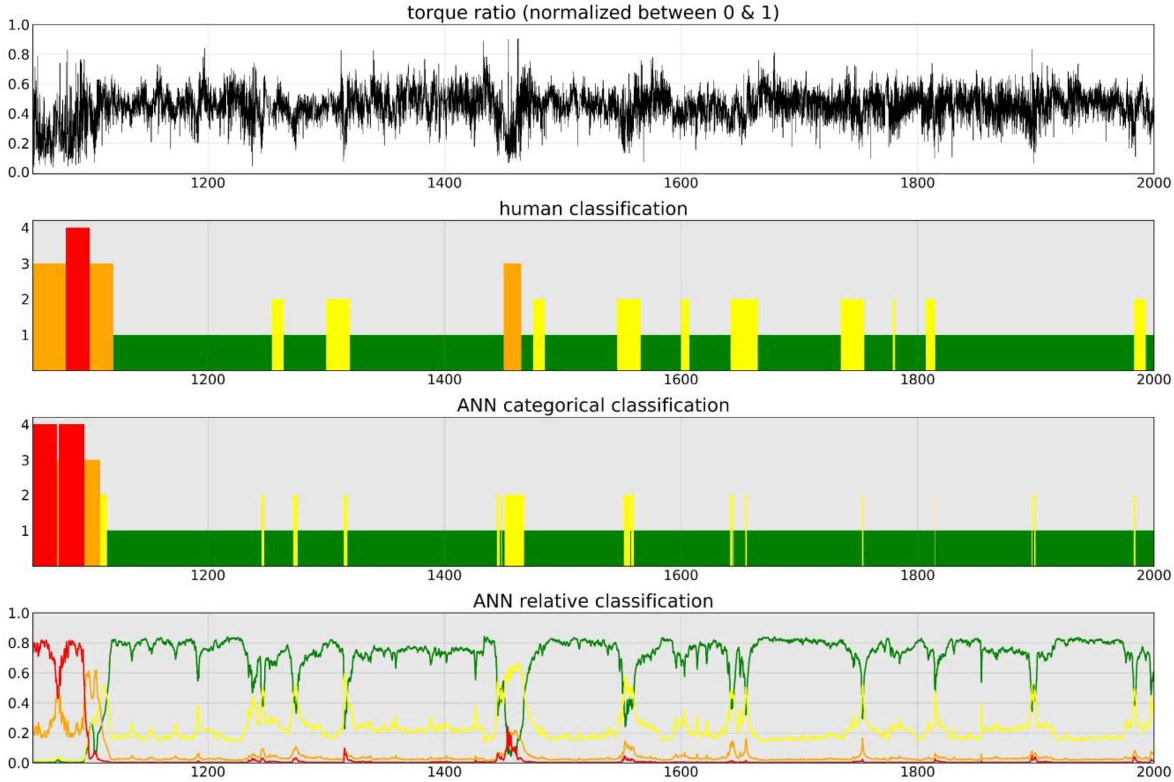

Fig. 5 LSTM-network classification of TM 1000 - 2000 (Erharter et al., 2019a).

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.

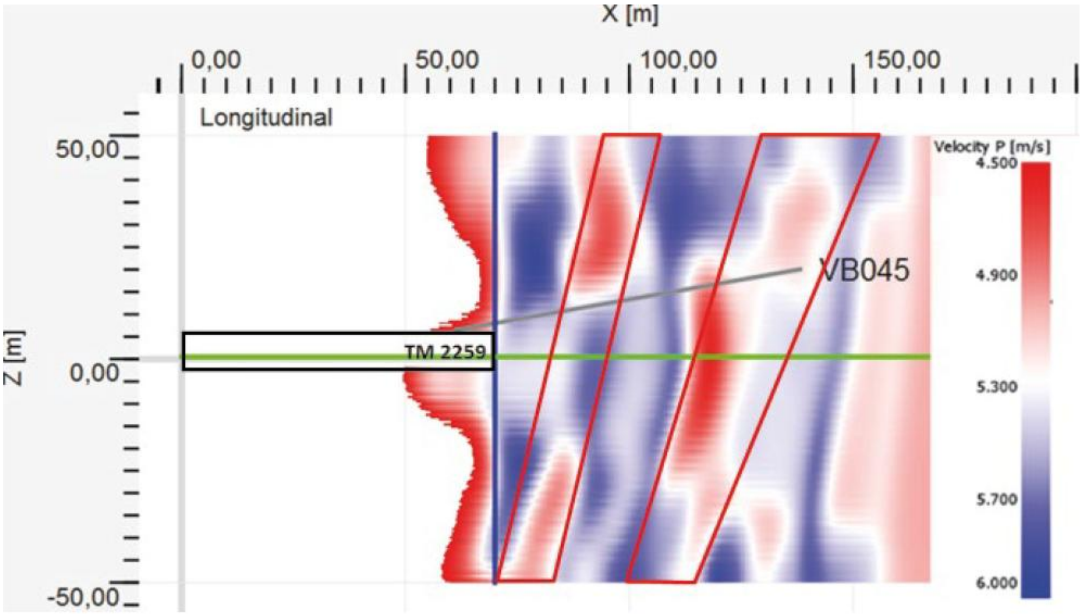

Fig. 6 Longitudinal section through seismic P-wave model (example from Reinhold et al., 2017).

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).

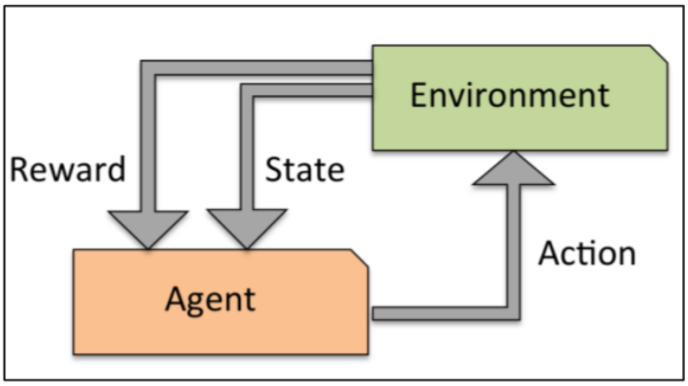

Fig. 7: Basic principle of reinforcement learning (taken from Raschka, 2017).

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.

REFERENCES

Adam D., Markiewicz R. (2010), „Nutzung der Geothermie mittels Erdwärmeabsorber und Grundwasserbrunnen", öwaw 5-6/2010.

Bergmeister K., Saurer E., Marcher T., Höser S. „Empfehlungen zur Ermittlung der Nutzungsdauer, der Einwirkungen und zur Bemessung von Tunnelbauten", «*Betonkalender 2014*» Bergmeister K. et al. (Hrsg.), Ernst & Sohn, 2014.

Bergmeister, K. 2015, "Life cycle design and innovative construction technology", *Swiss Tunnel Congress*, 2015.

Bergmeister, K., Reinhold, C. (2017), "Learning and optimization from the exploratory tunnel - Brenner Base Tunnel", *Geomechanics and Tunneling* 10, Nr. 5, S. 467–476.

Csesznák A., Järschke R., Wittke M. (2016), „B10 Rosenstein Tunnel – Designing a geothermal energy system in a spa protection area", *Geomechanics and Tunneling* 9 (2016), N.5.

Dickmann T., Groschup R. (2010), "Tunnel seismic exploration and its validation based on data from TBM control and observed geology". In: Beer, G. (Ed.), *Technology Innovation in Underground Construction*. CRC Press, Leiden, 189-201.

Dickmann, T. (2008), "Theoretical and Applied Case Studies of seismic imaging in Tunneling", *Geomechanik und Tunnelbau* 1 (2008), Heft 5, S. 436–441.

Dong Y., Wang J., Wang Z., Zhang X., Gao Y. (2019), "A Deep-Learning Based Multiple Defect Detection Method for Tunnel Lining Damages", *DOI 10.1109/ACCESS.2019.2931074*, IEEE Access.

Eckbauer, W., Insam, R. and Zierl, D. (2014), „Planning optimisation for the Brenner Base Tunnel considering both maintenance and sustainability", *Geomechanics and Tunnelling*, No. 5.

Erharter, G. H., Marcher, T. and Reinhold, C. (2019a), "Comparison of artificial neural networks for TBM data classification", *Proceedings of the 14th International Congress on Rock Mechanics and Rock Engineering (ISRM 2019)*, Rock Mechanics for Natural Resources and Infrastructure Development. Foz de Iguassu, Brazil, September 13 – 18, 2019.

Erharter, G. H., Marcher, T. and Reinhold, C. (2019b), "Artificial Neural Network based Online Rockmass Behavior Classification of TBM Data", *Proceedings of the 3rd International Conference on Information Technology in Geo-Engineering (ICITG 2019)*, Guimarães, Portugal, 29.09.2019 - 02.10.2019, Springer.

Erharter, G. H., Marcher, T. and Reinhold, C. (2019c) "Application of Artificial Intelligence for Underground Construction Chances and Challenges: Insights from the BBT exploratory tunnel Ahrental Pfons", *Geomechanics and Tunneling*, in press.

Goger G., Bisenberger T. (2018), "Tunneling 4.0 – Construction-related future trends", *Geomechanics and Tunneling 11.*

Hinton, G., Deng, L., Yu, D., Dahl, G., Mohamed, A.-r., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T. and Kingsbury, B. (2012), "Deep neural networks for acoustic modeling in speech recognition", *IEEE Signal Processing Magazine*, No. 29, pp. 82–97.

Hochreiter, S. and Schmidhuber, J. (1997), "Long Short-Term Memory", Neural Computation, No. 9, pp. 1735–1780.

Horner J., Naranjo A., Weil J. (2016), "Digital data acquisition and 3D structural modelling for mining and civil engineering – the La Colosa gold mining project, Colombia", *Geomechanics and Tunneling 9*, No. 1.

ITA WG 17. (2010), “Long Tunnels in Great Depth”.

Marcher T (2019), “Successful Implementation of >>SEM - Single Shell Lining Concept<< for the Emergency Tunnel at the Brenner Base Tunnel Project – Theory and Praxis of an Innovative Shotcrete Model”, *NAT conference proceedings*, Chicago

Radoncic, N., Hein, M. and Moritz, B. (2014), “Determination of the system behaviour based on data analysis of a hard rock shield TBM / Analyse der Maschinenparameter zur Erfassung des Systemverhaltens beim Hartgesteins-Schildvortrieb”, *Geomechanics and Tunneling*, Vol. 7 No. 5, pp. 565–576.

Raschka, S. (2017), “Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow, Community experience distilled”, *Second edition, fully revised and updated,* Packt Publishing, Birmingham, UK.

Reinhold, C., Schwarz, C., Bergmeister, K. (2017), “*Development of holistic prognosis models using exploration techniques and seismic prediction*”, *Geomechanics and Tunneling 10*, Nr. 6, S. 767–778.

Saurer E., Marcher T., Schädlich B., and Schweiger H.F. (2014), “Validation of a novel constitutive model for shotcrete using data from an executed tunnel”, *Geomechanics and Tunneling 7*, No. 4, 353-361.

Samiksha Mahajan (2014), “Reinforcement Learning: A Review from a Machine Learning Perspective”, *International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 4* No. 8, pp. 799–806.

Schubert, W., Grossauer, K., Matt, R., Bernd, M., Proprenter, M., Rabensteiner, K., Radoncic, N., Vavrovsky, G.M. and Weissnar, M. (2014), “Geotechnical Monitoring in Conventional Tunneling Handbook”, OEGG.

Schwarz, C., Schierl, H. (2017), “Integration of reflection seismic data into the documentation during the construction of the Brenner Base Tunnel/Einbindung von Reflexionsseismik in die Dokumentation beim Bau des Brenner Basistunnels”, *Geomechanics and Tunneling 10*, No. 5, pp. 552–560.

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T. and Hassabis, D. (2016), “Mastering the game of Go with deep neural networks and tree search”, *Nature, Vol. 529* No. 7587, pp. 484–489.

Teale, R. (1965), “The concept of specific energy in rock drilling”, *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts*, Vol. 2 No. 2, p. 245.