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Keynote Paper

Long infrastructure tunnels – future trends and challenges

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ABSTRACT

Digitalization will change the way of gathering geological data, the methods of rock classification as well as the application of design analyses in the field of tunneling. Tunnel construction processes and tunnel maintenance will be influenced by this digital transformation as well.

The paper at hand takes the experiences with the recent (long) base tunnel projects through the European Alps into account. In the last years a rapid increase in the successful application of digital techniques (Building Information Modelling – BIM and Machine Learning - ML) for a variety of challenging tasks can be observed. Potential for ML is seen in the automatic rock mass behavior classification utilizing tunnel boring machine (TBM) advance-data, in the update of geological prognosis ahead of the tunnel face and in the way of interpretation of monitoring results as well as in the way of inspecting and maintaining existing tunnels.

Design optimizations of tunnel linings, especially the use of single shell linings instead of double shell linings, aim to reduce construction time and costs. The thermal use of the tunnel environment (air, water, ground), the reduction of construction material (concrete and steel) required for the tunnel support as well as less transportation volume all eventually result in increased sustainable benefits and in lower carbon footprints.

1. MOTIVATION

The European North-South Railway Links from Rotterdam to Genoa (Western Corridor), from Berlin to Palermo (Central Corridor) and from Gdansk to Trieste (Baltic – Adriatic Corridor) are the most important connections in Europe. The main goal of the railway links will be to transfer trans-alpine traffic (goods and passenger transport) from roads to rails. The cores of these routes are the flat base tunnels in the center of the Alps, which will increase train transport in speed and volume considerably.

The first Alpine Base Tunnel for railway opened in 2007 (Lötschberg Base Tunnel in Switzerland). The Gotthard Base Tunnel opened in 2016, the Ceneri Base Tunnel will open in 2020 (all 3 belong to the western corridor and are situated in Switzerland).

The Brenner Base Tunnel and the Mont Cenis Base Tunnel connecting Austria with Italy respectively France with Italy have both started construction in 2006. Two additional base tunnels are under construction in Austria for the Baltic – Adriatic Corridor, namely the Semmering Base Tunnel connecting Vienna with Graz and the Koralm Base Tunnel connecting Graz with Klagenfurt. All these base tunnels intend to finish construction within the next 6 – 10 years.
Geological uncertainties and the ensuing risks in the construction of long tunnels at great depth have been described in the ITA Report no. 4 — Long tunnels at great depth (ITA 2010): "*the deeper the tunnel, the larger the uncertainties; the higher the probability of encountering adverse or unforeseen conditions for tunneling, the greater the effort and the cost for site investigations to reduce the uncertainties*".
Digitalization will change the way of gathering geological data, the methods of rock classification as well as the application of design analyses in the field of tunneling. Tunnel construction processes and tunnel maintenance will be influenced by this digital transformation as well. Another factor which will influence future challenges and trends in tunneling is related to the importance of sustainable solutions. Hereafter, the Brenner Base Tunnel Project will be used as an example to illustrate recent challenges and trends in tunneling.

2. BRENNER BASE TUNNEL PROJECT

The Brenner Base Tunnel (BBT) is a flat railway tunnel between Austria and Italy. It runs from Innsbruck to Fortezza. Including the Innsbruck railway bypass the entire tunnel system through the Alps is 64 km long. It is the longest underground rail link in the world.

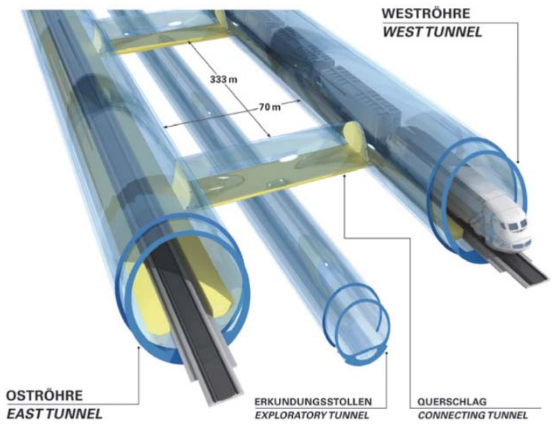

Fig. 1 Brenner Base Tunnel System with two Main Tunnels and the Exploratory Tunnel (Eckbauer et al., 2014).

This tunnel consists of a system with two single-track main tunnel tubes 70 meters apart that are connected by crosscuts every 333 metres (see Fig. 1). A service and drainage gallery lies about 10 - 12 meters deeper and between the main tunnel tubes. It is constructed ahead of the main tunnels and will be used as an exploratory tunnel for them. Four connection tunnels in the north and south link to the existing lines and

belong to the overall tunnel system with a total length of approx. 230 km. Three emergency stops, each about 20 km apart, are planned in Ahrental, St. Jodok and Trens (see Fig. 2).
The emergency stops serve to rescue passengers from trains with technical difficulties. In addition, all emergency stops are accessible through driveable approach tunnels. A detailed project description is provided e.g. in (Eckbauer et al., 2014).

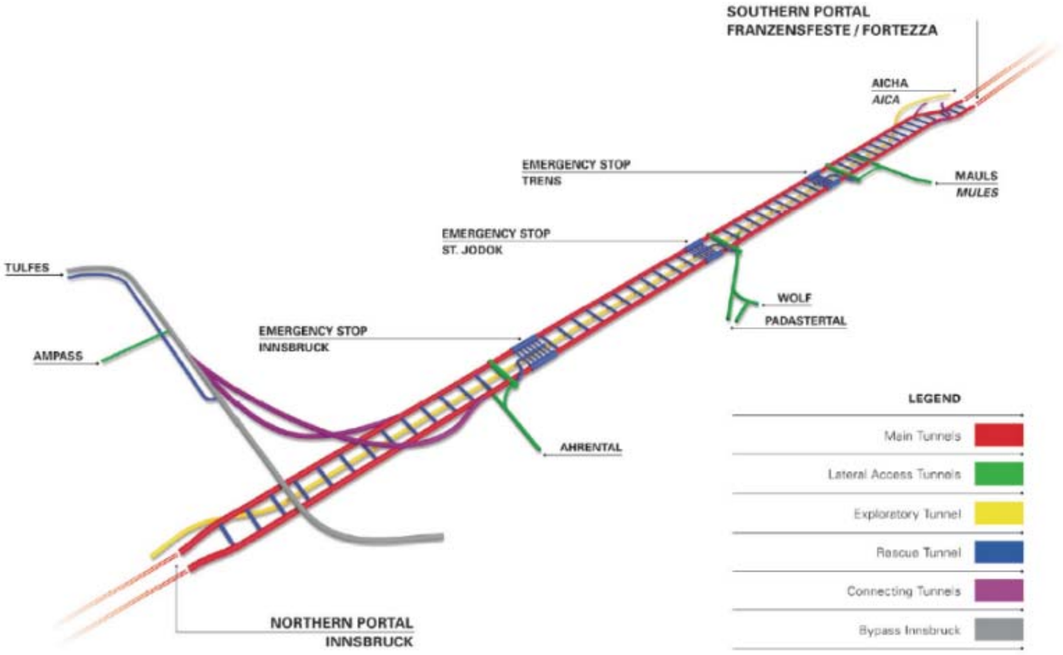

Fig. 2 Brenner Base Tunnel System including the connection to the Inn Valley Tunnel (Eckbauer et al., 2014).

This tunnel system within the Central Eastern Alps is crossing the collision zone of the European and the Adriatic (African) plate. The main lithological units are the Innsbrucker Quarzphyllites, the Bündnerschists, the central gneisses and the Brixener granites (see Fig. 3). From the hydrogeological point of view the water ingress is very limited in the homogenous sections of the phyllites, schist, gneisses and granites. The amount of water is expected to increase only with advance through fault zones or layers of marble. A lowering of the water table at the surface is prohibited in these fault zones because of environmental aspects.

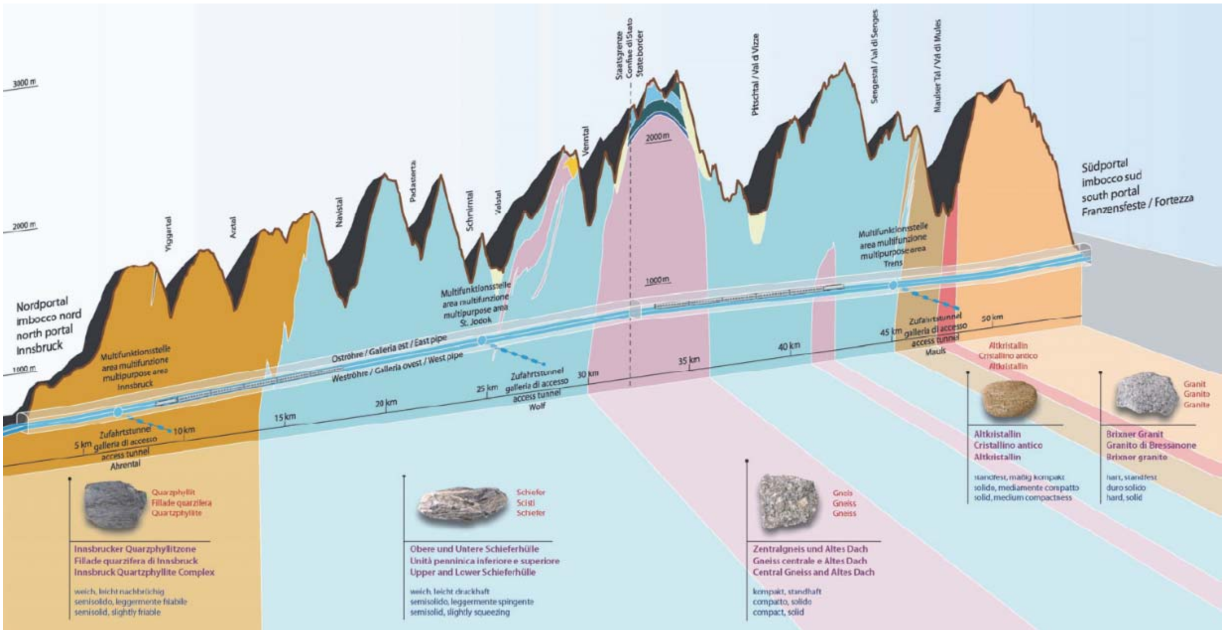

Fig. 3 Longitudinal profile of Geology with main Lithological units (Eckbauer et al., 2014).

The overburden varies between 1,000 and 1,500 m over most of the tunnel. The maximum of 1700 m will be reached in the central gneisses.
As outlined in the beginning, the exploratory tunnel is centred beneath the two main tunnel tubes (Fig. 1). It will be built in sections before beginning construction works on the main tubes, mainly to explore the rock conditions. The results of these geological and hydrogeological exploration will be used for the construction of the main tunnels. The exploration tunnel is excavated partly with conventional and partly with mechanized method.
With the goal to gather as much information on the encountered geology as possible, a 15 km long exploratory tunnel of the construction lot Ahrental - Pfons is excavated by an open tunnel boring machine (TBM) in advance of the main tunnel tubes. Efforts are undertaken to transfer gained knowledge from the exploratory tunnel to the main tubes as they will be driven by shield TBMs with limited possibilities to observe the geology that surrounds the tunnels (Bergmeister et al., 2017; Reinhold et al., 2017).
This will reduce construction risks and hence also construction costs and time. The whole exploratory tunnel will be designed for the service life of the tunnel system with the result that it can be converted into a drainage and service tunnel in long term.

3.1 The Digital Transformation of Tunneling

The use of Building Information Modelling (BIM) will have a tremendous effect on the design, construction and operation of tunneling projects (e.g. Goger et al., 2018). The digital transformation will be achieved through digital data, automation, networks and digital access and will affect both conventional and mechanized tunneling. This change

will influence payment and contract models, as well as software solutions for construction in general.
Digital data acquisition, data management and 3D modeling techniques will improve the way of how geological models, rock mechanical prediction models for tunnel projects will be prepared in future, e.g. Horner et al., (2016). The Institute for Rock Mechanics and Tunnelling (RMT) at the Graz University of Technology is focusing on this specific interface: geological data acquisition, rock mass classification and continuous update of geotechnical models during construction. Some of those aspects are outlined hereafter.

Automatic Rock Mass Classification Approach

With the goal to infer rock mass behavior from TBM machine data at the main tubes, efforts are undertaken to correlate the data from the exploratory tunnel with the encountered geology (Bergmeister et al., 2017). This type of "input – output mapping" (i.e.: TBM data in, rock mass behavior classification out) is a classical application of machine learning, where algorithms are used to make sense of data (Raschka, 2017). Artificial Neural Networks (ANN) are frameworks of algorithms that have shown success in accomplishing a variety of complex tasks (e.g. Hinton et al., 2012; Silver et al., 2016). In Erharter et al. (2019a) we compared the performance of two different kinds of ANNs in automatically classifying TBM data into different rock mass behaviour types. In Erharter et al. (2019b) the applicability of a special type of artificial neural network (ANN) for an automatic online classification of the rock mass behaviour solely based on TBM data has been explored. In Erharter et al. (2019c) we show how an AI system can be trained to achieve the best possible rock mass behaviour classification (in the sense of "as close to the human classification as possible"), or how such a system can be misused to yield a more optimistic, respectively pessimistic classification to fortify the interests of one party.

The TBM at the BBT of which the machine data serves as input records:

- the advance-speed [mm/min],
- the rotational-speed [rpm],
- the advance pressure [bar],
- the cutterhead torque [MNm],
- the total advance force [kN],
- the penetration [mm/rot],
- the pressure of crown-support-cylinder left and right [bar],
- the path of crown-roof-support-cylinder [mm] at an interval of 10 sec.

Additionally, the rotatory share of the specific energy [MJ/m3]) after Teale (1965) and the specific penetration and the torque ratio after Radoncic et al. (2014) are calculated. Data from tunnel meter (TM) 0 to 12000 is used in these studies (see e.g. Fig. 4). Due to standstills, starting peaks, data noise etc., extensive preprocessing of the raw data is imperative.

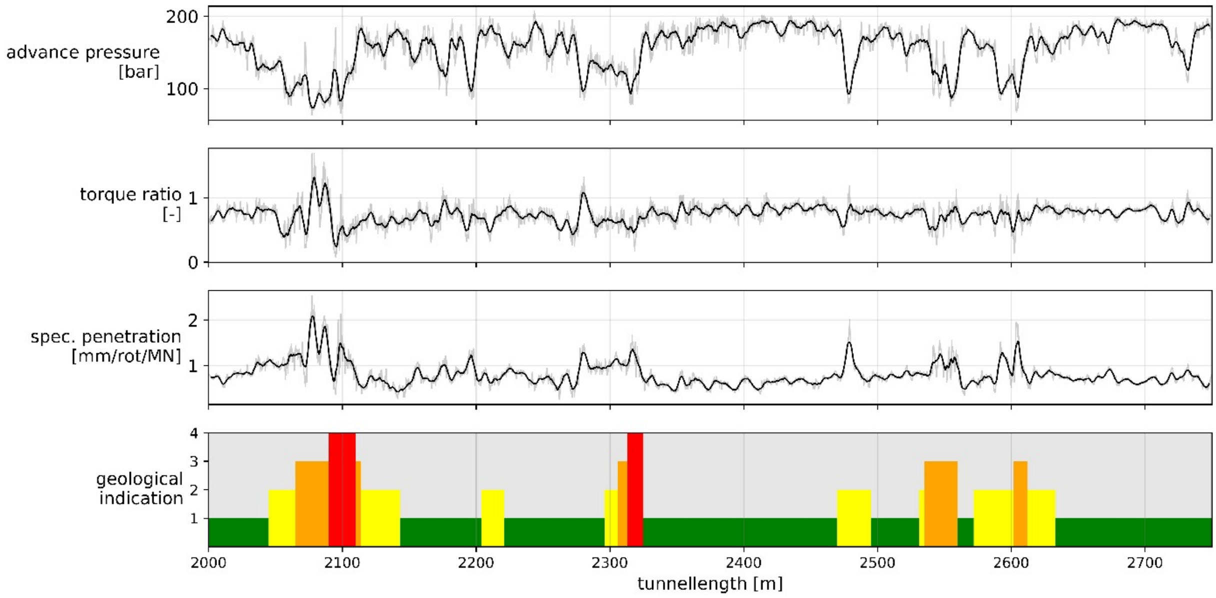

Fig. 4 Example section of the TBM parameters between TM 3500 and 4000; several features show a distinctive response to the encountered fault zone (Erharter et al., 2019a).

The used rockmass behavior type classification is a construction site specific system with four classes, called Geological Indication (GI) (after Reinhold et al., 2017). The classifi-cation relies on the onsite geotechnical engineer's assessment of the current rockmass behavior based on observation from within the TBM. GREEN means good rockmass quality with minor discontinuity-based influence and small deformations, YELLOW significates rock mass with unfavorable discontinuity intersections or minor faults respectively small deformations, ORANGE stands for squeezing rockmass, highly fractured rock mass, fault zones and high deformations and finally RED describes big, geotechnically relevant (core-) fault zones with very high deformations.
TBM data itself is not used for this subjective classification. The labels are converted to a binary representation (one-hot encoded vectors), e.g.: YELLOW = class 2 = [0, 1, 0, 0] (see Erharter et al., 2019a).
Subsequent results show the outcome of using Long-Short-Term Memory (LSTM)-network (Hochreiter et al., 1997) which are trained to automatically classify the TBM data. For details see Erharter et al. (2019a).
Fig. 5 shows a result for TM 1000-2000. The data of 10000 tunnel meter have been used as training. In the upper row the TBM data (normalized torque ratio) is given, the second row shows the "ground truth" (=human classification) and the third row shows the respective categorical classification of the LSTM network. The direct output of the last layer (i.e. a probability value for each individual class) is given in the fourth row and can be seen as an indication of how "sure" the model is about its classifications.

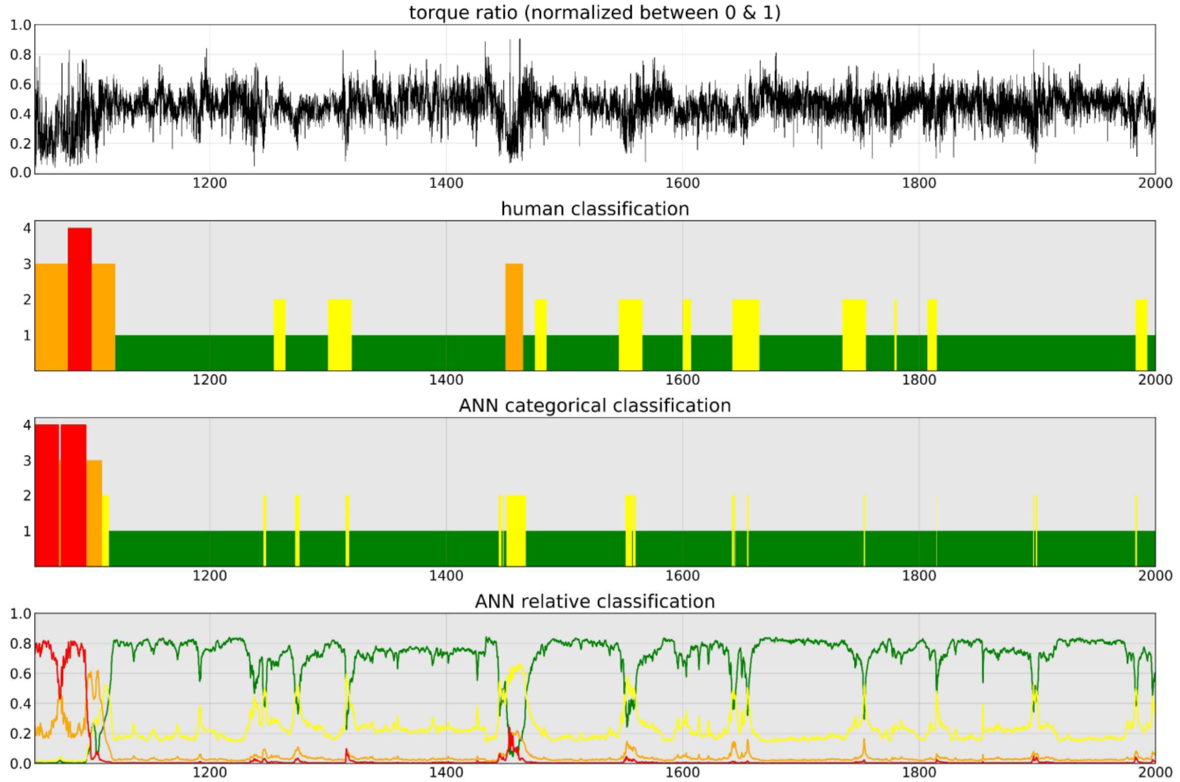

Fig. 5 LSTM-network classification of TM 1000 - 2000 (Erharter et al., 2019a).

The test set shows that satisfying accuracies as well as a good accordance between the ANN- and the human rock mass behavior classification can be achieved. Whereas the categorical classification makes the output directly comparable to the human classification, more information can be gathered from the probability values that result from the ANN's direct output. Even if a sample's classification is wrong in categorical terms, the relative output still gives an indication about the occurrence of other possible classes (more details see Erharter et al., 2019a).
The author sees great potential to apply unsupervised machine learning approaches for this subject. Most algorithms in unsupervised learning do not "learn" from the interaction with the data but "help the user" to learn information about a dataset. Typical practical applications of unsupervised learning are outlier detection (e.g. for monitoring tasks), clustering (e.g. do identify structure within data) or dimensionality reduction (e.g. to visualize high dimensional space).

Geological Prognosis Ahead

At the Brenner Base Tunnel the choice of exploration techniques has been made in a way to smoothly integrate them into the regular tunneling process in order to avoid extensive downtime. The exploration techniques were useful for the construction design of the exploratory tunnel itself but also to produce a reliable forecast for the subsequent main tunnels. The geological investigation consists of continuous tunnel face and circumferential mapping as well as of percussion drilling ahead of the tunnel boring machine. The exploration concept has been completed with a geophysical reflection

seismic method (for details see Reinhold et al., 2017).
Advance probing with percussion drilling technique is undertaken from a drill carriage installed directly behind the finger shield of the TBM. The probe holes are drilled overlapping with lengths of between 30 and 100 m. The information from this probe drilling is evaluated as follows: (a) analysis of flushed material, (b) camera surveying and (b) evaluation of the data from the drill datalogger. Especially the latter (c) is a subject of ongoing research with the goal to develop a similar classification system as for the TBM data (see chapter 3.1).
Such overlapping probe drilling provides one-dimensional information and therefore includes valuable indications of the rock mass structure in front of the TBM. The seismic investigations deliver information of a large three-dimensional area in front.
At the Brenner Base Tunnel the reflection seismic system TSP 303 (see Dickmann, 2008 and Dickmann et al., 2010) is used for geophysical investigation. Numerous non-destructive blasts send compression waves into the rock with their time points recorded. The waves spread from the source and are reflected from material contrasts. At the receivers, the arriving waves are registered and the ground movement with time is recorded as a seismic trace. Traces are recorded for each pair of source and receiver (see details in Schwarz et al., 2017). Finally, the reflections from the many seismic traces are converted by ray tracing migration into a 3D model (see Dickmann, 2008). The results show both the seismic velocities and the strength of the reflections to about 140 m in front of the tunnel and 50 m to the sides.
An example for the combination of probe drilling ahead and seismic investigation in the area of a fault zone is shown in Fig. 6.

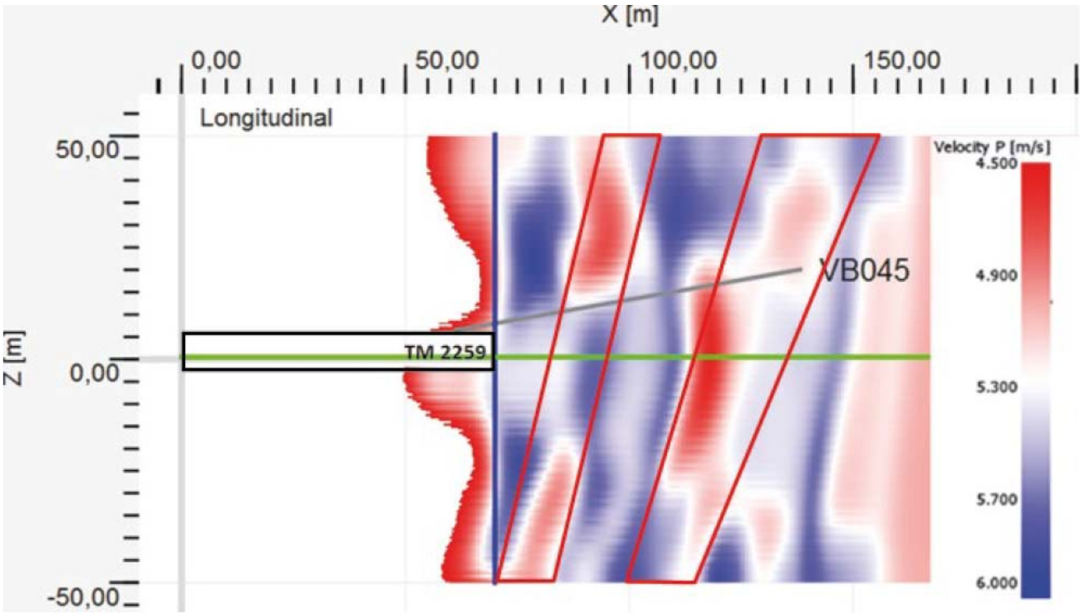

Fig. 6 Longitudinal section through seismic P-wave model (example from Reinhold et al., 2017).

In Fig. 6 the forecast fault zones are marked with red frames. A 2D longitudinal section is displayed instead of the seismic P-wave 3D-model. Nevertheless, low velocity zones are clearly apparent.

Interpretation of Monitoring Results

Geotechnical monitoring is an integral part of the tunnel construction process. The "observational method" is described in detail as part of the Eurocode 7. The observational method serves to review the design during construction when geotechnical behavior is difficult to predict accurately. From the technical side, the observational method addresses tunnel surface deformation methods (absolute geodetic measurements, distometers), deformations of the surrounding ground (extensometers) and monitoring of ground support (anchor forces), pressure cells implemented in the shotcrete liner (Schubert et al., 2014).

Several ways of analysis and interpretation exist. The first step is typically the evaluation of a time-displacement diagram. More sophisticated approaches involve the interpretation of displacement vector orientations (see Schubert et al. 2014).

The author believes that "unsupervised learning" shall be used to develop a warning system for monitoring data of tunnel drives (both conventional and mechanized tunneling methods). This warning system would consist of a multistep pipeline that takes raw displacement measurements as input and yields a binary classification whether or not a measuring point behaves "normal".

3.2 Design Optimization and Sustainable Solutions in Tunneling

Optimized Tunnel Lining Design

Long tunnels such as the Brenner Base Tunnel beside the main tunnels consist of a large network of service (non-public) tunnels. Such tunnels do not necessarily require a tunnel lining system with two shells, but under certain boundary conditions can be suppurted by a single shell lining approach. The required conditions and limitations for the single lining approach have been reflected and a proposal for structural verification is provided in Marcher et al. (2019). Shotcrete, a key support element in NATM tunneling, exhibits a significant time dependent behaviour, in particular during the initial hours of curing. This is important, because once applied as primary lining, the shotcrete is immediately loaded due to the excavation process. In practical tunnel-engineering crude simplifications are usually adopted with respect to modeling the mechanical behaviour of shotcrete in numerical analysis. Saurer et al. (2014) presents the application of a novel constitutive shotcrete model using realistic boundary conditions for a shotcrete tunnel lining excavation. The benefit of such calculation is that there is no longer need for manual adaptation of strength and stiffness with time. Of course, such an advanced constitutive model requires both a higher number of parameters and more detailed knowledge about construction time.

Taking into account the costs for major infrastructure tunnel projects on the one hand and the increased quality of construction material and its control on the other hand it seems evident that one has to rethink many of the design assumptions, especially also with regard to the specified life-cycle time. The Brenner Base Tunnel project takes into consideration a life-cycle of 200 years. Based on the Eurocode 2, the ultimate limit state is taken into account with a failure probability of Pf =10-7 per year which means a safety index of β=5.2. In addition the concrete cover is increased and the concrete admixtures have been optimized to increase the durability (details see Bergmeister et al., 2014 and Bergmeister, 2015).

Thermal Energy Use

RMT is leading a research consortium which investigates the geothermal use for heat generation (heat storage or cooling, if necessary) from the Brenner Base Tunnel project. The most important prerequisite for the geothermal use of underground structures is the existence of a customer (settlement areas) in the immediate vicinity. This is not only for reasons of cost (necessary infrastructure between the underground structure and the customer), but above all to reduce thermal losses low and to keep the efficiency of the system high. With the proximity of the city of Innsbruck and the surrounding communities to the Brenner Base Tunnel, this prerequisite is given. Another prerequisite is enough space for installation of the required technical systems for the geothermal use. In the case of the BBT this is automatically provided by the additional service and drainage gallery (which is the exploratory tunnel during construction). The study will also take into account experiences from prior pilot projects, such as the Inntal Valley Tunnel, Austria (Geothermiekraftwerk Jenbach, see e.g. Adam et al., 2010), the Lötschbergtunnel, Switzerland (Tropenhaus Frutigen 2005) or the B10-Rosensteintunnel in Germany (Csesznák et al. 2016).

Automatisation in Tunneling

Smart tunneling or tunneling 4.0 are not only modern slogans. They describe the use of machines that are remotely monitored as well as the integration of an entire intelligent system into a tunneling project. Machines will communicate with each other and with a central data processing unit. Networking with intelligent sensors and actuators as well as special software have to be applied therefore.

Reinforcement learning (RL), a research topic of RMT, is a very complex field of machine learning with still limited amount of practical applications. It consists of a combination of dynamic programming and supervised learning. It is based on the interaction of an agent which performs an action and its environment which gives positive or negative feedback, i.e. reward, without an external supervisor (see Fig. 7). The RL agent learns how to achieve a given goal by trial-and-error interactions with its environment and thereby maximizing a long-term numerical reward signal (Samiksha Mahajan, 2014).

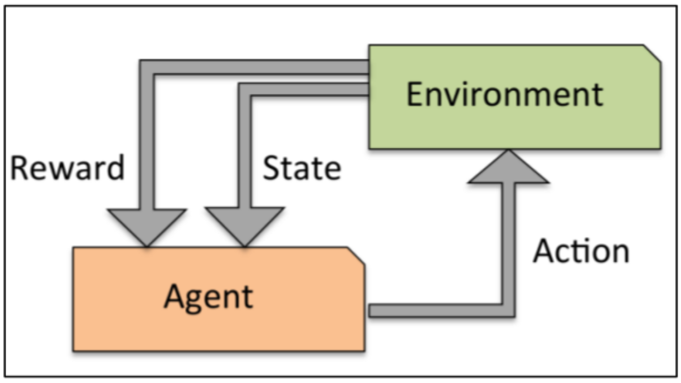

Fig. 7: Basic principle of reinforcement learning (taken from Raschka, 2017).

RL is already successfully used in many disciplines such as game theory (e.g. Chess), control theory (e.g. helicopter control), operation research (e.g. Vehicle routing), simulation based optimization etc. (Samiksha Mahajan, 2014). In the field of tunnel engineering however, reinforcement learning seems to be only part of ongoing research projects rather than already being in use for specific applications.

3.3 Tunnel Maintenance

Many railway tunnels around the world get older and maintenance (inspection and repair methods) of those tunnels becomes an important aspect. Traditionally, inspection works are done by observing the lining surface with visual inspection while walking through and by hammer knocking on “suspected surfaces”; often at night on closed tracks or roads. After inspection the data is time-consuming to process.
Digitalization will make this process easier and less subjective with regard to interpretation. Recently, inspections use images obtained by laser beams, slit cameras or line-sensor cameras. Non-destructive detection technologies have been introduced recently in order to automate the inspection processes. Especially, vision-based automatic inspection techniques are used for surface damage detections. Automatic methods are introduced to accurately recognize and distinguish the various types of structural damages (e.g. Dong et al., 2019, Schneider et al., 2019).

4. CONCLUSIONS AND OUTLOOK

The added value of optimization of the design of underground structures has to be seen in a reduction of construction time and cost. The benefit of reduced construction material and less transportation volume provides increased sustainability and lower carbon footprints.
The added value of applying digitalization has to be seen in an improvement of operational processes, quality assurance and increase of safety for the miners onsite.
With regard to Machine Learning the present examples show that training ANNs in a supervised manner works and yields valuable information. Nevertheless, supervised learning based artificial intelligence systems should only be used as an aid and not as a replacement for onsite personnel. This technology can be used to improve classification efficiency and self-consistency. Ethical use from all involved parties is imperative to build the necessary confidence that is required to make the most out of this technology.
Great potential is seen in unsupervised machine learning approaches where the final classification is not imposed upon the data, but learned from it. Finally, reinforcement learning seems to be trendsetting but not being in use for specific tunnel applications yet.

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