, for each tunnel, each one of them corresponded to an input neuron using the “one-of-c” coding principle. That means coding c binary target variables (0 or 1) corresponds to the c categories. These new variables are also known as “dummy” variables. The zero value is assigned to each one, except for the one corresponding to the correct category, which is given the value one. Thus, only the neuron corresponding to the actual encountered lithological type for the given data array is activated each time. The “One-of-c” coding used for the lithologies in the Maen tunnel case is shown in Table 3. According to the above, for the Maen tunnel, there were eight input neurons (6 for the lithological types), while for the Pieve tunnel, the number of input neurons was 7 (5 for the lithological types).

Table 1 Construction data for the tunnels under investigation

	Maen	**Pieve**
Surveyed section length (m)	1750	6400
Total excavation time (days)	413	809
Excavated diameter (m)	4.20	4.05
Tunnel slope (°)	24–35	≈0
TBM model	Wirth 340/420 E	Robbins 1111-234/3
TBM type	Open	Double shield
Number of cutters	36	27
Cutter diameter (in)	17’’	17’’
Maximum trust (kN)	7920	4602
Boring stroke (m)	1.5	0.63
Cutterhead rotation rate (rpm)	5.5–11	11.3

Table 2 Main characteristics of the geological formations

Tunnel	Rock type	UCS (MPa)	Tensile strength (MPa)	Mean Mohs' hardness	Knoop hardness (GPa)	Cutter Life Index	Young's modulus (GPa)
Maen	Serpentinite	124	—	3.6	—	30–70	—
	Metabasite	180	15	6.2	6.2	10–20	65
	Chlorite schist	17	—	2.8	—	60–90	—
	Metagabbro	138	10–12	6	5.1	15–25	39
	Calc schist	75	—	3.6	—	30–70	—
Pieve	Micaschist	124–	5–9	4.1	5.2–8.5	15–70	28
		215					
	Metadiorite	171–	8–13	5.1	6.2–7.0	15–40	46–
		221					100
	Meta	160–	—	6.4	—	15	—
	quartzdiorite	210					
	Metagranite	146–	0.7–7	6.6	7–10	10	24–38
		296					

Table 3 "One-of-c" coding used for the lithologies in the Maen tunnel case

Maen	SP	Serpentinite	1	0	0	0	0	0
	CHLSC	Chlorite schist	0	1	0	0	0	0
	TALC	Talc schist	0	0	1	0	0	0
	CLS	Calc schist	0	0	0	1	0	0
	MBAS	Metabasite	0	0	0	0	1	0
	MG	Metagabbro	0	0	0	0	0	1

The datasets from these two tunnels have been discerned into three subsets using a uniform sampling process: the training, the testing, and the validation.

From the 330 datasets for the Maen case and the 301 datasets available in the Pieve tunnel, about 60% was used for training. In contrast, the testing and validation subsets amounted to approximately 20% of the data. The training dataset is introduced to the ANN to properly adjust the weighting connections of the neurons against the target output. At the same time, the validation subset is used as a barrier to avoid data overfitting, as it stops the training when designated error levels are reached. Finally, the testing subset is used to evaluate the trained model's efficiency. The input data of this subset are unknown to the model as they are used only after the completion of the training process. The comparison of the model's estimates with the actual output data documents ANN's ability to generalize (predict). The ANN's performance is assessed in terms of the relative error level (Δ) achieved between the actual (*PRactual*) and the expected penetration rates (*PRpredicted*), following the expression:

$$\Delta = \frac{PRactual - PRpredicted}{PRactual}$$

This criterion can provide a clear aspect regarding the ANN behavior and makes possible the comparison between the ANN results and other methods or theoretical models focusing on advance rate prediction.

In both cases, the optimal results were obtained by utilizing two hidden layers, with increased neurons in the first. Table 4 gives the optimum ANN architectures for the two tunnel cases, along with the mean squared errors (MSE) of the training process and the relative error levels (Δ) for the generalization outputs. The most efficient behavior is achieved in the Maen tunnel's ANN, which has an 8x9x5x1 architecture. This particular structure type means that the ANN has a total of 4 layers, with eight neurons in the input level, same as the number of the parameters, two hidden layers with 9 and 5 neurons, respectively, followed by 1 neuron in the output layer that eventually generates the value of the penetration rate.

Table 4 ANN training and testing error for each examined tunnel.

	Maen	**Pieve**
Optimum ANN architecture	8x9x5x1	7x6x5x1
Training MSE	0,119	0,086
Relative error of ANN generalisation (%)	17,9%	21,5%

Beyond the presentation of the mean values for the relative error levels, evaluating the trained networks' overall behavior is of equal importance. This will ensure that the ability of the ANNs to provide reliable prognosis is spread throughout the dataset and not only focused on particular sections. This check can be made using Fig. 4, where the actual penetration rate for the Maen tunnel is presented in conjunction with the ANNs' output for all data incorporated in the testing subset, along with an additional bar graph illustrating the attained relative error. Furthermore, in Fig. 5, the scatter plot between the actual and modeled penetration rate is given.

All the above concur that the ANNs' generalizations present a satisfactory approximation level consistent throughout the dataset examined and consequently through their respective tunnel sections. They follow the changes experienced in the actual TBM's penetration rate with adequate levels of accuracy and finally attain a correlation coefficient that exceeds 75% in the two examined case studies.

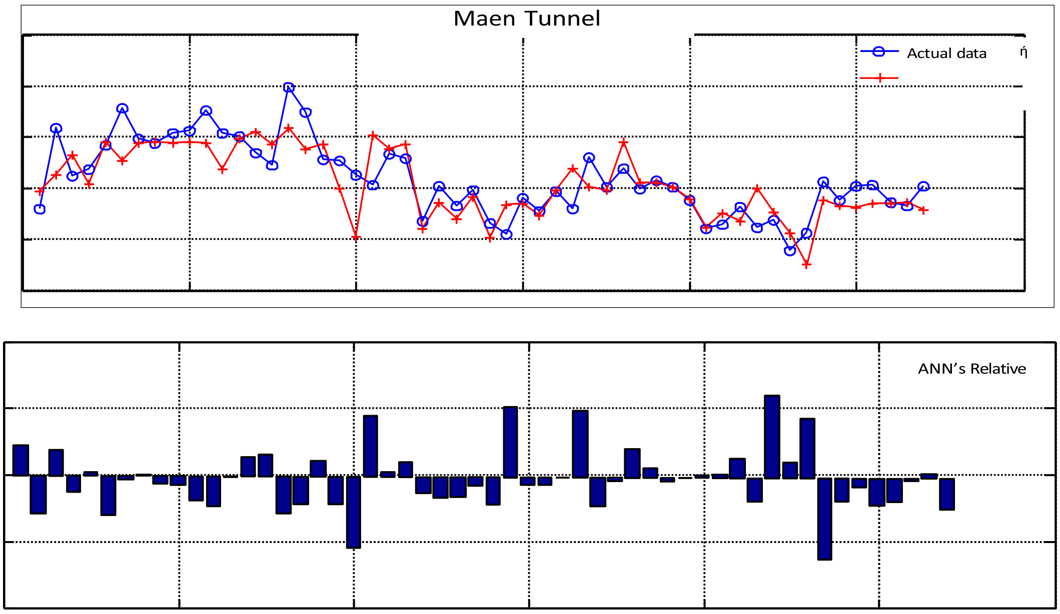

Figure 4 ANN generalisation for the complete testing subset of the Maen tunnel

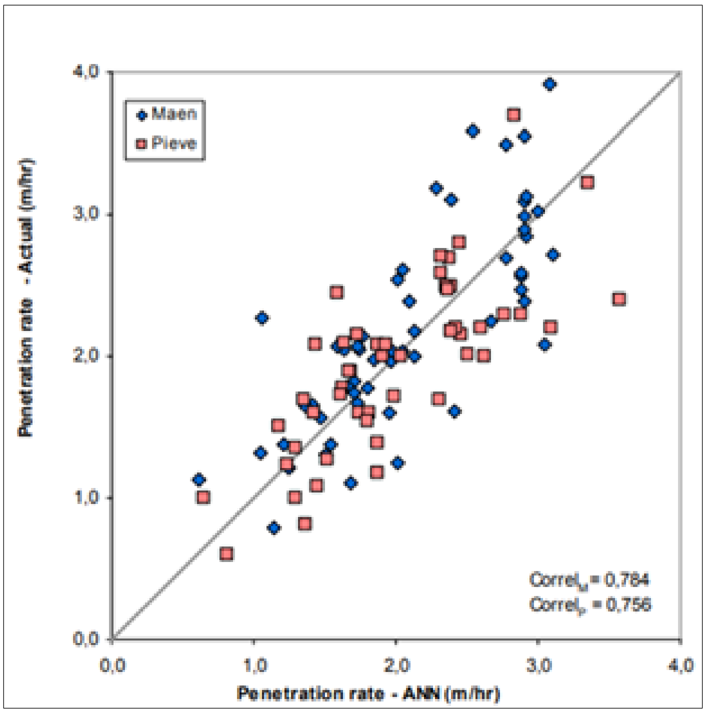

Figure 5 Scatter-plot of the measured PR values against the ANNs' predictions for the Maen and Pieve tunnels

3.4. Case study 3: Athens metro tunnel

The examined tunnel is located between the Katehaki and Panormou stations. The geological setting is a low-level metamorphic sedimentary weak rock system consisting of interbedded marly limestones, calcareous sandstones, siltstones, conglomerates, phyllites, and schists. The formations are intensely thrust, folded, and faulted with a variable and erratic degree of weathering and alteration. This particular excavation is the longest interstation tunnel in the Athens Metro, totaling 1129.36 m. The surveyed tunnel length is approximately 1077 m after excluding the first 53 m (learning curve period). The area is divided into 11 control areas (segments), in which data from 16 boreholes is collected and the selected geological properties are assessed. All data have been spatially modeled to identify the properties, especially within the 12m thick stratum in which the tunnel is being built, ranging, along the chainage, from the level of +120m to the level of +156m. The ANN's inputs are based on data relating to the geological and geotechnical characteristics of the subsurface and the specific site conditions. Although machine characteristics (e.g., thrust, torque) are very important for the overall TBM performance, in the case where tunneling is performed in soft rock or complex ground formations, the properties of the ground medium tend to be the most influential ones, as they govern the type and extend of possible failures. Subsequently, encountering ground conditions different from the TBM's working envelope affects the achieved tunneling rate and can give rise to claims. Thus, the model considers the geological setting the most dominant factor for the TBM performance; as many researchers have also noted, all possible problems and downtime directly affect the geotechnical conditions.

The parameters used in the model were selected considering their capability to credibly represent the ground behavior, hydrogeological environment, and site-specific conditions. These parameters are easily collected in the site-investigation phase and are available to all design stages of the project without the need for implementing special investigation techniques. More specifically, these are:

- Rock mass fracture degree as represented by RQD
- Weathering degree of the rock mass
- Overload factor – stability factor (N)
- Rock mass quality represented by RMR classification
- Uniaxial compressive strength of the rock
- Overburden - construction depth
- Hydrogeological conditions represented by the water-table surface relative to the tunnel depth
- Rockmass permeability

For each segment, a corresponding value for every principal parameter is taken. Allocating a representative value for the parameters is accomplished by the spatial modeling of the parameter's value and by incorporating statistical distribution that characterizes the parameter's behavior in each segment.

In the next step, the data is categorized into four interval scale classes, from 0 to 3, where 0 denotes the worst case and three the best. The limits in every class represent the specific site conditions and the machine characteristics. In the case of the Athens metro, the tunnel is constructed in relatively low depth and, in general, in weak rock conditions with a double shield TBM machine. The rating of each parameter is presented in Table 5.

Table 5 Rating of the parameters

(a)

Rockmass Fracture degree - RQD	
Value Class	*Rating*
< 10	0
10-30	1
30-60	2
> 60	3
Overload Factor (N)	
Value Class	*Rating*
> 5	0
3-5	1
1,25-3	2
< 1,25	3
UCS (MPa)	
Value Class	*Rating*
< 2	0
2-15	1
15-40	2
> 40	3
Water Table Surface (m)	
Value Class	*Rating*
> 10	0
5-10	1
0-5	2
< 0	3

(b)

Rockmass Weathering	
Value Class	*Rating*
Compl. Weath.-CW	0
High Weath.-HW	1

Med. Weath.-MW	2
SW, Fresh	3
Rock Mass Rating - RMR	
Value Class	*Rating*
< 10	0
10-30	1
30-60	2
> 60	3
Overburden (m)	
Value Class	*Rating*
< 7,5	0
7,5-12,5	1
12,5-17,5	2
> 17,5	3
Permeability (m/sec)	
Value Class	*Rating*
$< 10^{-4}$	0
10^{-4}-10^{-6}	1
10^{-6}-10^{-8}	2
$> 10^{-8}$	3

The limits of the proposed rating transform the continuous data to a discrete probability structure, a form that is finally used as input to the model. More specifically, the data is introduced to the ANN as the parameters' expected values (EV) (Table 6). For example, given V1, V2,…, Vn values having a respective probability of occurrence P1, P2,…, Pn, the expected value of the variable X, is estimated as:

$$E[X] = EV = \sum_{i=1}^{n} P_i \cdot V_i \,, \qquad \text{while, } \sum_{i=1}^{n} P_i = 1$$

The tunneling advance rate (AR), recorded in each segment (Table 7), is also introduced into the ANN model. Hence, the input vector of the parameters is tallied to the output vector of the mean achieved advance rate in each segment, expressed in m/day. Note that all externally originated delays (e.g., strikes, maintenance, etc.) have not been considered.

Table 6 Expected values of the parameters in each segment

Parameter	**Seg1**	**Seg2**	**Seg3**	**Seg4**	**Seg5**	**Seg6**	**Seg7**	**Seg8**	**Seg9**	**Seg10**	**Seg11**
RQD	0.13	0.88	0.90	0.64	0.72	1.37	1.62	1.26	0.55	0.66	0.74
Rockmass Weathering	2.52	2.52	2.24	1.97	1.99	1.89	1.95	1.93	1.96	1.94	1.93
Overload Factor	1.07	0.89	1.92	1.99	2.73	2.16	2.49	2.28	2.43	2.61	2.43
Rock Mass Rating	0.00	0.00	0.36	0.93	1.10	1.83	2.00	1.49	1.08	1.00	1.00

UCS	0.48	0.57	0.97	1.06	1.68	1.31	1.28	1.20	1.16	1.21	1.15
Overburden	0.42	1.00	1.17	1.97	2.86	2.35	1.16	1.45	1.13	0.99	0.88
Water Table Surface	3.00	2.32	1.71	1.00	0.23	0.02	0.94	1.40	2.17	2.40	2.75
Permeability	1.92	1.97	1.95	1.89	1.86	1.69	1.90	1.82	1.86	1.76	1.81

Table 7 Tunnelling advance rate data in each one of the control segments

Segment	Average AR (m/day)	Max AR (m/day)	Min AR (m/day)
1	4.00	8.8	0.0
2	4.54	8.8	0.0
3	6.25	10.4	2.8
4	4.35	13.5	0.0
5	9.82	12.1	0.5
6	9.09	13.7	7.3
7	16.67	21.0	14.7
8	11.11	18.3	4.4
9	10.85	17.0	6.1
10	12.50	17.3	1.6
11	14.07	14.8	10.4

The dataset of the whole 11 segments has been divided into two subsets. The first one (*training subset - A*) is used for the ANN's training, whereas the second (*testing subset - B*) is used for assessing the model's generalization capability. To ensure the ANN's performance, the testing subset consists of the most representative segments regarding the achieved advance rate, namely segments 2, 7, and 9, representing the worst, the best, and an average case. From the various network architectures examined, the ANN that was finally selected has an 8x9x4x1 topology. The mean squared error (MSE) of training approximates 1.4x10-27 and is attained after 103 training epochs. The results from the trained model were very satisfactory, as the relative error (Δ) between the model outputs and the testing subset ranges in the region of 6% and 8% (Table 8).

Table 8 ANN generalisation output and actual AR data for the testing subset

Segment	ANN generalisation results	Actual data	Relative error
2	4.854	4.54	0.0693
7	17.687	16.67	0.0610
9	9.942	10.85	-0.0837

3.5. Real-Time Monitoring and Early Fault Detection

In tunnel construction, real-time monitoring isn't just a buzzword—it's a lifeline. Working deep underground, with limited access to the TBM and rapidly changing ground conditions, makes instant data visibility a game-changer. Real-time monitoring has evolved from passive observation to active fault detection and prediction thanks to AI and ML.

Modern TBMs are embedded with hundreds of sensors tracking everything from oil temperature and cutterhead torque to vibrations and excavation speed. All this data is streamed in real-time to centralized control rooms, where AI-driven platforms analyze the inputs continuously. Unlike traditional systems that wait for values to breach thresholds before issuing an alert, ML algorithms are trained to detect patterns, trends, and anomalies—often before they manifest into visible problems.

The vibration sensor data shows subtle irregularities—too minor to trigger alarms but slightly off the usual pattern. A machine learning system, trained on previous vibration patterns that led to gear failures, can raise a red flag well in advance. Early detection means maintenance teams can inspect the component during a planned break rather than experience an unexpected halt that disrupts the entire excavation process.

The beauty of real-time AI monitoring lies in its learning capability. The more data it receives, the smarter it gets. Over time, it becomes better at spotting faults and more accurate in predicting how long a component will last under current conditions. This transforms the maintenance strategy from calendar-based to condition-based, saving time and money.

More importantly, early fault detection improves safety. The cost-benefit of catching an issue early outweighs the cost only in environments where machinery failure could put people at risk, and seeing it early and saving lives is paramount. That's the future AI is building for tunnel construction: one where machines speak, and we're finally learning to listen.

4. Data-Driven Decision Making in Tunnel Projects

4.1. Importance of High-Quality Data Collection

In tunnel construction, the quality of your data can make or break your project. Think about it—every decision you make hinges on what the data tells you. If that information is inaccurate, outdated, or incomplete, your entire project strategy could be based on a flawed foundation. And when you're working deep underground with million-dollar machinery and tight timelines, those mistakes are costly.

The right tools do matter (sensors, IoT devices, digital logs, drones, laser scanners, monitoring, etc.) that help get high-quality data or information. It's not so simple as having the gadgets, however. They need to be calibrated and synced to collect the right metrics. Consistency is key, whether it's TBM cutter wear, soil pressure, tunnel alignment, or labor hours.

One of the most overlooked elements of data quality is context. A 10mm/min penetration rate might mean efficiency on soft ground but spell trouble on hard rock. The numbers don't tell the full story without metadata—like location, time, machine configuration, and geological context.

Equally important is data validation. Like a surveyor double-checks measurements, data systems need built-in checks to flag anomalies, fill gaps, and reduce noise. Inaccurate data leads to poor AI predictions, unreliable reports, and wrong decisions. You want your AI systems to learn from gold, not garbage.

And let's not forget accessibility. Data locked in spreadsheets on someone's desktop doesn't help anyone. A cloud-based centralized platform means everyone from the TBM operator to the project executive has a single source of truth.

High-quality data, far from being precise, is empowering. This will fuel your AI model to forecast accurately, let managers act confidently, and provide everyone in the team the clarity to move ahead together. In a world of uncertainty, clean data is your biggest ally.

4.2. Real-Time Analytics and Visualization Tools

Imagine standing in a control room and watching your tunnel project unfold in real-time—data streams flowing in, risks flagged as they emerge, and performance metrics updating by the second. That's the power of real-time analytics and visualization tools. They don't just inform you—they guide you, empower you, and, in many cases, protect your project from falling off track.

Real-time analytics turn raw data into instant insights. For example, if the TBM starts losing penetration rate while cutter head torque rises, the system can instantly identify this trend, compare it with historical data, and raise a flag. Operators don't need to dig through logs or wait for a weekly report—it's all there, in real time, on a user-friendly dashboard.

Visualization is where the magic happens. Instead of endless rows of numbers, team members see charts, heatmaps, color-coded alerts, and 3D renderings. You can instantly grasp trends, outliers, and bottlenecks. Got a pressure spike? It flashes red. Hitting productivity targets? It's green across the board. These visuals bring the underground to life like data tables never could.

Beyond operations, these tools aid in strategic planning. Managers can simulate "what-if" scenarios based on live data. What if we increase TBM pressure? What if we reroute resources? With predictive analytics layered into the system, these tools visualize the now and forecast the next.

Collaboration is also enhanced. When everyone sees the same real-time data—from site engineers to execs across the globe—decisions get made faster and with more alignment. No more delays waiting on updates or endless meetings to get everyone on the same page.

In tunnel construction, where time is money and risk is ever-present, real-time analytics and visualization are your eyes, ears, and sixth sense. They don't just help you see the tunnel—they help you control the journey through it.

4.3. Closing the Feedback Loop between Field and Office

One of the biggest gaps in tunnel construction has always been the disconnect between what happens underground and what gets reported to the project office. Crews in the field gather tons of data, make on-the-spot decisions, and adapt to ground conditions daily. Meanwhile, managers at headquarters often rely on static reports or outdated logs. This lag creates a dangerous blind spot. But with AI and real-time data systems, we can finally close that loop.

Closing the feedback loop means providing in near real-time at the data collection point: the collected data is transmitted, analyzed, and fed back to decision-makers in the field and office. This finds applications where engineers in the tunnel can make decisions utilizing insights backed by AI while those in the office can have a real-time view of progress, cost, or risk.

Let's say a field team detects higher-than-expected cutter headwear. They log the observation, which immediately updates the central system. The AI engine compares the rate to past wear patterns, recognizes an anomaly, and recommends adjusting pressure and scheduling an inspection. This alert goes back to the field crew in seconds—and also notifies the maintenance team, procurement for spare parts, and the scheduler to adjust timelines. One insight, shared across the board, leads to unified, proactive action.

It also works in reverse. If the office updates the tunneling sequence or risk profile based on new data, the field team sees it immediately—on tablets, wearable devices, or smart dashboards. This keeps everyone on the same page and eliminates costly miscommunication.

The benefits go beyond productivity. A closed feedback loop fosters a culture of responsiveness, transparency, and accountability. Teams in the field feel heard and powerful, and managers trust the data and what it tells them to do.

Field and office syncing in real-time is a game changer in tunnel projects where time and coordination are of the essence. Communication is not enough; it's about unifying, being agile, and smarter across the entire end.

5. Challenges in Implementing AI-Augmented Controls

5.1. Technical, Financial, and Ethical Concerns

Applying AI-augmented controls in tunnel construction is similar to injecting a new player into a well-acquainted basketball team. More than that, concern arises along technical, financial, and ethical dimensions.

Integrating AI has many technical challenges, as it is not a plug-and-play affair. One of the significant problems is the legacy systems in which we may face such issues that these systems do not seamlessly communicate with modern AI solutions. In addition, training and running AI models demand large amounts of good-quality data. The problem with data in most cases is that it is inconsistent and incomplete, which may impede the effectiveness of AI predictions and recommendations.

Financial Concern: The payoff of investing in the integration of AI within a company can take quite some time, and the initial investment can be high. In addition to the actual cost of the technology, infrastructure upgrades, data storage solutions, and skilled personnel (when required) training are expenses that can quickly go beyond a few dollars here and there. Organizations must compare these upfront costs to projected long-term benefits to decide whether such investments are viable.

Beginning with the Effects of AI Transmission, you will discuss ethical considerations regarding how AI systems can potentially be biased to perpetuate existing biases in the training data if not properly designed. This creates issues in terms of fairness and equity in decision-making processes. Moreover, because some AI models are 'black boxes' where it is possible not to be able to trace the pathways that led to action, accountability and trust become tough.

All these multifaceted problems require integrated solutions, including technological advancements with the wisdom of investing money and taking responsibility.

5.2. Data Privacy and Cybersecurity Risks

Introducing AI into tunnel construction projects requires addressing very important data privacy and cybersecurity considerations.

Data Privacy: Like any decent AI system, mine would often handle geological data as well as proprietary methods of construction. This data has to be kept confidential. External unauthorized access or data breaches compromise the competitive advantages or violations of the regulatory standards.

In the Threat case of Cybersecurity, there are adversarial attacks against the AI: malicious entities can change the input data so that the AI gives incorrect outputs. For example, changes in data that are not so visible can deceive AI models, leading to wrong decision-making.

With ever-changing data protection regulations globally, organizations must guarantee that their approaches to AI follow GDPR or CCPA, and so on. Noncompliance comes at a hefty penalty and damage to reputation.

These risks can be mitigated using robust encryption methods, regular security audits, and following the best data governance practices. Working with cybersecurity professionals during AI integration can also help build additional defenses against any threats.

6. Future Trends in AI for Tunnel Construction

6.1. Predictive Maintenance and Automation

One of the most promising frontiers regarding using AI in tunnel construction is the prediction of maintenance and automation. With these technologies, the rest of the team can make smart, data-driven foresight rather than reactive fixes to equipment reliability and lifecycle planning.

Traditionally, tunneling maintenance is based on a time cycle, the machinery being serviced after a certain set mileage or operational hour. However, this is not always the most efficient approach to the challenge. Also, if the problems remain undetected, it may cause unnecessary downtime or, even worse, catastrophic failures. Enter predictive maintenance.

Predictive maintenance systems can now predict failures before they occur using AI algorithms trained on historical and real-time sensor data. For instance, AI can detect that the cutterhead motor of a TBM has started to overheat or buzz excessively and suggest its inspection be taken care of without further delay—in other words, before the machine is about to break down completely. Extending the life of equipment and slashes in unplanned downtime and repair costs.

Automation brings a second layer of sophistication. Based on the input of the changing ground condition, a driven system could autonomously modify its operational parameters, such as cutter head speed, thrust forces, and even soil conditioning fluid volume. This is about making your TBM come with his built-in pilot that never sleeps. This degree of autonomy over time could eliminate the need for continual human watch over the work in a hazardous environment, making tunneling safer and more efficient.

In the future, we'll experience more use of autonomous maintenance drones and self-healing systems that can perform tasks alongside robotic assistants and AI systems. These trends aren't just futuristic—they're already piloted in advanced infrastructure projects worldwide.

6.2. Use of Generative AI for Scenario Planning

Generative AI is rapidly moving from buzzword to business tool, and its implications for tunnel construction are nothing short of revolutionary—especially in scenario planning.

In complex underground projects, anticipating every possible event or risk is nearly impossible. There's a sea of unknowns, from unexpected geological formations to equipment malfunctions or logistics delays. In the case of generative AI, it brings a change by making synthetic scenarios because it processes thousands of inputs and outcomes to create virtual simulations of what might happen.

We plan to excavate a tunnel segment underneath a densely populated urban area. When applied [sic] to TBM fleets, generative AI can generate hundreds of potential outcomes where variables like soil type, TBM wear, labor availability, or even climate conditions change. After that, it can evaluate the impact of each scenario on the budget, time, safety, and resources for decision-makers to achieve the least resistance.

Generative AI is also quite unlike traditional simulation tools that take many hours of manual input and significantly curated programming before running the simulation. It discerns patterns that are too small for humans to see and may give birth to strategies that have never been used before. It makes it a very powerful assistant to engineers and project managers during the design and planning steps.

Negative AI can simulate hundreds of potential outcomes by tweaking variables such as soil type, TBM wear, labor availability, and even climate conditions. It can then assess each scenario's impact on budget, time, safety, and resources—helping decision-makers choose the path of least resistance.

Unlike traditional simulation tools requiring extensive programming and manual input, generative AI adapts and learns in real time. It identifies patterns humans may overlook and can suggest novel strategies that haven't been tried before. This makes it a powerful assistant for engineers and project managers, especially during the design and planning phases. All these scenarios can be safely explored in a virtual model, and contingency plans can be created before you ever break ground.

This technology increases strategic foresight and operational readiness, making projects more shock and uncertainty-resistant.

Furthermore, generative AI can aid in crisis simulation—what if a flood hits the worksite? What if a machine breaks down? What if a regulatory delay halts operations for a month

It's not just about working smarter—it's about seeing around corners.

6.3. Integration with BIM and Digital Twins

The most exciting future trend is the deepening integration of AI with Building Information Modeling (BIM) and digital twin technologies. This trio—AI, BIM, and digital twins—forms a powerful ecosystem for next-gen tunnel construction.

Let's break it down. BIM provides a digital representation of a physical asset. It includes geometry, spatial relationships, geographic information, and quantities—essentially a 3D blueprint of your project. A digital twin takes this further by adding real-time data from the field: sensor inputs, environmental conditions, machine performance, and more.

Now, throw AI into the mix.

AI can analyze the digital twin's live data and compare it against the BIM model to detect discrepancies, predict risks, and optimize real-time schedules. For example, excavation progress is slower than expected in one section. In that case, AI can pinpoint the bottleneck—perhaps an equipment issue or unexpected soil resistance—and recommend solutions based on past data.

This level of situational awareness allows teams to make data-driven decisions faster and more accurately than ever. Think of it as having a living, breathing dashboard of your entire project—one that learns and improves daily.

7. Conclusion

Tunnel construction is no longer a matter of debate, and AI has surely become a game changer in this field. Its applications have been from predictive maintenance to intelligent shift planning, redefining how complex underground projects are managed and delivered. Although AI is becoming a real contender to the futuristic notion, it is now becoming a practical tool for engineers and project managers to provide accuracy, safety, and efficiency on the job sites.

The trick to making AI so transformative is that it enables data to become action. AI sheds light and gives foresight to contracting on the tunnel (given that even small inefficiencies can grow substantially in tunnel projects and lead to very large dollar value overruns). Teams can benefit by not basing the decisions from the gut but rather on data-driven strategies specific to the given conditions of each tunneling operation. Sparse data and uncertainty about the conditions in which a tunnel boring machine (TBM) is operating make it essential that decision support is both tactical (e.g., optimization of the performance of an operating machine in real-time) and strategic (e.g., forecasting the geological risks of a proposed excavation).

Furthermore, AI works in no isolation. It is the one that comes to the picture seamlessly and fits in with other digital construction tools like BIM and digital twins to create a cohesive ecosystem that gives you a 360-degree view of the entire project lifecycle. Integrating these two makes decision-making easier while bringing all stakeholders on the same page regarding a single source of truth (hence, no miscommunication & a smoother flow from design to delivery).

There is more value in applying AI in tunnel construction beyond short-term gains in efficiency. Project delivery works due to predictability, which AI strengthens as a core. Machine learning algorithms are equipped to spot anomalies — from projected delays, equipment failures, and budget overruns — with AI, so teams are left with the advantage of preempting and reducing risk in advance.

By being proactive, people have more consistent outcomes on their projects. Confidence can be instilled in stakeholders to plan with the confidence of knowing all the systems in place are constantly learning and adapting to historical and real-time data. Tighter control over timelines and costs predicted by righting scheduling, optimized logistics, and resource balancing lowers the propensity for last-minute surprises characteristic of normal tunneling methods.

Moreover, there is an AI culture of continuous improvement. There is more data with each new tunnel project that feeds back into the models of this next project. This self-reinforcing cycle means, over time, smarter systems and more agile construction practices are set as expected in terms of quality and as examples to be desired throughout the industry.

For tunnel construction firms, embedding AI into project controls provides future-proofing in their operations and resilience in their workflow, putting them at an advantage against growing complex infrastructural demands.

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