Unleashing the power of AI and measure-while-drilling for enhanced overbreak prediction of a cavern project

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ABSTRACT

Drill-and-blast excavation is crucial for constructing underground spaces, and artificial neural network control has far-reaching implications for the success of these projects regarding safety, time, cost and environmental aspects. Although this method has been widely adopted in Hong Kong since the first Lion Rock Tunnel in the 1960s, the research on artificial neural network prediction from local projects is very limited. Adequate attention and qualitative enhancement of artificial neural network control are lacking in Hong Kong. In addition, the traditional perspective suggests that predicting artificial neural network is challenging due to its strong correlation with irregular and random geological features, as well as the complex interactions between blasting parameters. Consequently, the control and prediction of real-world outcomes of artificial neural network through a theoretical approach may not be deemed practical or reliable. Our project team therefore took help from the international experience to tackle the issue and went a step further by integrating the drilling data recorded from Measure-While-Drilling into Artificial Intelligence to predict the artificial neural network. A total of 114 sets of input data were analysed by using an artificial neural network to predict artificial neural network, and a model with a high level of accuracy (R^2=0.8234) was developed for the current project and also other projects in the future.

KEYWORDS Drill-and-blast excavation, overbreak prediction, cavern project, geological and blasting factors, measure-while-drilling, artificial neural network
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1. Introduction

Underground cavern construction via drill-and-blast excavation faces numerous challenges and uncertainties, while overbreak is one of the major issues. Overbreak is defined as the excessive excavation of rock beyond the design profile. It is often quantified in terms of either thickness/distance or as a percentage of rock that exceeds the intended limit of an excavation (Singh, 1994; Jang & Topal, 2013). More than 85% of the energy that is produced in the blasting operation is not used in the process of rock fragmentation and pulling out of the rock from the tunnel face (Mottahedi et al., 2017), but causes damage to the host rock resulting in failures, unstable ground and overbreak. According to some researchers (e.g., Sing & Lamond, 1994; Verma et al., 2016), the rock mass damage zone, as shown in Figure 1, is categorised into three zones which are the overbreak zone (or failed zone), damaged zone and disturbed zone. The damaged zone is a zone of fine networks of micro-cracks and fractures induced by the blasting and excavation process. It is characterised by the deterioration in the mechanical and physical properties and the increase in the transmissivity properties. The disturbed zone is a zone in the rock mass immediately beyond the damaged zone where the changes in the rock mass properties are insignificant and reversible. Excessive overbreak could pose safety risks to workers and have a significant impact on both project costs and completion time.

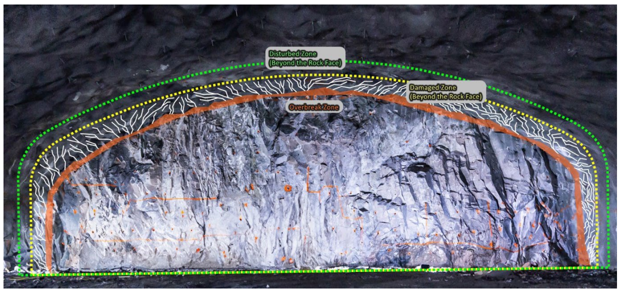

Figure 1. Illustration of overbreak, damaged and disturbed zones.

Overbreak is caused by two major groups of factors, namely geological and blasting (Mahtab et al., 1997; Jang & Topal, 2013; Verma et al., 2016; Mottahedi et al., 2017). Among the geological parameters, jointing is the primary factor that affects overbreak. This includes orientation, spacing and filling of joints. Other factors such as intact rock strength, and in-situ ground stress conditions also contribute (Ibarra et al., 1996). These factors are inherent properties of the rock mass and are considered uncontrollable. On the other hand, blasting parameters are controllable factors resulting from the blasting design aimed at reducing overbreak and minimising vibration effects on the surrounding environment. These parameters include the type of explosive, powder factor, charge concentration, maximum instantaneous charge (MIC), perimeter blasthole pattern, delay timing, etc. Ibarra et al. (1996) further suggested that the perimeter part of the blast is most likely to result in overbreak and the central part of the blast usually to a lesser extent. In addition to the geological factor and blasting factor, another influential factor in overbreak is the geometrical parameters. The parameters are considered semi-controllable, as they are determined during the detailed design phase and can be adjusted to some extent through construction sequences. Geometrical parameters include excavation shape and size. There is high potential of overbreak occurrences in excavations with a complex excavation profile (Mahtab et al., 1997). Apart from that, workmanship factors also contribute a negative phenomenon. Ibarra et al., (1996) suggested that a drilling deviation in collaring and in drilling direction may be considered as the most common contributing factors. Mottahedi highlighted the importance of accurate drilling at contour holes such that any deviation from the intended hole pattern can cause the drilled holes to either deviate away from or toward the target hole endpoints. This can subsequently lead to an increase or decrease in the explosive concentration within the holes (Mottahedi et al., 2017).

Attempts at predicting overbreak have been made by numerous researchers. Ibarra et al. (1996) adopted multiple linear regression analysis by considering the perimeter powder factor (PPF) and the rock mass quality value (Q-value) as input variables in developing the prediction model. Murthy et al. (2003) used statistical methods to develop the prediction model by considering the MIC only, which seem to over-simplify the complex relationship involved. Verma et al. (2016) formulated an empirical equation for predicting overbreak for a wide range of Q-value between 0.03 and 17.8. However, the prediction of overbreak remains a non-trivial challenge. The relationship between various causing factors and the occurrence of overbreak exhibits a considerable degree of complexity and lacks a clear definition. A distinct well-defined correlation that accurately depicts overbreak in relation to the causing factors does not appear to exist. Therefore, artificial intelligence (AI) may offer significant advantages to solve the problem. Jang and Topal (2013) and Sun et al. (2013) adopted an artificial neural network (ANN) for overbreak prediction. However, they only considered geological factors and neglected the other factors in their models. They believed that the influence of blasting factors can be negligible when using an advanced smooth blasting method. Mohammadi et al. (2015) considered both blasting and geological factors in the prediction model for better capturing the various causing factors. Their model was more precise than the previous models. It is therefore important to consider most overbreak causing factors (Mottahedi et al., 2017). The workmanship factor in blasting hole drilling, particular at the perimeter holes, has a direct impact on the overbreak extent and has never been quantitively considered in previous research. In view of this, our project team went a step further to incorporate the drilling data recorded by Measure-While-Drilling (MWD), accounting for the workmanship factors in the AI prediction model.

2. Insights of resident supervision staff (RSS) on the need for overbreak control

Drill-and-blast excavation was carried out in our cavern project and effective control of overbreak was of paramount importance regarding safety, cost, progress, quality and environmental aspects.

2.1. Safety considerations

Significant overbreak and excessive damage to the surrounding rock increase the risk of intercepting with adverse geological features which thus increase the likelihood of a falling rock mass before the construction of temporary support. In addition, the larger the overbreak extent, the heavier the temporary support so that more rock bolts and thicker shotcrete are required for stabilisation. The construction of rock bolts and shotcreting are considered high-risk activities due to factors such as working at height, working against gravity and operating in a confined space. In order to achieve a one-day blasting cycle, temporary supporting measures are usually constructed during the nighttime, further adding the risk. Particularly during this time, there may be challenges for working personnel in maintaining high levels of safety awareness due to fatigue.

2.2. Cost implications

Excessive overbreak incurs direct and indirect costs, including additional resources for remediation, surface finishing, and reinforcement measures. The need for supplementary materials, equipment, and labour to address overbreak-related issues contributes to cost overruns and budgetary challenges. Effective cost management practices, coupled with proactive overbreak prevention strategies, are essential to mitigate the financial implications of excessive overbreak in cavern blasting projects.

2.3. Progress

The presence of excessive overbreak necessitates additional remedial measures, leading to project delays and disruptions to the construction schedule. The need to address overbreak-induced instabilities and surface irregularities can introduce inefficiencies in the construction process, impacting the overall project timeline. Delays in cavern development can have cascading effects on the broader project schedule, highlighting the importance of managing overbreak to ensure smooth project progress.

2.4. Quality implications

Excessive overbreak can lead to irregular and unstable cavern surfaces, compromising the structural integrity and overall quality of the excavated space. The resulting irregularities may necessitate additional support measures and surface finishing, leading to deviations from the project's original design intent. The quality implications of overbreak underscore the need for precision blasting management to minimise detrimental effects on cavern quality.

2.5. Environmental impact

Overbreak generates excess rock debris and dust, posing environmental concerns related to air quality, water runoff, and ecosystem disruption. Dust and debris management becomes critical to minimise the environmental impact of cavern blasting, necessitating the implementation of stringent control measures. The environmental implications of overbreak underscore the need for sustainable construction practices that prioritise environmental protection and preservation. One of the environmental practices is shotcreting inside the cavern, as shown in Figure 2. The stream of spray concrete may not adequately adhere to the surface, resulting in rebound and suspension of particles in the air and thereby deteriorating the air quality inside the cavern.

Figure 2. Shotcreting inside Sha Tin cavern.

3. Navigating overbreak prediction and control with expertise

3.1. Customising overbreak prediction models

The RSS acknowledge the significance of previous research as a crucial guideline for the development of overbreak prediction models. The findings of these studies, summarised in Appendix A, provide fundamental insights into the factors influencing overbreak and serve as valuable foundations for formulating effective prediction models.

While the RSS have adopted methodologies and equations from prior researchers to predict overbreak, the accuracy of these adopted models, however, is often limited. It is therefore important to recognise that applying these models to local practices may be constrained due to site-specific factors, including geological conditions, construction approaches, and regional variations, etc. Overbreak prediction is a complex task involving interconnected parameters and mechanisms, posing challenges for accurate forecasting. To address this, the RSS advocated for the integration of AI techniques. AI has the capability to process and analyse large volumes of data, encompassing geological parameters, blasting parameters, and drilling parameters obtained from MWD. By leveraging AI, it becomes possible to predict and manage the unpredictable phenomena. The effective processing and interpretation of diverse data inputs via AI offer promising prospects for enhancing overbreak prediction accuracy. The specifications of an AI engine and the AI room on site are shown in Figure 3. An AI overbreak prediction model with the input page is shown in Figure 4.

Figure 3. AI engine for overbreak prediction in the AI room at Sha Tin cavern's site office.

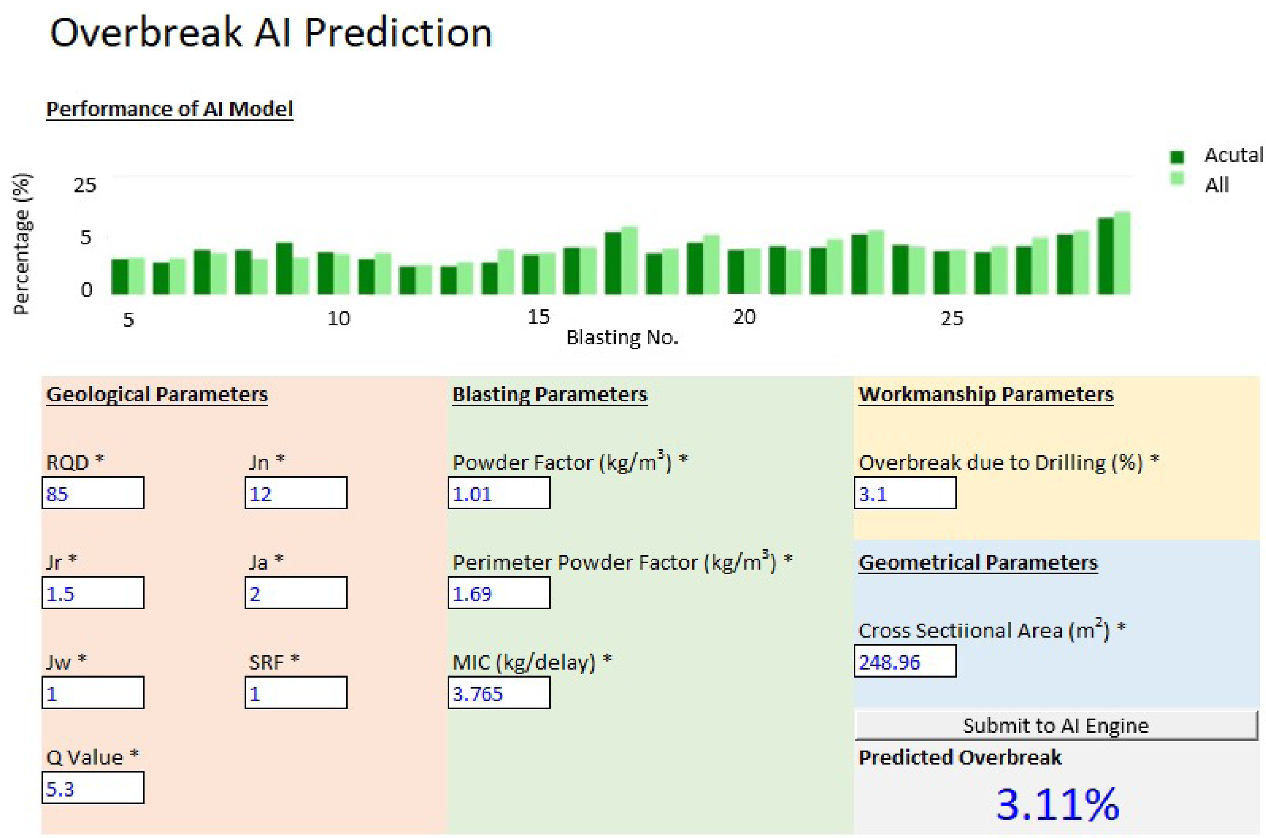

Figure 4. Input page of the AI overbreak prediction model.

3.2. RSS collaboration on overbreak prediction and control

The detailed workflow shown in Figure 5 demonstrates the proactive site supervision conducted by the RSS to enable overbreak prediction and control. All the causing factors of overbreak are input into the AI engine to predict the overbreak. The team then collaboratively reviews the prediction results, approving the blast design if the predicted overbreak is deemed acceptable or revising the blast design if it exceeds limits. Post-blasting data, such as drilling records and survey results, enable the AI's continuous learning for further improving the accuracy.

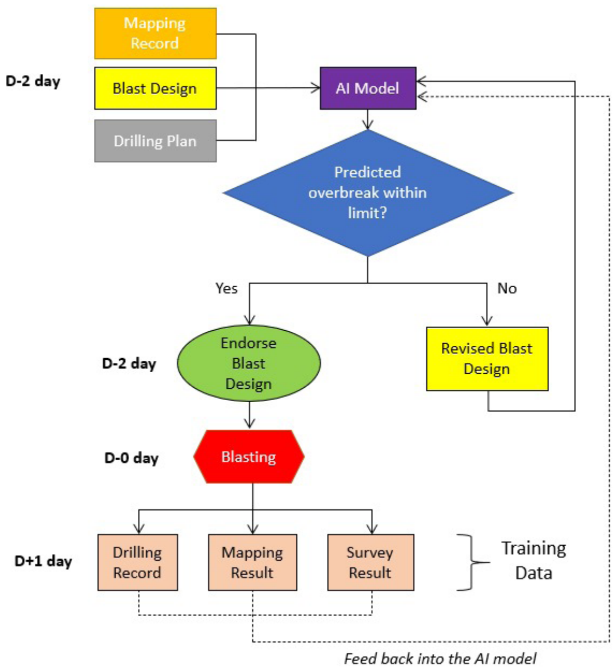

Figure 5. Detailed workflow of the RSS in overbreak control.

3.3. RSS collaboration on geological factors

In Hong Kong, the rock mass quality is typically qualitatively expressed in terms of the Q system and is determined by the contractor's geologist based on the exposed rockface after each round of blasting. The Q system is a function of six geological parameters: rock quality designation (RQD), number of joint sets (Jn), joint roughness (Jr), joint alteration (Ja), water reduction factor (Jw), and the stress reduction factor (SRF). The RSS therefore adopted the Q-value representing geological factors to be adopted in the overbreak predictive model. The RSS reviewed the Q-value with the geologist to assess its representativeness in relation to the geological conditions. They closely monitored the variations in Q-value for effective overbreak management. They paid particular attention to any abrupt changes in value during the cavern excavation.

3.4. RSS collaboration on blasting factors

The RSS took reference from previous research and conducted trial-and-error tests to find the appropriate blasting parameters to be adopted in the overbreak predictive model. These include the PPF, powder factor and MIC. The PPF is defined as the weight of explosives in the perimeter blastholes and the next row in, divided by the volume of rock within this annulus. The powder factor is defined as the explosive weight divided by the volume of rock blasted, which averages out the explosives used in the entire blast area. The MIC refers to the maximum amount of explosives which can be detonated at one specific delay. The RSS has taken proactive measures to enhance overbreak management. In the event of a rapid change in Q-value recorded by the geologist, the RSS will review the blasting parameters adopted in the contractor's blast design in relation to the overbreak prediction model. Subsequently, they will advise the blasting engineer on optimising the blast design for a more desirable overbreak outcome.

3.5. RSS collaboration on workmanship factors

Drilling deviation alters the spacing and burden between successive rows of blast holes, which is significantly important for the perimeter holes in overbreak control (Simon & Elton, 2022). The RSS actively implements the MWD technique to enhance the site supervision practice. The drilling jumbos are equipped with sensors and routers, as shown in Figure 6, to gather crucial drilling data comprising three-dimensional as-built alignment for 100% blast holes such that real-time monitoring of drilling operations can be conducted at any time and any locations whether in the office or on site. If the RSS discovers that any blast holes deviate significantly from their intended position or alignment, most probably due to carelessness or wrong setting of drilling jumbos, remediation can then be carried out immediately to rectify the situation. The RSS diligently embrace the use of real-time data to control the overbreak from workmanship factors, thereby enhancing the safety and quality of drill-and-blast operation.

Drilling deviations can be challenging to completely avoid, even with direct and active site supervision. These deviations can occur at the beginning of the blast hole due to local irregularities on the rock surface, as well as during the drilling process when the drill bit encounters geological features that cause deflections in the drilling direction. The drilling deviation at the perimeter holes has a significant impact as it can alter the desired excavation boundary and affect the PPF used in the blast design. However, with the assistance of MWD technology, the impact of drilling deviation can be quantitatively assessed and incorporated into the overbreak prediction model. This allows for a more accurate assessment of overbreak. The as-built layout of blast holes in 3D view is shown in Figure 7.

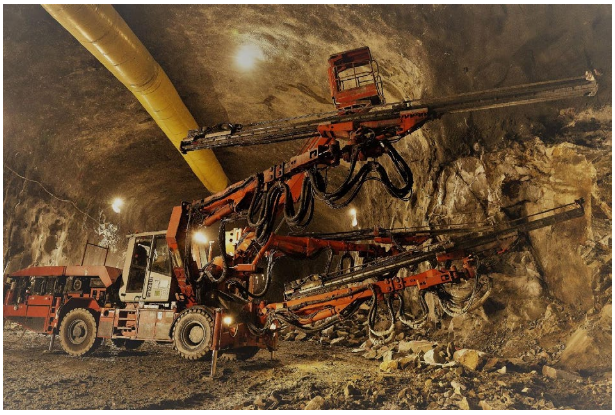

Figure 6. Jumbo equipped with MWD sensors.

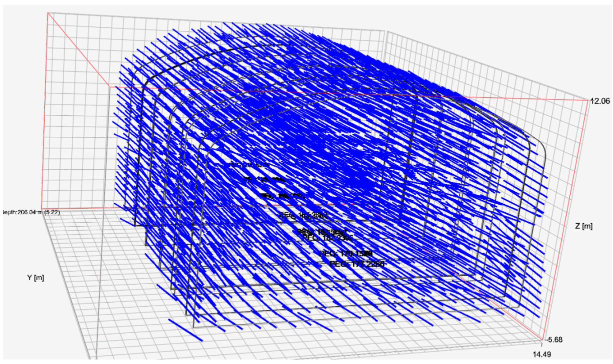

Figure 7. As-built layout of blast holes in 3D view.

3.6. RSS collaboration on the measured overbreak

Laser scanning has emerged as a valuable tool for the accurate assessment of cavern profiles and measurement of overbreak after blasting in underground construction. The scanning process generates highly dense point cloud data, enabling the reconstruction of a detailed three-dimensional

(3D) model of the cavern section. This technology allows for precise measurements of the overbreak volume, providing crucial insights into the excavation process. The laser scanning is conducted by a dedicated survey team after the scaling process, ensuring that potential dangers associated with falling rock fragments are mitigated. The result of a 3D laser scan is shown in Figure 8.

The RSS goes above and beyond by paying close attention to the measured overbreak after each round of blasting. They conduct a detailed review when the measured overbreak exceeds a certain limit, such as 8%. They analyse all the influencing factors, meticulously examining the excavation process and identifying any potential areas for improvement. This comprehensive review allows the RSS to provide valuable insights and recommendations to optimise future blasting operations, enhancing safety and efficiency.

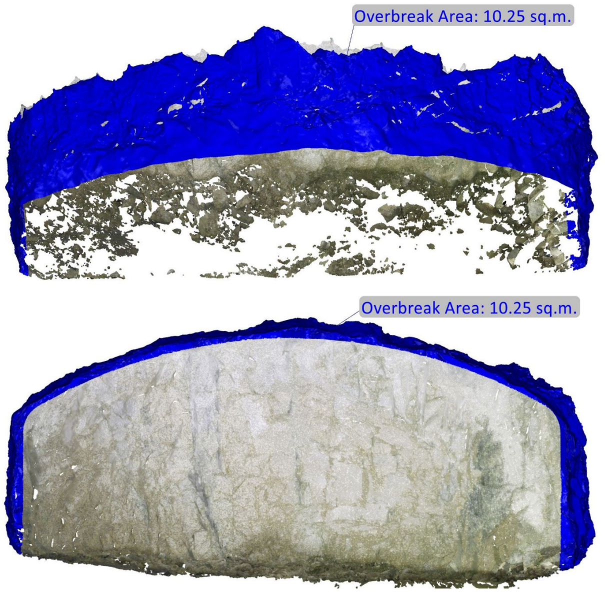

Figure 8. 3D laser-scanned rockface.

4. Site description

The Relocation of Sha Tin Sewage Treatment Works (STSTW) to Caverns is a prominent underground drill-and-blast excavation project in Hong Kong which began in 2019. The general view of the project site is shown in Figure 9. The completed cavern hall, which consists of five parallel caverns along the longitudinal axis of the cavern complex, will be around 380m x 350m with a maximum span of 32m. The upcoming cavern complex for the relocated STSTW will be the largest of its kind ever constructed in Hong Kong. Figure 10 shows the Building Information Modelling (BIM) of the upcoming cavern complex. In stage 1, a 260m-long Main Access Tunnel (MAT) and a 90m-long Main Access Tunnel West (MATW) were constructed. The tunnel section is horseshoe-shaped with a span of 18m and cross section area of around 270m^2. The tunnels and cavern complex are mainly located in rock with more than half the span of rock cover above the tunnel crown. The tunnels will be blasted in two stages consisting of top heading and bottom benching. Figure 11 shows the typical blast design adopted for top heading and bottom benching excavation.

Figure 9. General view of the project site.

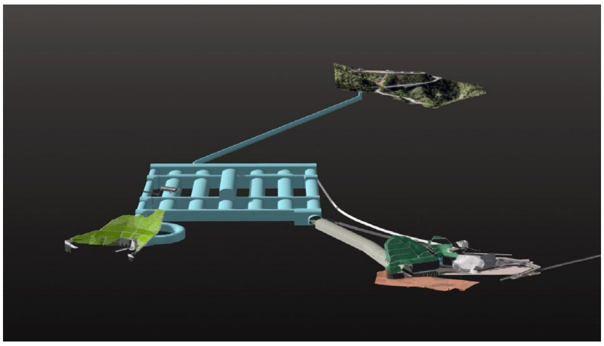

Figure 10. BIM model of the future cavern completed.

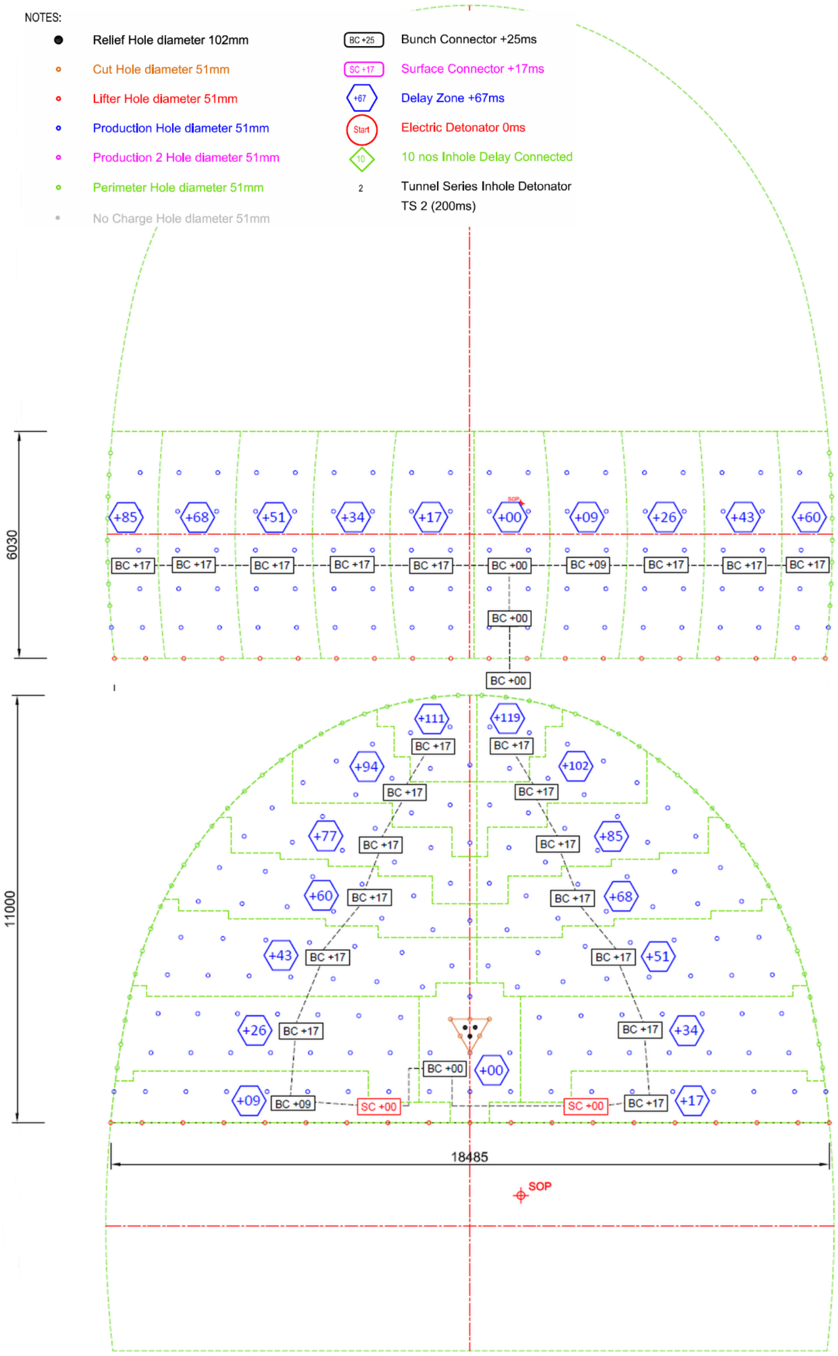

Figure 11. Typical blast design for top heading and bottom benching.

4.1. The geology

The slope surface above the MAT is mainly overlaid by a layer of colluvium or topsoil with a thickness of 0.5m to 2m with reference to the boreholes along the Main Access Tunnel footprint. Below the colluvium, a variable thickness of weathered granite is encountered in the majority of boreholes. A very thin layer of Residual Soil (RS) with a maximum thickness of 1.5m is found only in a few boreholes and trial pits. Completely Decomposed Granite (CDG) is commonly found below the colluvium and RS layer. The access tunnel from the two Main Portals MAT & MATW will be mined in soft/mixed ground conditions with rock head less than one tunnel diameter above the crown for up to 200m in length. The material is likely to be core stones with Grade V granite as well as fractured rock. The geological sections of the MAT and MATW are shown in Figure 12. The fair rock mass with a Q-value lying between 3 and 5 was mapped.

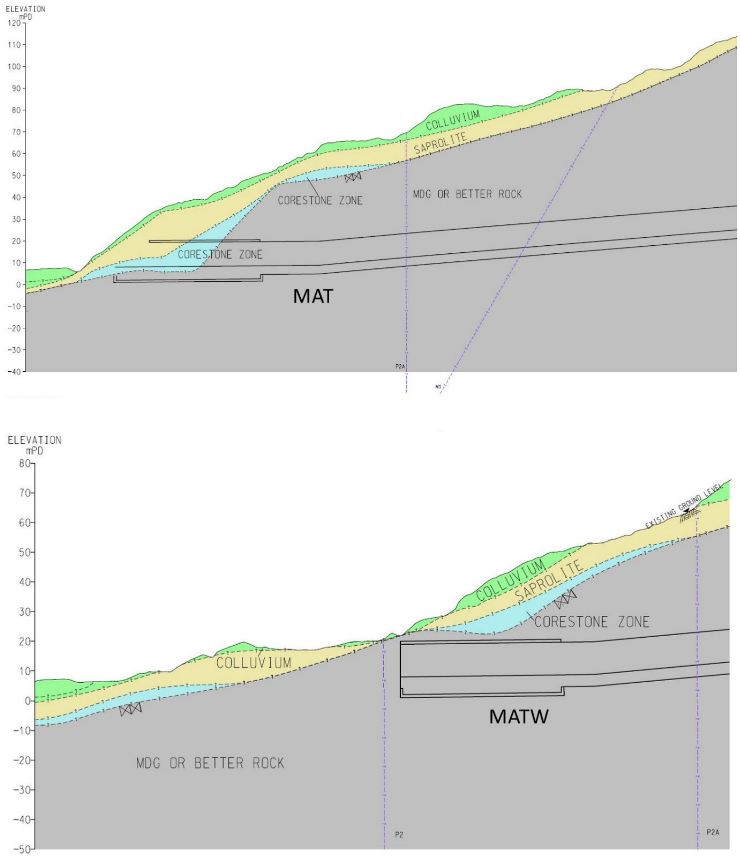

Figure 12. Geological section of the MAT and MATW.

5. Overbreak prediction model

5.1. Data set collection

A total of 114 items of set data including geotechnical, blasting, geometrical and workmanship due to drilling deviation were obtained from the blasting operation in this project and are summarised in Table 1.

Table 1. Summary of input and output parameters adopted in the ANN.

Type of Influencing Factors	Parameters	Symbol	Unit
Input			
Geological Factors	Q-value	Q	-
Blasting Factors	Perimeter Powder Factor	PPF	kg/m^3
	Powder Factor	P	kg/m^3
	Maximum Instantaneous Charge	MIC	kg/delay
Geometrical Factors	Cross Area	A	m^2
Workmanship Factors	Overbreak due to drilling	OBD	%
Output			
	Overbreak	OB	%

5.2. ANN

An ANN is a computing method inspired by the processing of the human brain. A typical ANN consists of three key components: the network architecture, the learning algorithm, and the transfer function. An ANN is one of the AI methods and it is a computation inference model simply mimicking the biological structure of the human brain (Jang & Topal, 2013).

An ANN is composed of node layers, including an input layer, one or more hidden layers and an output layer. Nodes or neurons are simple processing units and are connected to each other in a complex network. It is the neurons, which act like a human brain, which receive intensified or weakened signals from other neurons via appropriate activation functions, and the connection weights modulate input signals as a synapsis performs in the human brain. If the output of any single node is above the specified threshold value, that node will be activated and send the data to the next layer of the network. Otherwise, no data will be sent through to the next layer of the network. The architecture of a typical ANN is shown in Figure 13. Backward propagation with momentum is adopted as the training method to train the neural network in a supervised way.

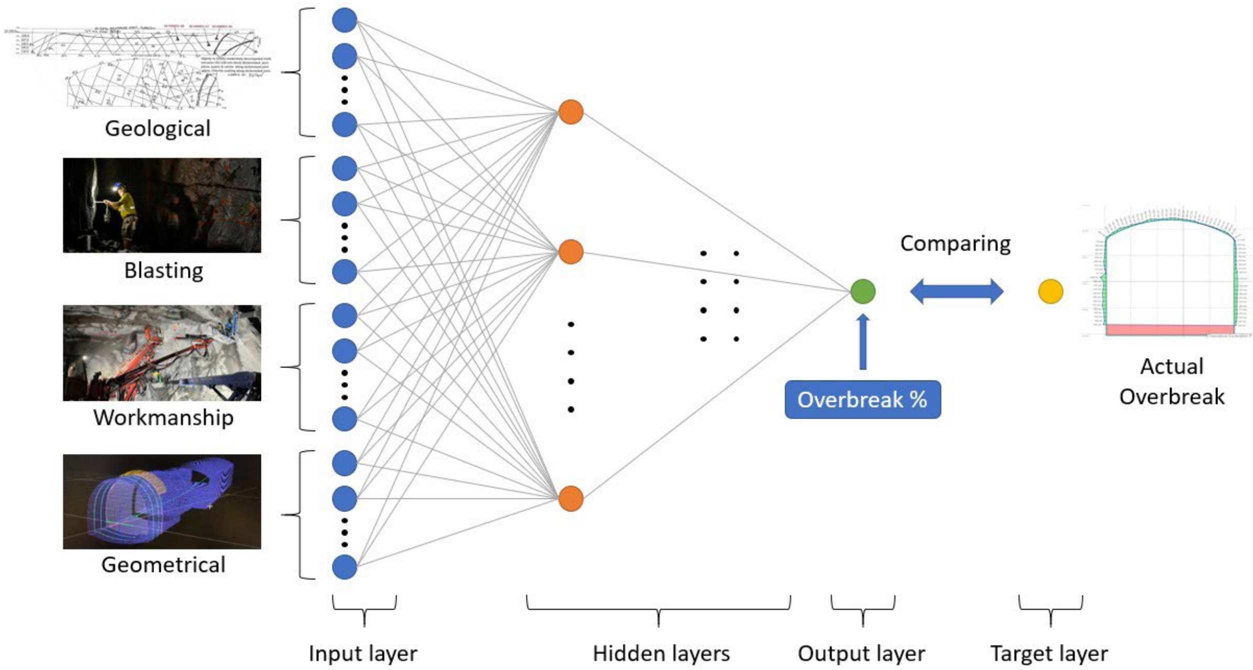

Figure 13. The architecture of a typical ANN.

5.3. Assessment and comparison of the model's performance

All available datasets were used for training the AI model and testing its accuracy. The overbreak prediction models based on an ANN were developed for overbreak prediction during the cavern excavation. AI models with the highest R2 equal to 0.8234, as shown in Figure 14, with RMSE equalling to 0.006850567 were developed. The comparison of the measured and predicted overbreak is shown in Figure 15.

Overbreak prediction models serve as a pre-blasting warning system for tunnelling and mining projects, enabling the RSS to anticipate overbreak incidents and implement preventive measures. By utilising these models, the RSS can review and advise engineers on adjusting controllable parameters to minimise overbreak occurrences. This proactive approach allows for the optimisation of blast design, with the RSS playing a significant role in helping the project effectively reduce the overall amount of overbreak. This, in turn, enhances project efficiency and safety.

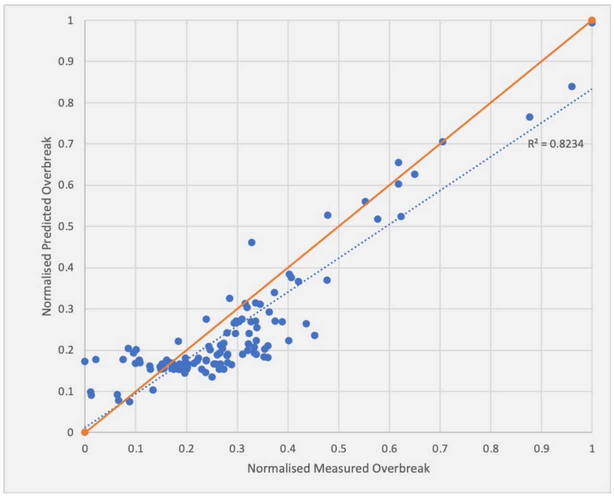

Figure 14. Comparing the measured and predicted overbreak.

6. Discussion

6.1. Issue and need for further verification

The AI model was developed using all available datasets for both training and testing its accuracy. This decision was driven by the limited amount of data, allowing for maximised learning from the existing information. The performance of the AI model should be continuously reviewed with new data inputs to verify its robustness and ability to generalise effectively.

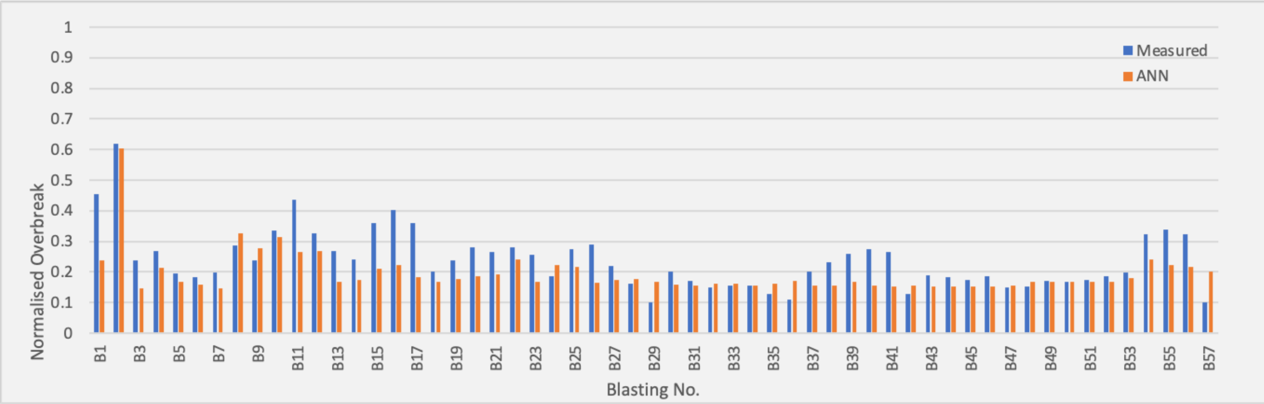

Figure 15. Comparison between the measured and predicted overbreak.

6.2. RSS's commitment to innovation

The Relocation of Sha Tin Sewage Treatment Works to Caverns project, as a pilot project, follows the trend of Construction 2.0 for future cavern development in Hong Kong. The RSS of the project endeavoured to adopt various technologies to evolve the old-fashioned technique. They took a proactive approach by incorporating drilling data recorded by MWD and AI to develop an overbreak predictor model for controlling and minimising these undesirable effects, rather than relying solely on contractors. The RSS have successfully developed an overbreak prediction model that demonstrates a high level of accuracy and reliability. The primary objective of this prediction model is not to only predict the unpredictable phenomena but to effectively control the occurrence of overbreak for future cavern projects. By utilising the overbreak prediction model, the RSS aims to provide engineers with valuable insights and proactive measures to mitigate overbreak. The development of this prediction model by the RSS signifies a significant step forward in ensuring the control and management of overbreak.

6.3. Overbreak prediction 2.0

In the developed overbreak prediction model, the Q-value is used to represent the geological factor. However, it has limitations. The Q-value, determined by geologists, is a qualitative parameter that may not provide a precise description of the rock mass condition. The subjective nature of its determination can introduce variability and uncertainty into the analysis. Additionally, the Q-value is determined solely based on observations of the entire exposed rockface. This approach fails to specifically focus on the jointing at the perimeter of the blast face, which has a greater influence on the extent of overbreak. Moreover, geological mapping for the Q-value is typically conducted on the blast surface at intervals of 3m to 5m after each round of blasting. The determination of the rock mass condition is discretely based on the mapped sections. An assumption is made that the rock mass condition beyond the blast face can be represented by the blast face, which may not be applicable in locations with complex geological settings.

Considering the mentioned limitations, the RSS proposes the full adoption of live data from MWD, leading to a more accurate and effectively managed approach in "Overbreak Prediction 2.0". The real-time collected data during the drilling of each blast hole serve as ground-investigation drillholes, providing a fast and efficient way to reveal the geological condition ahead of the blast face. The extended function of MWD can provide precise and numerical geological indicators, including the Fracture Index, Rock Drilling Resistance, Water Indicator, and Rock Quality Number. This approach allows for obtaining specific geological indicators at the perimeter of the blast face, enabling more accurate overbreak prediction. By fully integrating MWD data into the prediction model, a more accurate model can be achieved.

6.4. Big data, the construction industry and the future

While the AI-based model is highly adaptable and scalable, it requires more data from diverse site settings to generalise its use in overbreak prediction across different locations. For example, the current version of the model does not include the shape and span of the tunnel as input parameters. This limitation stems from the monolithic geometrical data specific to the tunnel section in this project. Consequently, the model is tailored to this particular configuration. Its direct applicability to other tunnel shapes or spans in different projects would necessitate data from different sites to adequately validate its effectiveness. The neural network architecture and training approach can be readily applied to new datasets from other excavation sites. By incorporating the relevant geological, blasting and drilling parameters, the model can be fine-tuned to deliver accurate overbreak predictions for different project settings. The comprehensive database assembled through this research serve as a valuable foundation. As this data repository is expanded with information from upcoming cavern projects, the model's accuracy and reliability will continually improve through ongoing learning and refinement. Future project teams can leverage the valuable insights gained from this work to better anticipate and proactively mitigate overbreak challenges. In addition, the methodological approaches employed in this study, such as the integration of MWD data with AI modeling, can be replicated and adapted for use in a wide range of other construction activities. This cross-pollination of knowledge and best practices has the potential to drive continuous improvement and foster innovation within the construction industry as a whole.

7. Conclusion

In conclusion, overbreak prediction and control in drill-and-blast excavation, particularly in cavern projects, are of utmost importance for ensuring safety, minimising costs, and optimising project timelines. This technical research paper discusses the practical supervision experience gained by the RSS in the Sha Tin Cavern Project, focusing on overbreak prediction and control through the utilisation of AI and MWD. The RSS of the project has taken a proactive stance in controlling and minimising the risks associated with overbreak, moving beyond reliance solely on contractors. Their vision advocates for the industry to shift from being simply responsive to events that have already occurred to proactively identifying risks and their causes. The RSS recognises the unlimited potential of Big Data, not only in overbreak control and prediction but also in predicting other phenomena that may occur during construction. The project team has established a database for overbreak prediction as a pilot project for cavern development, with plans to continually expand it by incorporating data from other projects in Hong Kong. In the long term, it is believed that Machine Learning and Big Data analysis will be widely adopted in predicting phenomena in various construction activities, revolutionising the industry.

Data are the new dollar, and the value of Big Data in the digital age is almost limitless. The doctrine is to cross over with the industry to move away from being simply responsive to an event that has already happened to proactively identifying risks and their root causes. Predicting and controlling the overbreak in blasting by applying Machine Learning and Big Data analysis is just one of the examples of successfully applying the technology being developed in this project. As the industry accumulates more and more information, the data do indeed grow bigger, but so does the necessity to condense them into manageable bites. In the long term, it is believed that Machine Learning and Big Data analysis will be widely adopted in the prediction of phenomena happening in many other construction activities and bring revolutionary changes to the drill-and-blast industry.

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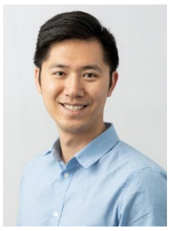
Mr Simon C M Leung currently holds the position of Chief Resident Engineer at AECOM Asia Company Ltd. With over 22 years of on-site experience, he has successfully led a wide range of large-scale projects such as Liatang/Heung Yuen Wai Boundary Control Point and the Relocation of Sha Tin Sewage Treatment Plant to Caverns and is currently overseeing the Northern Metropolis Development - Hung Shui Kiu Effluent Polishing Plant Project. He possesses specialised expertise in overseeing the construction of viaducts, drill and blast tunnelling, TBM, and sewage treatment facilities. Mr. Leung is committed to advancing Construction 2.0 principles and actively pursues innovative methods to enhance productivity, efficiency, safety, and sustainability in site supervision.



Mr Matthew M K Chan is currently the Resident Engineer at AECOM Asia Company Ltd. responsible for the supervision of drill-and-blast excavation of the Relocation of Sha Tin Sewage Treatment Works to Caverns Project. Mr. Chan is a chartered civil and geotechnical engineer, with over 15 years of engineering experience and had extensive experience in construction, drill-and-blast excavation, and geotechnical design including site formation, slope stabilisation, excavation, and lateral works.

Mr Felix C S Yu graduated from the University of British Columbia in Canada and is currently Senior Engineer in the Drainage Services Department. He has over 22 years of practical working experience and has participated in numerous large-scale and prestigious civil engineering projects, including the

Relocation of Sha Tin Sewage Treatment Works to Caverns Project, and the Upgrading of Central and East Kowloon Sewerage Project. He has previously been involved in the design, supervision and administration of various highways projects. In the past 8 years, Mr Yu has been transferred to the Drainage Services Department and is actively involved in sewerage projects such as the upgrading of urban sewerage and sewage treatment works.

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Appendix A - Summary of the methodology adopted by previous researchers

Researchers	Methodology	Findings
Singh (1994)	A predictive model uses blast vibration monitoring to locate damage at the critical particle velocity (Vd), considering the rock tensile strength (Ts), longitudinal wave velocity (Vp) and elastic modulus (E). By analysing vibration data and Ts/E values, it estimates the likely damage areas during blasting, aiding engineers in assessing and mitigating rock mass damage.	Vd (mm) = Vp Ts / E
Ibarra et al. (1996)	The Q-factor shows the strongest correlation with rock mass characteristics and overbreak. The Perimeter Powder Factor (PPF) is a key parameter for blasting design. By using multiple regression analysis, these factors are employed to predict overbreak.	Overbreak (%) = -0.12 + 15.07 PPF – 2.55 log(Q)
Innaurato et al. (1998)	Rock Mass Rating (RMR) is widely used to describe rock mass characteristics in tunnel design. By analysing data from 17 tunnels, graphical plots are used to confirm the influence of RMR on the blasting quality.	The ratio of the length of half cuts of holes remaining in the contour after blasting to the total length of contoured boreholes (HCF) decreases with overbreak. There is no clear relationship observed between the ratio of the theoretical pull of the round (η) and RMR, as well as between the powder factor and RMR. However, it is possible that the specific consumption of explosives (c) is largely influenced by the tunnel section.
Murthy et al. (2003)	The study examines the literature on PPV-based damage estimation models from previous researchers. It emphasises two stages of rock failure in overbreak: blast-induced crack growth and crack widening from gas expansion. Identifying these thresholds is crucial to understanding overbreak onset. By statistically analysing vibration monitoring data from trial blasts, the study evaluates the relationship between maximum charge per delay and measured overbreak.	Overbreak (%) = 0.2867 $X^{1.999}$ where X is the maximum charge per delay in kg
Schmitz et al. (2006)	Geomechanical data, including Rock Mass Rating (RMR), stratigraphy, lithology, and discontinuity spacing, are digitised and overlaid with geometric overbreak data.	Overbreak is influenced by multiple factors, making the relationship with rock mechanical data complex. Specifically, Rock Mass Rating (RMR), discontinuity spacing, and orientation relative to the tunnel and gravity play significant roles in overbreak occurrence.
Jang and Topal (2013)	Geological and blasting factors are identified as the two main categories influencing overbreak. Overbreak prediction models are developed by employing linear multiple regression analysis, nonlinear multiple regression analysis, and artificial neural networks, specifically considering the RMR and RMR criteria.	1. Overbreak (cm) = 54.825 + 0.114Sc + 0.338RQD – 0.910Js + 0.883Jw – 0.785RMR 2. Overbreak (cm) = 53.607 – 1.210 Ja -1.919 Js 3. Overbreak (cm) = 3.457 – 0.072[quadratic]Js + 272.58/Ja where Sc = unconfined strength of rock Js = joint spacing Ja = joint state
Sun et al. (2013)	A Wavelet Neural Network and statistical theory are combined for improved overbreak prediction.	An ANN is proposed as a soft computing method inspired by the human brain, comprising three components: network architecture, learning algorithm and transfer function. It enables advanced data processing.
Barton and Grimstad (2014)	The Q-value offers more advantages compared to RMR or GSI due to its logarithmic scale of quality, spanning six orders of magnitude from around 0.001 to 1000. An unconventional combination of Q-parameters, specifically the joint set (Jn) and joint roughness (Jr), is employed to predict overbreak by utilising the overbreak facilitating ratio.	Overbreak is highly probable when the predominant value of the Jn/Jr ratio is greater than or equal to 6.
Verma et al. (2016)	The Q-factor is the preferred method for classifying rock mass in civil construction, particularly for tunnels. Through multilinear regression analysis, overbreak is found to be associated with specific charge (q), maximum charge per delay (W), perimeter charge factor (qp), advancement factor (Af) and confinement factor (Cf), based on field data.	1. Overbreak (%) = 6.52 (qp/Af) + 0.78 2. Overbreak (%) = 0.64 (100 Cf/Q) + 7.51 3. Overbreak (%) = 0.854 q/Q0.15 (Wd/a + 3.89qp/Af) + 0.69 where q = specific charge W = maximum charge per delay qp = perimeter charge factor Af = advancement factor = pull (l) / hole depth (d) Cf = confinement factor = hole depth (d) / cross sectional area of a tunnel (a)
Mottahedi et al. (2017)	Geological and blasting parameters are identified as the two primary factors impacting overbreak. Utilising previous research and collected data, overbreak prediction is conducted through multiple linear regression analysis, multiple non-linear regression analysis, ANNs, fuzzy logic models, Adaptive Neuro-Fuzzy Inference Systems (ANFISs), and Support Vector Machines (SVMs).	Similar to an ANN, a proposed approach involves utilising a multi-layer perceptron neural network.