Revisiting Rock Engineering Empirical Standards in the Era of Machine Learning to Benefit the Mineral Resources Sector in British Columbia

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Introduction

The past decade has seen an increased interest in the application of machine learning (ML) to mining and geotechnical engineering, especially in the mineral resources development sector. There are numerous benefits to ML, including increased efficiency through the ability to quickly sort and characterize large amounts of field data, and increased accuracy by being able to detect relationships and patterns in complex data, all with minimal human intervention (Morgenroth et al., 2019). Even though ML is a powerful tool, the success of ML algorithms depends on the quantity and quality of the data (Schmidt et al., 2019). For rock engineering, in particular, one of the main challenges is that it is difficult to obtain high quality, unbiased and objective data, and it is even more difficult to obtain high quality data in the large quantities needed for ML. These difficulties associated with rock engineering data can be attributed to the highly variable nature of geological materials as well as the qualitative nature of the data collection process and the empirical approach to design. A significant portion of the empirical design process in rock engineering involves the use of empirical industry standards developed from experiences several decades ago when the nature of rock engineering projects was significantly different to that of today. Key examples include rock mass classification systems used to quantify rock mass quality to aid engineering decision making, and rock mass characterization used to scale laboratory rock properties to field-scale properties required for numerical analyses. Even though these standards have become routine in rock engineering practice, they are not without their limitations. They include a relatively high degree of subjectivity due to various forms of bias, geological constraints and engineering constraints. However, rock engineers in both industry and academia often ignore these limitations and treat these empirical standards as standards. As rock engineering is increasingly integrating the design process with ML and other advanced computational techniques, a critical review of these empirical industry standards is needed to examine the feasibility of integrating them with ML. This study provides a critical review of commonly used rock mass classification systems with the goal of helping rock engineers integrate them with ML.

Background

The following section provides an overview of i) common empirical rock mass classification systems used in rock engineering and ii) ML.

Rock Mass Classification Systems

Rock mass classifications systems have become an industry standard and their use can be found in most rock engineering projects. They can be traced back to Terzaghi (1946), who created a system that linked rock mass characteristics to rock mass behaviour and failure mechanisms. Presently, the most common rock mass classification systems used in practice are the Rock Mass Rating (RMR; Bieniawski, 1973, 1976, 1989), the Q-system (Barton et al., 1974) and the Geological Strength Index (GSI; Hoek, 1994; Hoek and Marinos, 2000). Separate from these is the Rock Quality Designation (RQD), which was developed by D.U. Deere in 1964 (Deere et al., 1969) to define rock mass quality from borehole cores; this was subsequently adopted as an input parameter by the RMR and Q-system. It is defined as the summation of all sound core pieces greater than 10 cm (4 in.) in length divided by the total length of the core run and is expressed as a percentage (Deere et al., 1969).

The RMR was first introduced by Bieniawski (1973) based on experiences in South African tunnelling, with subsequent updates in 1976 and 1989. It is defined as the summa-

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tion of the ratings assigned to five parameters deemed the most important for rock mass quality:

- strength of the intact rock material
- rock quality designation
- spacing of discontinuities
- condition of discontinuities
- groundwater flow

Once RMR is calculated, it can be used to determine the support needed for a tunnelling, mining or slope stability project based on experiences from projects with similar RMR values. The RMR has been modified over the years in order to be more relevant to specific applications (e.g., caving methods and slopes). Some commonly used modified RMRs include the Mining Rock Mass Rating developed by Laubscher (1977) for mining applications and the Slope Mass Rating introduced by Romana (1985) for slopes.

The Q-system was first introduced by Barton et al. (1974) based on experiences in Scandinavian tunnelling and consists of six parameters organized as quotients (the ‘Q’ system) as shown in the following equation:

$$Q = (RQD / J_n)(J_r / J_a)(J_w / SRF)$$

where RQD is the rock quality designation as previously defined, J_n is the number of joint sets, J_r is the joint roughness coefficient, J_a is the joint alteration coefficient, J_w is the water reduction factor and SRF is the stress reduction factor. The SRF distinguishes the Q-system from the RMR and speaks to the respective experience base from which the two systems were developed. Scandinavian tunnelling projects have to contend with high horizontal stresses related to the geological history of the Scandinavian shield and therefore this was seen to be an important influencing parameter on rock mass behaviour. This is not the case in South African tunnelling and thus there was no stress factor included with its rating system.

Once a Q value has been calculated, the support for a tunnel can be determined from a support chart, which is similarly based on experiences from projects with different Q values.

The GSI was introduced by Hoek (1994) to provide a visually based estimation of the rock mass quality. It has undergone numerous updates since its introduction, going from a simple equivalency with RMR to a chart that combines the blockiness of the rock mass and the condition of discontinuities (Yang et al., 2021b). Although it was based on the RMR system, it differs from the RMR and Q-system in that it is not intended to rate the rock mass for support design classes; rather, it is used as a scaling parameter in combination with the Hoek-Brown failure criterion (Hoek and Brown, 1980) to determine the strength of the rock mass.

It is important to keep in mind that even though RMR, Q-system and GSI result in a numeric value, they are still quantifications of qualitative descriptions and are subject to the limitations of nominal and ordinal scale measurements. Additionally, these rock mass classification systems are subjective, with engineering judgement playing an important role, and they suffer from a lack of standardization between individual or company practices despite being treated as industry standards. Notwithstanding, they are often (wrongly) perceived as unbiased and objective.

Machine Learning

Machine learning is a subset of artificial intelligence in which mathematical models are used to help a computer find relationships among data. It enables a computer system to learn without direct instruction and to continue learning and improving on its own (Azure, 2021). In other words, ML enables a computer system to build a predictive model from data and that model can then be used to make predictions from new data (Google Developers, 2021a). Machine learning is divided into classification (where a label is predicted) and regression (where a numeric value is predicted). As previously mentioned, the success of ML algorithms depends on both the quality and quantity of data. A common saying in ML is ‘garbage in equals garbage out’; if the data used to train the model are of poor quality, the results of the model will also be of poor quality and unreliable (Google Developers, 2021b). Poor quality data come in many forms, including, but not limited to, wrong data (i.e., data input error), biased data and irrelevant data. Poor quality data, especially those that are biased, can have a significant impact on the results of a ML model. The importance of good quality data has long been recognized in the ML field (Sessions and Valtorta, 2006) and there has been significant research on how to mitigate biases (e.g., Dixon et al., 2018; Das et al., 2019); however, rock engineering has arguably yet to consider this sufficiently and biased data, such as rock mass classification values, are increasingly being incorporated in ML training. The other important aspect needed for a successful ML model is having enough relevant, good quality data so that the model is trained on a variety of scenarios and can find the relevant relationships between parameters (Google Developers, 2021b). Rock engineering often lacks the amount of relevant and good quality data needed to allow for a robust ML model.

Revisiting Rock Mass Classification Systems

The lead author’s research into the use of ML in rock engineering began in 2020, and the following section highlights the published progress to date. As discussed in Yang et al. (2021b), the use of ML in rock engineering is made difficult by the lack of standardization and need to statistically analyze databases that have been created through a quantification of qualitative assessments, such as in the use of rock mass classification systems. In order for data compilation to progress in rock engineering, rock engineers need to address how to digitize rock engineering information effectively and uniquely and how to better consider failure mechanisms. To accomplish this, rock engineers need to consider the original definitions and development of commonly used rock mass classification systems, something that is often overlooked in practice. Palmstrom and Broch (2006) highlighted the importance of this by stating that the use of rock mass classification systems required a good knowledge of their basis, their structure and their limitations. Yang et al. (2020, 2021b) provided an in-depth discussion on the development and limitations of the most commonly used rock mass classification systems (RQD, RMR, Q-system and GSI), which is summarized below.

As discussed in Yang et al. (2020), the RQD was developed based on observations that poorer quality core resulted in a significantly higher number of smaller core pieces (Deere et al., 1969). The RQD has two main applications: i) it is a quantitative measure to compare geological conditions at different sites, and ii) it is a red flag indicator to bring attention to what factors cause low core recovery (Deere and Deere, 1989). Of note is the arbitrariness associated with the 10 cm threshold when calculating RQD and the acknowledgment by Deere and Deere (1989) that the weighted RQD (calculated by counting all the core pieces and squaring the lengths of the pieces shorter than 30 cm) would have been better but the 10 cm threshold remained in use because of its early adoption and familiarity gained over time. Additionally, the use of RQD has four main requirements that have been largely overlooked: i) the core run length should be no longer than 1.5 m, ii) the core diameter should ideally be 54.7 mm (but larger core diameters can be used), iii) the core pieces should be hard and sound, iv) the core logging should occur at the same time as drilling (especially in shale and claystone). The limitations of RQD have been widely discussed since its development; however, they have also been largely overlooked by rock engineers. These limitations include i) the subjectivity surrounding the 10 cm threshold, ii) the difficulty in differentiating between mechanical and natural fractures, iii) the subjectivity in determining if the core is hard and sound, iv) its sensitivity to the relative orientation of the fractures with respect to the orientation of the borehole or scanline (i.e., orientation bias), and v) the ignoring of the effects that incipient fractures and veins have on rock mass strength (Yang et al., 2020).

The development of RMR by Bieniawski (1973) involved 49 initial case histories in 1973, followed by an additional 62 cases in 1984 and another 78 cases in 1987. By 1989, RMR had been used in 351 case histories, which contributed to its development. Approximately 63% of the case histories used in its development are in sedimentary rocks, whereas only 19% are in igneous rocks and 16% in metamorphic rocks. The majority of the case histories are in shale (98 cases or 28% of the case histories), followed by mudstone (31 cases) and sandstone (27 cases; Bieniawski, 1989). In contrast, 212 case studies were used in the development of the Q-system by Barton et al. (1974); 48% of the case histories are in metamorphic rocks, whereas only 38% are in igneous rocks and 13% in sedimentary rocks. The majority of the case histories are in granite (46 cases or 22% of the case histories), followed by schist (17 cases) and gneiss (14 cases). These differences again highlight the empirical nature of the development of the RMR and Q-system, and specifically, the geology encountered in tunnelling projects in South Africa (primarily sedimentary) that shaped the RMR versus that encountered in the Scandinavian shield (primarily crystalline) that shaped the Q-system. Based on the case histories used in the development of RMR and Q-system, RMR might be considered more applicable for projects in sedimentary rocks, whereas the Q-system more applicable for projects in igneous and metamorphic rocks. However, as shown in Yang et al. (2021b), these geological constraints have been ignored and RMR and Q-system have been used to describe rock mass conditions for projects in various rock types. Even though rock mass classification systems can be expanded to scenarios outside those in their original databases, Barton (1988) noted that it should be done with caution and careful consideration of the geological setting. Despite this, current practices in rock engineering have seemingly created a geological equivalency between RMR and Q-system.

It is also important to note that the case histories used in the development of RMR and Q-system are from several decades ago when the scale of projects was much more limited compared to today's projects. For RMR, the majority of its case histories involved tunnelling and shallow mining projects; most of these case histories have a span of up to 10 m and are limited to depths of up to 250 m. Similarly, the case histories for Q-system show that most of the projects used in its development had spans of up to 15 m and were at depths of up to 250 m. These case histories show that RMR and Q-system were not developed for deeper projects. This raises the question: should rock engineers use RMR and Q-system for current projects that are not only bigger but deeper? An important consideration is the potential failure mechanism, which depends in part on the size and depth of the project, as well as the geology.

As previously mentioned, the development of GSI differs from that of RMR and Q-system in that it was introduced to better characterize poorer quality rock masses and thus assist in determining input values for the Hoek-Brown failure criterion. Specifically, Hoek wanted a new system that "would not include RQD, would place greater emphasis on basic geological observations of rock mass characteristics, and reflect the material, its structure and its geological history" (Marinos et al., 2005). Initially, GSI was taken as being equivalent to RMR76 with the rating for water set to 10 (dry). As a result, it can be assumed that GSI was born out of the same geology database as RMR.

The current method of using rock mass classification systems ignores the geological and engineering constraints associated with their development and homogenizes the different nature of the geological and structural processes at play, which may be unique for a given regional or tectonic setting. The current classification process treats rock like other engineering materials (e.g., concrete) and generalizes its response to engineering activities; however, it is important that rock engineers recognize the role geology, and in particular structural geology, has not only on rock mass strength but also ground performance. One method of recognizing the inherent geological variability in rock masses is by reporting a range of classification values rather than one value that is often misconstrued as being 'accurate' and 'precise'.

Another limitation of rock mass classification systems that is often overlooked is that the rating values are nonunique and on their own do not provide any information on the rock mass conditions. As shown in Yang et al. (2021a), there are many combinations of parameter ratings in RMR, Q-system and GSI that can lead to the same classification value. For example, according to the GSI chart from Hoek and Marinos (2000), a GSI of 50 is associated with a rock mass that has a blocky structure and fair joint surface conditions (e.g., due to weathering) as would a rock mass that is very blocky but has good joint surface conditions (e.g., if it was unweathered). Even though both rock masses have the same GSI, they have different rock mass conditions. Yang et al. (2021a) showed that the majority of combinations are in the 'Fair' rock mass class for RMR (RMR = 40–60) and the 'Very good' rock mass class for the Q-system (Q = 40–100). This means that there is more uncertainty surrounding the classification values in these ranges because of the variability in rock mass conditions. As a result, it is imperative that rock engineers report the parameter ratings they used to determine their classification values.

The Future of Rock Engineering Standards for Machine Learning

There has been increasing pressure to integrate rock mass classification systems with ML in recent years under the guise of providing more accurate and precise RQD, RMR, Q-system or GSI values. However, as shown in the previous section, the notion that classification values are accurate and precise does not reflect the inherent geological variability found in rock masses or the subjectivity in quantifying them. Even though it is possible to incorporate ML in rock mass classification systems, it is important to always keep in mind the aforementioned limitations of these systems (both geological and engineering constraints) and the original purpose behind their development. If rock engineering is to continue moving forward with the incorporation of ML into its design processes, then more objective and unbiased parameters need to be developed. Some examples of objective parameters currently under development are the Representative Elementary Length (REL) introduced by Elmo and Stead (2018) and the Network Connectivity Index (NCI) introduced by Elmo et al. (2021). The REL is a new rock mass quality indicator that is more objective, whereas NCI is a new rock mass classification system that is more objective and considers failure mechanisms. Both of these new parameters are not subject to the same limitations and subjectivity as their predecessors and, as a result, they can be more easily integrated with ML techniques. These parameters will benefit the mineral resources sector in British Columbia by improving the efficiency of the exploration and design process, as well as improving the accuracy of the design. Ultimately, this will result in improved sustainability during mineral exploration and mine design.

Future Work

The next steps include developing a set of guidelines for the use of ML in rock engineering as well as building on Elmo and Stead (2018) and Elmo et al. (2021) to refine the concepts of REL and NCI and incorporate them within ML algorithms. Both the development of the guidelines and refinement of REL are currently underway and are expected to be completed in the upcoming year. Additionally, the guidelines are expected to be published in a conference and journal paper in the upcoming year. It is anticipated that this research will be completed by 2024.

Conclusion

The rock engineering design process is highly empirical and dependent on empirical industry standards, such as the Rock Quality Designation, Rock Mass Rating, Q-system and Geological Strength Index. As rock engineering transitions into the era of digitalization and machine learning, it is essential that these empirical industry standards are revisited in order to better understand their development and limitations. The geological and engineering constraints of rock mass classification systems are not widely acknowledged by rock engineers, and subjectivity and bias make it difficult for them to be easily integrated with machine learning. If rock engineers want to continue using current rock mass classification systems, then they should ensure that their geological and engineering constraints are recognized. However, the development of more objective and unbiased rock mass classification systems can help rock engineering transition to successfully implementing machine learning by ensuring that the data is of good quality. In order for rock engineering industry standards to be the best available solution, they should undergo continuous revisions and improvements.

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