

**ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY**

**SUGGESTION OF PERFORMANCE PREDICTION MODELS FOR IMPACT
HAMMER USED IN LEVENT-HİSARÜSTÜ METRO TUNNEL**

M.Sc. THESIS

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**Department of Mining Engineering
Mining Engineering Programme**

AUGUST 2015

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**LEVENT-HİSARÜSTÜ METRO TÜNELİNDE KULLANILAN DARBELİ
KIRICI İÇİN PERFORMANS TAHMİNİ MODELLERİNİN ÖNERİLMESİ**

YÜKSEK LİSANS TEZİ

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FOREWORD

The present study is a scientific endeavor to define reliable and accurate prediction models for performance of hydraulic impact hammers. Statistical methods were investigated as a means of achievement to the goal. At last, three statistically reliable models were developed. Compared to the formerly developed models, the predictors suggested in the current study show a more powerful correlation with the corresponding independent variables.

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ABBREVIATIONS

ANFIS	: Adaptive Neuro-Fuzzy Inference
ANN	: Artificial Neural Network
ASTM	: American Society For Testing And Materials
BAM	: Bidirectional Associative Memory
BTS	: Brazilian Tensile Strength
BTS_T	: Transformed Brazilian Tensile Strength
CAI	: Cerchar Abrasivity Index
GSI	: Geological Strength Index
HP	: Horse Power
IBR	: Instantaneous Breaking Rate
ISRM	: International Society For Rock Mechanics
MLA	: Multiple Regression Analysis
MLR	: Multiple Linear Regression
MRA	: Multiple Regression Analysis
NAF	: North Anatolian Fault
NATM	: New Austrian Tunneling Method
R	: Coefficient Of Correlation
R²	: Coefficient Of Determination
RMR	: Rock Mass Rating
RQD	: Rock Quality Designation
RQD_T	: Transformed Rock Quality Designation
RSI	: Rock Structure Index
SH	: Schmidt Hammer
SHH	: Schmidt Hammer Hardness
SHH_T	: Transformed Schmidt Hammer Hardness
SHRV	: Schmidt Hammer Rebound Values
SS	: Shore Scleroscope
SSH	: Shore Scleroscope Hardness
TBM	: Tunnel Boring Machine
UCS OR σ_c	: Uniaxial Compressive Strength
UCS_T	: Transformed Uniaxial Compressive Strength
WRBI	: Weak Rock Breakability Index
ρ_T	: Transformed Density

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SUGGESTION OF PERFORMANCE PREDICTION MODELS FOR IMPACT HAMMER USED IN LEVENT-HİSARÜSTÜ METRO TUNNEL

SUMMARY

Hydraulic hammer excavation can serve as a fast method requiring lower capital cost. Compared to drilling and blasting method, mechanical excavations can also offer more control on strata and a safer working environment.

To choose the best method of excavation, one should consider feasibility, installation problems, ability of negotiation with adverse geological conditions, total cost and advance rate. Therefore, determining the advance rate (performance) of an excavator is an indispensable task even from the very early phase of feasibility studies.

Impact hammers have been widely used in mining and in the field of construction since 1960. Lower capital cost compared to Tunnel Boring Machines (*TBM*) and Roadheader, makes impact hammer a desirable choice when the conditions are favorable. Being able to operate flexibly is another advantage of impact hammer, which makes it irreplaceable in terms of mining engineering. The flexibility makes the operator able to either follow irregular ore bodies through bulk material or use foliations or beddings to ease excavation process.

Although, there had been studies on performance prediction of impact hammers in the past years, most of them are solely focused on the properties of the rock mass. Moreover, the previously proposed models suffer from either limited range of application or shortage of accuracy and reliability. . The aim of this study is to assess multiple regression analysis (*MRA*) and artificial neural network (*ANN*) using a new and ample set of data (60 rock samples) gathered from Levent-Hisarüstü metro project in Istanbul, to suggest more accurate and reliable performance prediction models for impact hammer using a simpler combination of the most commonly used physical and mechanical properties of rocks. The optimum prediction model will be the one that provides the highest reliability and accuracy (compared to the other models developed during this study and previously developed prediction models by the other researchers) while requiring the most comparatively few, common, and easy to access set of predictors. To fulfil such a goal, physical and mechanical properties of excavated rocks in Levent-Hisarüstü metro tunnel were investigated using the most accepted standards in test procedures. The unshaped rock samples were collected from the tunnel face and sharpened using the preliminary instruments such as small diameter saw and core drill machine. Physical and mechanical property tests include uniaxial compressive strength, Brazilian tensile strength, Shore scleroscope hardness, Schmidt hammer rebound values, Cerchar abrasivity index, point load test, and density. In addition, performance of the impact hammer used in Levent-Hisarüstü metro tunnel was carefully monitored and recorded. Moreover, *RQD* values were calculated using Brown's method and volumetric joint counts for each individual tunnel ring and the types of rock along the tunnel alignment were determined. Sandstone is the main rock (60%) encountered with compressive strength values ranging from 68.6 to 145 MPa and *RQD* values from 40 to 60%.

Siltstone is met in 20% of the tunnel with compressive strength from 45.8 to 123.3 MPa and *RQD* 38-44%. In the tunnel route, 10% of the rock formations are composed of diabase with compressive strength ranging from 158.7 to 195.6 MPa and *RQD* 45-60%. Mudstone and shale are met in 10% of the tunnel with compressive strength from 8.9 to 40.1 MPa and *RQD* of 10-40%.

Next, multiple regression analysis (*MRA*) methods were used to investigate the relationship between the physical and mechanical properties and recorded *IBR* values. The multiple regression analysis yielded a performance prediction model for impact hammers. Finally, the analysis of variance technique, F-test and student's t-test statistics, which are based on sum of squares of errors, were applied to the data in order to understand the reliability of the suggested models. Analysis indicated that the proposed models are statistically meaningful with overwhelmingly very high confidence level and/or very low significance value in two-tail analysis. Among all the recorded data, collinear pairs of parameters were identified. Knowing linearly parallel parameters can lead into better test design and significant cost reduction for the future studies.

An ANN model was developed to increase the prediction accuracy even further. It provided extremely high correlation between predicted and target data. Meanwhile, the MSE is significantly low. The associated final weights and biases of the network were reported in order to make the network more handy and transcend the technical limitations.

The developed ANN and MLR models provide better correlations of all the available data along with considerably lower MSE values. For the test data, although the proposed model by Bilgin et al. (1997) shows surprisingly good correlation, it carries a considerably high MSE compared to the developed ANN and MLR models. The reason can either be the steep technological achievements during the last two decades that can affect performance of the machine or the fact that the data that were used to develop this model did not include *RQD* values between 38 to 78.

The developed prediction models contribute to reliable and accurate prediction of instantaneous breaking rate of impact hammer requiring the least number of the most commonly used and versatile rock properties as predictors.

The developed MLR model shows that an increase in *RQD* and UCS causes the *IBR* to decrease. As a result, one may say that higher rates of breaking can be achieved when the mentioned factors have lower values.

This study also showed that the relationship between *IBR* as predicted value and *CAI* and *SSH* as predictors is extremely weak. This indicates that *CAI* and *SSH* do not contribute to prediction of *IBR* for impact hammers.

This research reappraised the belief that increasing the number of the samples will result in an increase in accuracy of the model.

Since the effect of machine's power on the performance of the impact hammer is not investigated in this study, it is highly recommended to perform future studies on this subject. In addition, by gathering more data the range of application for the future models will be extended. Finally, incorporating the operator's effect will increase accuracy and reliability of the future models.

LEVENT-HİSARÜSTÜ METRO TÜNELİNDE KULLANILAN DARBELİ KIRICI İÇİN PERFORMANS TAHMİNİ MODELLERİNİN ÖNERİLMESİ

ÖZET

Hidrolik kırıcılar ilk yatırım maliyetleri düşük ve hızlı bir üretim yöntemi olarak kullanılabilir. Delme patlatma yöntemiyle kıyaslandığında, daha güvenli ve kontrol edilebilir çalışma imkanı sunmaktadır.

En iyi kazı metodunun seçimi, detaylı fizibilite çalışmaları, karşılaşılabilecek problemlerin analizi, zor zemin şartlarının önceden belirlenmesi, toplam maliyet analizlerin detaylıca yapılması ile tespit edilebilir. Böylece, makine ilerleme hızı ve performansı istenmeyen her koşul göz önüne alınarak tahmin edilebilir.

Darbeli kırıcılar, özellikle madencilik ve inşaat sektörlerinde 1960'lı yıllardan buyana çok yaygın bir şekilde kullanılmaktadır. Bu makineler, ilk yatırım maliyetleri yüksek olan Tam Cepheli Tünel Açma Makineleri (TBM) ve Kollu Galeri Açma Makineleri (Roadheader) ile kıyaslandığında kendilerine önemli bir kullanım alanı edinmiştir. Diğer bir önemli avantajı ise, bir yerden bir yere kolay olarak nakil edilerek hızlıca kullanıma imkan sağlamasıdır. Ayrıca bu makinelerin, yataklanma ve tabakalanma yönünde kazı yapması da diğer bir avantajıdır. Bu özellikleri madencilik alanındaki kullanımlarını önemli ölçüde artırmaktadır.

Darbeli kırıcıların performans tahmini ile ilgili bu güne kadar birçok araştırma yapılmıştır, bu çalışmaların çoğu kaya kütlelerinin özelliklerinin performansa etkisi üzerinedir. Geliştirilmiş modellerin sınırlı sayıda uygulama ve veri ile yapıldığı söylenebilir. Bu çalışmanın amacı ise kayaçların fiziksel ve mekanik özelliklerinden yola çıkarak güvenilir bir performans tahmin modellerinin oluşturulmasıdır.

Doğru ve güvenilir performans tahmin modelleri, fizibilite ve planlama aşamalarında proje yüklenicilerine kazı süresi tahmini için önemli bilgiler verir. Bu amaca ulaşabilmek için darbeli kırıcının çalıştığı Levent-Hisarüstü metrosundan numuneler laboratuara getirilerek fiziksel ve mekanik özelliklerini belirlenmiş ve geçilen birimler yerinde tanımlanmıştır. Şekilsiz kayaç örnekleri tünel kazısından toplanmıştır. Daha sonra ise laboratuarda küçük çaplı testere ve sondaj makinesi ile numuneler deneyler için uygun boyutlara getirilmiştir. Fiziksel ve mekanik özellikler; tek eksenli basınç dayanımı, Brezilyan çekme dayanımı, Shore Scleroscope sertliği, Schmidt çekici sertliği, Cerchar aşındırıcılık indeksi, nokta yük dayanımı ve yoğunluk deneyleri ile belirlenmiştir. Bu deneyler, 60 numunenin üzerinde uygulanmıştır. Her numune, tünel güzergahı boyunca her bir ringin kazısından elde edilmiştir. Ek olarak, Levent-Hisarüstü metro tünelinde kullanılan darbeli kırıcıların performansı $m^3/saat$ cinsinden kayıt altına alınmıştır. Ayrıca, RQD değerleri, Brown (1981) yöntemi kullanılarak hesaplanmıştır. Yapılan arazi incelemelerinde tünel boyunca kumtaşı birimi % 60 olarak gözlemlenmiş ve basınç dayanımı 68,6 ile 145 MPa arasında, RQD değeri ise %40 ile 60 olarak belirlenmiştir. Silttaşı tünelin % 20'sinde gözlemlenmiş ve basınç dayanımı 45 ile 123,3 MPa arasında, RQD değeri ise % 38 ile 44 olarak belirlenmiştir. Tünel

güzergahı boyunca % 10 olarak karşılaşılan diyabaz biriminin basınç dayanımı 158,7 MPa ile 195,6 MPa arasında, RQD değeri ise 45 ile 60 arası değişmektedir. Tünelin % 10'un da görünen çamurtaşı ve shale'in basınç dayanımı ise 8,9 MPa ile 40,1 MPa arasında, RQD değeri ise 10 ile 40 arası değişmektedir.

Tekli regresyon analizleri; anlık kırma oranı (IBR) ile kayaçların fiziksel ve mekanik özellikleri arasındaki ilişkileri bulmak için yapılmıştır. Trend analizinde kullanılan belirleme katsayısı (R^2), karşılaştırması yapılan iki parametrenin güvenilirliğinin belirlenmesinde kullanılmıştır. Yanıt ve belirleyicisi arasındaki korelasyonun yüksekliği iyi bir ilişki olduğu fikrini vermektedir. Bazı karşılaştırmalarda, yanıt ve belirleyicisi arasındaki korelasyon tatmin edici bulunamamıştır, daha iyi sonuçlar için belirleyicilerin dönüşümü yapılmıştır. Veri dönüşümünün hedefi; tepki ve yanıt arasında daha anlamlı bir ilişki kurmaktır. Dönüştürülmemiş belirleyicisi ve tepki ile dönüştürülmüş belirleyici arasındaki ilişki karşılaştırıldığında, kararlılığının daha yüksek katsayısına sahip olduğu gözlenmiştir. Her bir belirleyicinin uygun dönüşümünü bulmak için, belirleyici ile Microsoft Excel'de ölçülen IBR karşılıklı olarak çizilmiştir. En uygun trend çizgisini belirlemek için mevcut tüm seçenekler kullanılmış ve böylelikle en uygun trend belirlenmiştir. Denklem ilişkisini belirlemek için bir dönüşüm olarak kullanılmak üzere en iyi uyan hat seçilmiştir.

Ayrıca, darbeli kırıcının her ring kazısındaki performansı yerinde incelenmiş ve kayıt altına alınmıştır. Daha sonrasında, istatistiksel model oluşturabilmek için regresyon analizleri yapılmıştır. Kayaçların fiziksel ve mekanik özellikleri modellerin girdi parametresi olarak, makine performansı (IBR) ise çıktı parametresi olarak belirlenmiştir. Çoklu regresyon analizleri sonucunda bir model elde edilmiştir. Bu modelin istatistiksel olarak güvenilirlikleri F-test ve t-test istatistiksel test yöntemleri kullanılarak araştırılmıştır. Yapılan çift kuyruk testler sonucunda istatistiksel olarak güvenilir bir model elde edildiği görülmüştür.

Performans tahmininin güvenilirliğinin artırabilmek için Yapay Sinir Ağı (YSA) modeli geliştirilmiştir. Bu yöntem, gerçekleşen ve tahmin edilen değerler arasında oldukça yüksek bir ilişki ortaya koymuştur. Böylece, oldukça düşük ortalama karesel hata elde edilmiştir.

Yapay sinir ağı (YSA) ve çoklu regresyon modelleri (MLR) oldukça düşük karesel hata (MSE) değerleriyle birlikte mevcut tüm verilerle daha iyi korelasyonlar sağlamaktadır. Verilerin testi için, Bilgin et al. (1997) modeli ile karşılaştırma yapılmıştır. Bu model, YSA ve MLR modellerine göre oldukça yüksek MSE değerine sahiptir ve şaşırtıcı derecede iyi bir korelasyon göstermektedir. Nedeni hem son yirmi yıl içinde teknolojik gelişmeler hem de bu modellerde RQD değerlerinin 38 ile 78 arasında olmaması olabilir. Geliştirilen öngörü modelleri, daha güvenilir ve doğru performans tahminine yol açmıştır.

Bu çalışmada elde edilen MLR modeline göre RQD ve UCS arttıkça IBR'nin azaldığı görünmüştür. Sonuç olarak, söz konusu olan faktörler daha düşük değerlere sahip olduğunda IBR oranlarının daha yüksek olduğunu söyleyebiliriz.

Bu çalışmada IBR (tahmin değeri olarak) ile CAI ve SSH (belirleyici) arasında anlamlı bir ilişki olmadığı gözlenlenmiştir. Böylelikle bu çalışma CAI ve SSH değerlerinin hidrolik kırıcı performansının belirlenmesine katkıda bulunmadığını göstermiştir.

Bu araştırmada, numunelerin sayısının artırılması ile modellerin doğruluğu artmaktadır. Bu çalışmada makine gücünün darbeli kırıcı performansı üzerindeki etkisi araştırılmamıştır, dolayısıyla gelecek çalışmalarda bu konu üzerinde incelemeler yapılması tavsiye edilmektedir.

Ek olarak, daha fazla veri toplanarak bu modellerin güvenilirliđi gelecekte artırılmalıdır. Operatör etkisinin araştırılması da gelecekte oluşturulacak olan modellerinin doğruluđunu ve güvenilirliğini artıracaktır.

Kayıt altına alınan veriler arasından, kolineer (dođrudan) çiftler belirlenmesi gelecekteki çalışmalar içinde yapılmalıdır. Böylelikle, lineer olarak paralel olan parametrelerin bilinmesi daha sonraki çalışmalar için daha iyi test dizaynının yapılmasına imkan sunacaktır.

1. INTRODUCTION AND PURPOSE

Mechanical excavation can serve as a fast method requiring lower capital cost. Compared to drilling and blasting method, mechanical excavations can also offer more control on strata and a safer working environment (Robbins, 2000). Although there are some limitations in urban area, drilling and blasting becomes a necessity when the length of operation is short or the rock is so abrasive and hard that mechanical excavation cannot be economically used (Iphar, 2012).

To choose the best method of excavation, one should consider feasibility, installation problems, ability of negotiation with adverse geological conditions, total cost and advance rate (Terezopoulos, 1987). Therefore, determining the advance rate (performance) of an excavator is an undeniable task even from the very early phase of feasibility studies (Aksoy et al., 2013).

Impact hammers have been widely used in mining and in the field of construction since 1960 (Rodford, 1974; Pelizza et al., 1994). Lower capital cost compared to Tunnel Boring Machines (*TBM*) and Roadheader, makes impact hammer a desirable choice when the conditions are favorable. In Istanbul and in some zones with *RQD* of 0 to 80, impact hammers have excavated almost 20 km of metro tunnels. Being able to operate flexibly is another advantage of impact hammer, which makes it irreplaceable in terms of mining engineering. The flexibility makes the operator able to either follow irregular ore bodies through bulk material or use foliations or beddings to ease excavation process (Tuncdemir, 2008).

There have been studies on performance prediction of impact hammers in the past years. Different methods of data analysis have been used to find prediction models. “Artificial Neural Network (*ANN*)” and “Multiple Linear Regression (*MLR*)” are the most statistically reliable and accurate methods.

Artificial Neural Networks (*ANN*) has emerged as a new tool for analyzing the geotechnical problems. This technique allows generalizing from a training pattern, presented initially, to the solution of the problem. Once the network has been trained

with a sufficient number of sample data sets a new input having a relatively similar pattern will be predicted based on the previous learning pattern (Gholamnejad and Tayarani, 2010). *ANN* has been used to analyze the rock properties in recent years. Yang and Zhang (1997), Shahin et al. (2001), Singh et al. (2001), Roy and Singh (2004), Sonmez et al. (2006), Yilmaz and Yuksek (2008), Dehghan et al. (2010), Manouchehrian et al. (2012), Ceryan et al. (2012), Enayatollahi et al. (2014) are among the researchers who studied *ANN* approach for this purpose. Research studies for mining and tunneling projects have been carried out to analyze the performance of mechanical excavators by using *ANN*. Alvarez Grima et al. (2000), and Benardos and Kaliampakos (2004) modeled *TBM* performance by using *ANN*. Bilgin et al. (2006) used *ANN* for predicting rock cuttability from rock properties. Kahraman et al. (2006) estimated the sawability of carbonated rocks from shear strength parameters by using *ANN*. Tiriyaki (2008) used *ANN* to predict the cuttability of rocks by drag tools. Tiriyaki (2009) developed new predictive models for rock cutting by using *ANN*. Javad and Narges (2010) estimated the penetration rate of tunnel boring machine (*TBM*) by using *ANN*. Jain and Rathore (2011) used *ANN* approach to predict cutting performance of diamond wire saw machines in quarrying of marble. Salsani et al. (2013) studied *ANN* modeling for roadheader performance prediction.

Multiple Regression Analysis (*MRA*) is based on the same concept as single regression analysis. The main difference between single and multiple versions is that in the latter one input parameters are more than one. With multiple regression analysis, a linear correlation can be established between three or more parameters (one output and two or more inputs). Some statistical techniques can measure reliability of the model and compare the impact of the different parameters on the output. Since *MRA* has the ability to work with multiple variables, this approach has been widely in use in the field of science and engineering.

An accurate and reliable model is of a high value for the stages of project design and planning. Although a number of prediction models were already developed, they suffer from either limited range of application, shortage of accuracy and reliability, or dependency on less commonly used rock properties that require special equipment to be measured. The aim of this study is to assess multiple regression analysis (*MRA*) and *ANN* methods using a new and ample set of data (60 rock samples) gathered from Levent-Hisarüstü metro project in Istanbul, to suggest more accurate and

reliable performance prediction models for impact hammer using a simpler combination of the most commonly used physical and mechanical properties of rocks. The optimum prediction model will be the one that provides the highest reliability and accuracy (compared to the other models developed during this study and previously developed prediction models by the other researchers) while requiring the most comparatively few, common, and easy to access set of predictors. To ensure statistical significance of the proposed model, F-test and student's t-test were performed.

In addition to the common tests (such as *UCS* and *BTS*), different rock properties were measured in order to investigate the relationship between *IBR* and the previously uninvestigated properties of rocks (such as *CAI*, Shore scleroscope hardness, Schmidt hammer hardness, and density). In order to help the future researchers find appropriate sets of predictors more easily, the results were also used to investigate the linear relationship between all possible pairs of the rock properties. Depending on the desired accuracy of the future studies, one of each linearly dependent (collinear) properties can be eliminated in favor of either reducing costs or simplifying the outcomes.

2. LITERATURE REVIEW

Nowadays, many different methods can be applied for tunnel excavation. To select the best method, one should consider the following:

- Tunnel dimensions,
- Tunnel geometry,
- Length of tunnel, total volume to be excavated,
- Geological and rock mechanical conditions,
- Ground water level and expected water inflow,
- Vibration restrictions,
- Allowed ground settlements.

Tunneling methods fall into two main categories; “drilling and blasting” and “mechanical excavations”. Although drilling and blasting is the older and more common one, from 1950’s, mechanical excavation has been a competitor for it Table 2.1 gives basic advantages of mechanical excavations over drilling and blasting. Mechanical methods can be split further to partial face (e.g. roadheaders, hammers, excavators) or full face (*TBM*, shield, pipe jacking, and micro tunneling) (Heiniö, 1999).

Table 2.1: Basic advantages of mechanical excavations over drilling and blasting
(Bilgin et al., 2013)

Safer and more environment-friendly operation (no explosive handling—forbidden in urban areas, no blast vibrations in urban areas, no noxious gases, no dust, better workmanship, lesser accidents)

Minimum ground disturbance (lesser overbreak, lesser scaling-support-ventilation requirement, minimized support maintenance, superior ground control in jointed/broken rocks)

Uniform muck size (easy muck/excavated material haulage, no secondary breakage of large rock chunks, lower crushing and mineral processing costs)

Table 2.1 (continued): Basic advantages of mechanical excavations over drilling and blasting (Bilgin et al., 2013)

Selective mining/excavation capability (minimum ore dilution/minimum mixing with gang, increased ore recovery, separate excavation of rock layers in different strengths making excavation easier)

Continuous operation (not periodic, conducive to automation, excavation—loading—ground supporting simultaneously)

Higher production/excavation rates in favorable ground conditions (higher economical benefits/saving money, earlier mining of high-grade ore, earlier job completion)

2.1 Mechanical Excavation Methods

Mechanical excavation can be defined as excavation by means of machines transferring the energy as a force from cutting tools (cutters, bits) to the rock/ground by generating concentrated stresses. Mechanical methods can be categorized further into “Full Face” and “Partial Face” excavation (Copur, 2015). Figure 2.1 shows the classification of mechanical excavation machines. Table 2.2 shows the main differences between full and partial face excavation machines (Copur, 2015).

Table 2.2: General comparison of full-face and partial-face underground excavation machines (Bilgin et al., 2013).

Criterion	Full-Face	Partial-Face
Cutable Ground Types	Very hard rock to soft ground, up to very abrasive rocks.	Medium strength to soft rocks, no or low abrasive rocks.
Mobility	Since they are very large and heavy machines, they are not mobile. It is very difficult or impossible to move these machines from one face to another.	Since they are small machines, they are mobile. It is easy to move these machines from one face to another.
Flexibility	They are not flexible: cannot excavate sharp turns, can excavate only circular cross-section shape, not easily adaptable to a working mine design.	They are flexible: can excavate sharp turns, can excavate any cross-section shapes, easily adaptable to a working mine.
Selective Excavation	They are not suitable	They are suitable

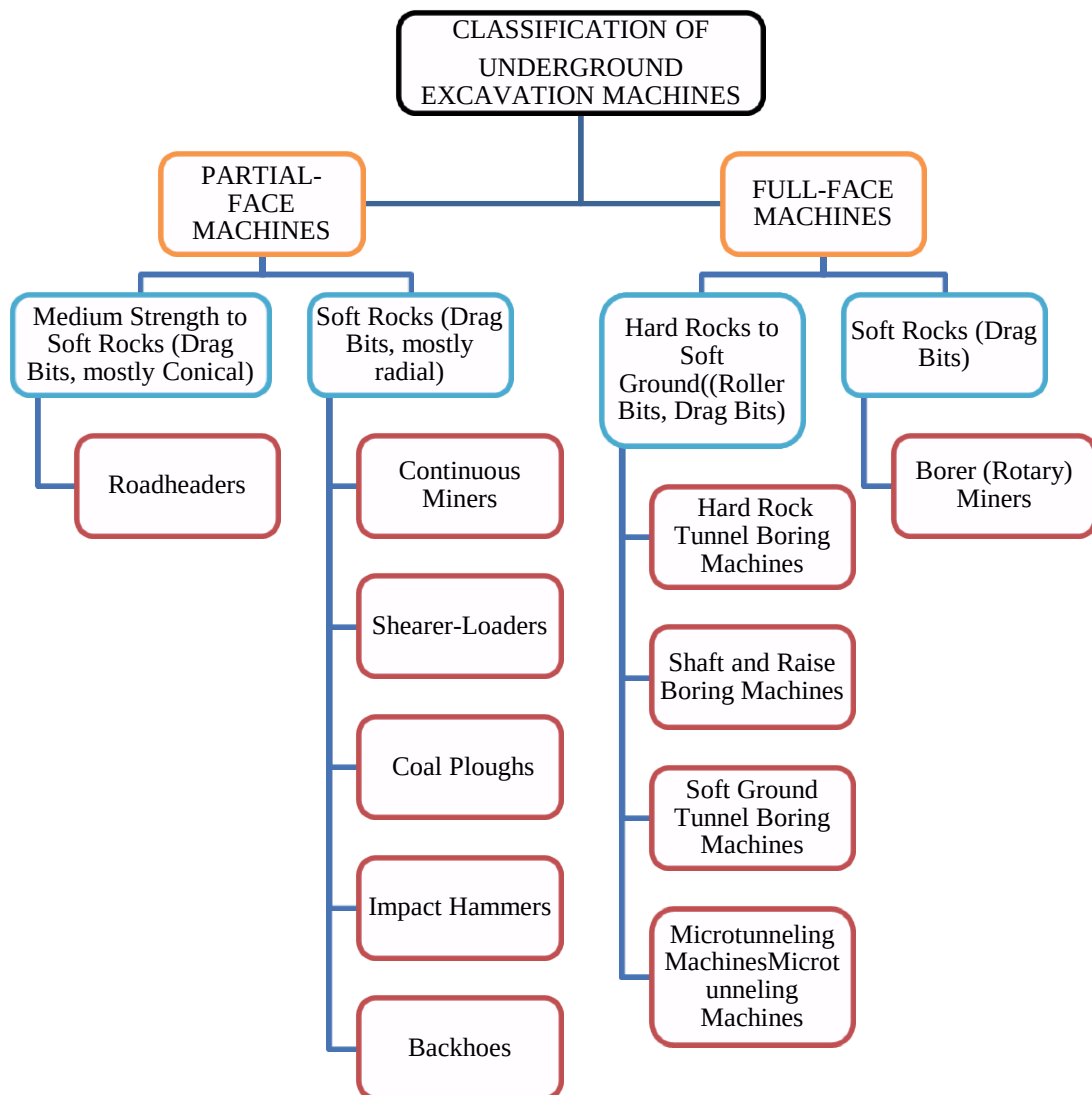


Figure 2.1: Classification of mechanical excavation machines (Copur, 2015).

2.1.1 Full face machines

In this type of machines, all the cutters are in contact with tunnel face simultaneously. All the full-face machines can only excavate in circular shape, with exception of borer miners and multihead *TBM*s which respectively are used to excavate “soft minerals” and “soft grounds with short length”. Since they are capable

of installation of roller cutters, full-face excavators have the ability to cut very hard rocks (Bilgin et al., 2013).

2.1.1.1 Hard rock Tunnel Boring Machines

Hard rock *TBM*s may be classified as open type (open gripper, Kelly beam, or main beam), single shield, and double shield, with *TBM*s working in open and closed modes (EPB) in some special cases (Bilgin et al., 2013).

They usually use disk cutters as a means of excavation. The required thrust force for cutters is provided by thrust cylinders located behind the cutterhead. The thrust cylinders use either grippers or segmental linings as a support. Hard rock *TBM*s can work in open mode only. Hence, they are not capable of working in grounds with a high amount of water ingress. Commonly, the excavated material is brought to the surface by conveyers (Bilgin et al., 2013). Figure 2.2 shows a typical view of a single shield *TBM*.

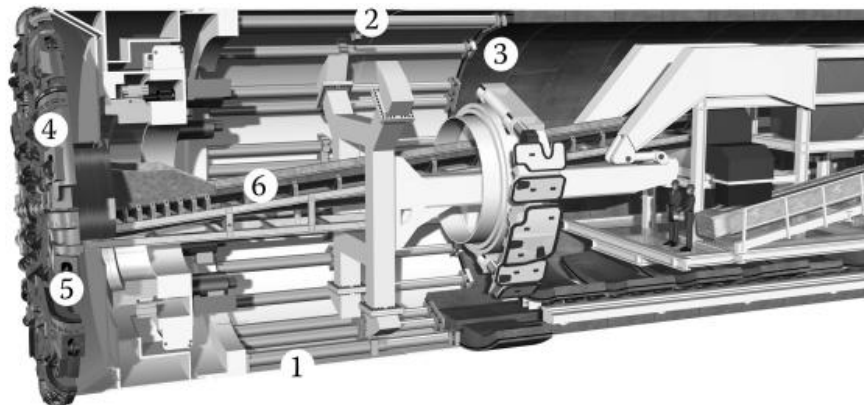


Figure 2.2: General view of a single-shield TBM. (With the courtesy of Herrenknecht.) 1) Shield, 2) Hydraulic thrust cylinders, 3) Segmental lining, 4) Cutterhead, 5) Muck bucket lips, 6) Conveyor

2.1.1.2 Soft ground Tunnel Boring Machines

The two facts that “construction of the infrastructures are in shallow grounds under the aquifer level” and “most of the urbane area are located on soft grounds (very weak and weathered rocks are also considered as soft ground in addition to soils)”, have led the demand for soft ground tunneling to an increase in such area. As a result, the stability related issues such as excavated face collapse and surface settlement are of a great importance in this type of excavation (Bilgin et al., 2013).

Consequently, in order to adopt the appropriate stability and safety measures, shielded and face pressurized tunnel boring machines have been developed over the past 30-40 years (Maidl et al., 1996). Table 2.3 shows a general classification of soft ground *TBM*s based on “face support”, “muck haulage system”, and “working mode” criteria.

Table 2.3: General classification of soft ground *TBM*s (Copur, 2015).

Machine Type	Face Support	Muck Haulage	Mode
Earth pressure balance <i>TBM</i> s (EPB <i>TBM</i> s, auger <i>TBM</i> s)	Pressured muck + one or more of water, foam, polymer, bentonite (processed muck)	Dry muck haulage (rail, conveyor belt, truck)	Closed, open
Slurry pressure balance <i>TBM</i> s (SPB <i>TBM</i> s, hydroshields, bentonite shields)	Pressured water or water + bentonite (or + polymers)	Hydraulic muck haulage (steel pipe)	Closed, open
Compressed air shields (mostly partial face excavation)	Pressured air (against only water ingress, not against earth pressure)	Dry muck haulage (rail, conveyor belt, truck)	Closed, open
Polyshields (Mixshields)	Combination of two or more of the above methods	Combined muck haulage (dry and/or hydraulic)	Closed, open
Blind (extrusion) shields, shields with pressure relieving gate	Mechanical plates	Dry muck haulage (rail, conveyor belt, truck)	Partly open

2.1.2 Partial face machines

2.1.2.1 Roadheaders

Roadheaders were originally designed for mechanical extraction of coal in European mines (Kogelmann and Schenck, 1982). Roadheaders are a type of partial face mechanical excavators that are partially in contact with the face while excavating (Bilgin et al., 2013). On account of their higher comparative mobility, flexibility, and ability for selective mining, roadheaders are considered to be one of the most popular excavation machines in tunneling and underground mining as well as surface operations (Copur et al., 1997; Bilgin et al., 2013).

2.1.2.2 Continuous miners

Continuous miners (Figure 2.3) account for about 45% of the underground coal production in the room and pillar mining method (Bilgin et al., 2013). They also utilize conveyors to transport the removed coal from the seam. They may excavate coal seams from 0.8–6 m high. Remote-controlled continuous miners are used in a variety of difficult seams and conditions and robotic versions controlled by computers are becoming increasingly common (Bilgin et al., 2013). Continuous miners are amongst the machines that play a key role in modernization of underground mining. From 1940s to present time, these machines immeasurably contributed to speed and efficiency of coal mining. Standard continuous miners have the maximum production capacity of 38 ton/minute, while an average mineworker could achieve in a whole day. They are also able to extract coal from coal seams with thickness of 0.8 to 6 m (Bilgin et al., 2013). The working principles for this machine have been quite the same from its birth. It uses a large rotating steel drum with tungsten carbide bits to cut coal (Figure 2.3) (BPM, 2015).



Figure 2.3: A typical continuous miner.

Recently, remotely controlled continuous miners are introduced to coal mining industry. They are more powerful, highly productive and adaptable to variety of mining and seam conditions.

2.1.2.3 Hydraulic impact hammers

Since 1960, impact hammers had been widely in use in mining and in the field of construction (Rodford, 1974; Pelizza et al., 1994). Lower capital cost compared to *TBM* and Roadheader, makes impact hammer a desirable choice when the conditions are favorable. In Istanbul and in some zones with *RQD* of 0 to 80, impact hammers have excavated almost 20 km of metro tunnels (Bilgin et al., 2013). Being able to operate flexibly is another advantage of impact hammer, which makes it irreplaceable in terms of mining engineering. The flexibility makes the operator able to either follow irregular ore bodies through bulk material or use foliations or beddings to ease excavation process (Tuncdemir, 2008). In 1994, Pelizza announced that hydraulic impact hammers have gained a wide acceptance in Italian construction industry. This is thought to be rooted in stringent Italian rules on use and transportation of explosives. The following are mentioned as support for choosing hydraulic hammers over other excavation machine in Italian tunneling projects (Pelizza et al., 1994):

- Heavily altered and geologically disturbed surrounding ground
- Highly variable geomechanical characteristics of the rock along the tunnel axis
- Proneness of other choices (*TBMs* and Roadheaders) toward discontinuous and uneconomical performance in such an environment

A typical impact hammer working in a tunnel is seen in Figure 2.4 (Bilgin et al., 2013).



Figure 2.4: A typical impact hammer.

Working Principles and Operational Features

To produce impact energy, impact hammer is designed to use a piston which has a perpendicular movement towards/from the excavation surface. A hydraulic accumulator is used to magnify the impact energy produced by the piston (Bilgin et al., 2013). Based on the past researches, the specific energy is in inverse proportion with blow energy. During the following years afterwards, scientific endeavors have been made to increase blow energy of the impact hammers by means of increasing piston speed/weight and hammer's operational weight (Bilgin et al., 2013). Equations 2.1 and 2.2 demonstrate the relationship between piston weight, piston velocity, specific energy, and impact energy (Hughes, 1974).

$$SE = K / \sqrt{E_i} \quad (2.1)$$

$$E_i = MV^2 / 2 \quad (2.2)$$

where SE is the specific energy, E_i is the impact or blow energy, M is the weight of the piston, V is the piston velocity, and K is a constant.

Hydraulic impact hammers are compatible with a variety of excavators with different hydraulic systems (Bilgin et al., 2013). To match hammer and excavator is a very important task in order to maintain safety and efficiency of the operation (Bilgin et al., 2013). Since the excavator/carrier is more expensive than the hammer, the manufacturers tend to design hammers with higher “blow energy over weight” ratio (Wyllie, 1985).

In spite of the fact that impact hammers are very popular excavation machines in today's mining and civil industries, there is still no reliable standard for comparing their performance. The technical data provided by the producers are inconsistent and even misleading in some cases. Nonetheless, adequate comparisons can be achieved by uniformly analyzing the basic information of the different hammers. ”Hammer efficiency (the ratio of output power to input power is the “hammer efficiency)”. can be a reliable criterion for this approach. Equations 2.3 to 2.5 demonstrate the related calculations (Tuncdemir, 2008):

$$\eta = \frac{P_{output}}{P_{input}} \quad (2.3)$$

$$P_{input} = Q \times p \quad (2.4)$$

$$P_{output} = E_i \times n \quad (2.5)$$

where P_{input} is the input power in kW, Q is the oil flow in $m^3/hour$, p is the oil pressure in kN/m^2 , P_{output} is the output power in kW, E_i is the energy of a single blow in $kN.m$, and n is the blow frequency in $blow/second$, and η is the hammer efficiency.

2.2 Performance Prediction Models for Hydraulic Impact Hammer

There had been studies on performance prediction of impact hammers in the past years. Bilgin et al. (1996) proposed a model (Equation 2.6) based on multiple regression analysis of the data collected from Istanbul metro drivages:

$$IBR = 4.24 \times P \times RMCI^{-0.567} \quad (2.6)$$

where IBR is the Instantaneous breaking rate of an impact hammer, P is input the power of the machine in Horse Power (Hp), and RMCI is the Rock Mass Cuttability Index in MPa, which is calculated using the equation 2.7:

$$RMCI = \sigma_c \times \frac{RQD}{100}^{\frac{2}{3}} \quad (2.7)$$

where σ_c is the uniaxial compressive strength of the intact rock in MPa and RQD is the Rock Quality Designation in percentage.

In 2002, Bilgin et al. (2002) investigated the relationship between performance of impact hammer, RQD and Schmidt hammer rebound values. This study yielded a relatively good correlation (equation 2.8) between Schmidt Hammer Rebound Values ($SHRV$) and instantaneous breaking rate (IBR) of the impact hammer for rocks with $0.25 < RQD < 0.49$:

$$IBR = -1.05 \times SHR V + 70.1, R^2 = 0.83 \quad (2.8)$$

where *IBR* is the instantaneous breaking rate of the impact hammer in m³/hour and *SHRV* is the Schmidt hammer rebound values associated with the excavated section of tunnel.

Aksoy (2009), Aksoy et al. (Aksoy et al., 2011; Aksoy et al., 2013), have implemented *ANFIS* (Adaptive Neuro-Fuzzy Inference) and multiple regression analysis methods to investigate the connection between performance of impact hammer and different factors such as block punch index, machine power, *GSI* (Geological Strength Index), and *WRBI* (Weak Rock Breakability Index).

The following model (equations 2.9 and 2.10) was developed for rocks with *RQD* value of less than 0.2:

$$IBR = 15.423 \times P^{0.057} \times WRBI^{-0.229} \quad (2.9)$$

$$WRBI = \frac{265 \times BPI^{0.25} \times GSI^{0.2}}{20} \quad (2.10)$$

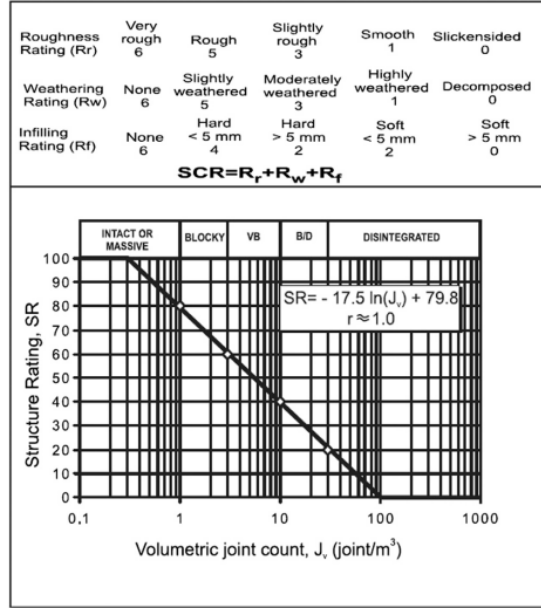
where *WRBI* is the Weak Rock Breakability Index, *BPI* is the Block Punch Index (MPa), *GSI* is Geological Strength Index, *P* is excavator power (*Hp*), and *IBR* is the Instantaneous Breaking Ratio (m³/hour). There is a good correlation between observed and predicted values of *IBR* using this model (*R*= 0.9630).

Given in equation 2.11, the above formula was updated in 2013 (Aksoy et al., 2013):

$$IBR = 202.13 \times RSI^{-1.04} \times P_{out}^{0.47} \quad (2.11)$$

where *IBR* is instantaneous breaking ratio (m³/hour), *RSI* is rock structure index, and *P_{out}* is power of impact hammer (*kW*). *RSI* can be calculated/estimated using Table 2.4. The coefficient of correlation (*R*) between observed values of *IBR* and the values predicted using this model is 0.8377.

Table 2.4: Rock structure index based on volumetric joint count (Aksoy et al., 2013).



In 2011, Kucuk et al. developed a model for performance prediction of impact hammer using artificial neuro-fuzzy inference system (*ANFIS*). The rules of the developed model can be explained as (Kucuk et al., 2011):

If (*BPI* is L) and (*GSI* is W) and (*P* is L) then $f_1 = p_1 BPI + q_1 GSI + r_1 P + s_1$

If (*BPI* is L) and (*GSI* is W) and (*P* is M) then $f_2 = p_2 BPI + q_2 GSI + r_2 P + s_2$

If (*BPI* is L) and (*GSI* is W) and (*P* is H) then $f_3 = p_3 BPI + q_3 GSI + r_3 P + s_3$

If (*BPI* is L) and (*GSI* is S) and (*P* is L) then $f_4 = p_4 BPI + q_4 GSI + r_4 P + s_4$

If (*BPI* is L) and (*GSI* is S) and (*P* is M) then $f_5 = p_5 BPI + q_5 GSI + r_5 P + s_5$

If (*BPI* is L) and (*GSI* is S) and (*P* is H) then $f_6 = p_6 BPI + q_6 GSI + r_6 P + s_6$

If (*BPI* is H) and (*GSI* is W) and (*P* is L) then $f_7 = p_7 BPI + q_7 GSI + r_7 P + s_7$

If (*BPI* is H) and (*GSI* is W) and (*P* is M) then $f_8 = p_8 BPI + q_8 GSI + r_8 P + s_8$

If (*BPI* is H) and (*GSI* is W) and (*P* is H) then $f_9 = p_9 BPI + q_9 GSI + r_9 P + s_9$

If (*BPI* is H) and (*GSI* is S) and (*P* is L) then $f_{10} = p_{10} BPI + q_{10} GSI + r_{10} P + s_{10}$

If (*BPI* is H) and (*GSI* is S) and (*P* is M) then $f_{11} = p_{11} BPI + q_{11} GSI + r_{11} P + s_{11}$

If (*BPI* is H) and (*GSI* is S) and (*P* is H) then $f_{12} = p_{12} BPI + q_{12} GSI + r_{12} P + s_{12}$

The consequent parameters of the output functions (*f*) are given in Table 2.5. The σ and *c* values for the untrained initial membership functions are given in

Table 2.6. The coefficient of determination R^2 for the *ANFIS* model is 0.9978.

Table 2.5: The consequent parameters of the output functions (f).

Output Function	P_i	Consequent Q_i	Parameters r_i	S_i
f_1	0.4542	-0.2568	1.122	0.04185
f_2	-0.2926	-0.1261	0.942	0.03161
f_2	-4.011	-0.2521	1.303	0.04097
f_4	-10.64	0.9123	3.219	0.1201
f_5	-0.09838	-0.06785	0.9563	0.03209
f_6	-8.563	1.037	1.058	0.03327
f_7	10.85	2.732	-2.813	0.105
f_8	-0.7028	0.6273	0.3629	0.01218
f_9	-4.916	0.2062	1.612	0.05068
f_{10}	0.1677	-4.294	-5.196	-0.1939
f_{11}	8.553	0.2435	-0.8724	-0.02928
f_{12}	0	0	0	0.03426

Table 2.6: The σ and c values for the untrained initial membership functions.

Input variable	Linguistic variable	σ	C
BPI	Low (L)	2.104	2.197
	High (H)	2.681	8.466
GSI	Weak (W)	9.053	16.500
	Strong (S)	6.340	37.670
P	Low (L)	0.796	26.720
	Moderate (M)	0.616	29.320
	High (H)	0.532	31.990

Aksoy et al. (2011) used “Multiple Regression Analysis” to develop a performance prediction model for impact hammers (equations 2.12 to 2.14):

$$IBR = 289.28 \times p^{0.036} \times GSI^{-0.73} \times BPI^{-0.17} \quad (\text{For slope excavation}) \quad (2.12)$$

$$IBR = 1596.71 \times p^{-0.025} \times GSI^{-1.025} \times BPI^{-0.11} \quad (\text{For tunnel excavation}) \quad (2.13)$$

$$IBR = 406.87 \times p^{0-0.064} \times GSI^{-0.76} \times BPI^{-0.15} \quad (\text{For combination of slope and tunnel excavations}) \quad (2.14)$$

where *IBR* is instantaneous breaking rate in m³/hour, *p* is the power of the machine in kW, and *GSI* is the geological strength index.

In 2011, Iphar (Iphar, 2012) suggested two new methods of performance prediction for impact hammer. These models were created by implementation of Artificial Neural Network (*ANN*) and *ANFIS*. Table 2.7 shows their performance against a multiple regression based model:

Table 2.7: Results of the statistical performance analysis.

Model	VAF (%)	RMSE	Standard error of estimation	Correlation coefficient, <i>r</i>
Multiple regression model	39.75	6.4	6.73	0.63
<i>ANN</i> based model	74.68	4.16	4.33	0.87
<i>ANFIS</i> based model	88.14	2.9	2.83	0.95

2.3 New Austrian Tunneling Method

The New Austrian Tunneling Method (*NATM*) was developed by Austrian tunneling specialists Von Rabcewicz, Pacher, and Müller-Salzburg over the time span of 1957 to 1961. The term “new” was added to the title in order to distinguish this method from the old Austrian method. The dominant approach in this method is to build the tunnel conventionally, to support it minimally and to value the observational method (Bhawani Singh, 2006).

In order to prevent softening and loss of strength, the *NATM* requires the ground distortion to be kept in the lowest possible level. Meanwhile, adequate deformation is a necessity for stimulation of the ground strength. As a result, stiff and thick linings, which do not entirely adjoin the surrounding rock, are not a choice of interest anymore. There had been a protracted disagreement over the definition of *NATM*. According to Research Society for Road Engineering of the Austrian Union of Engineers and Architects, *NATM* starts a bearing ring in the encompassing ground.

However, this statement has come into question on the ground of the fact that any cavity in the rock, regardless of the excavation method, is at least partially supported by the rock itself (Kolymbas, 2005).

Another debate surrounding *NATM* is the designation of “Austrian”. Many people, including Von Rabcewicz himself, claim that use of shotcrete in tunneling projects is older than *NATM*. Although Austrian engineers contributed to foundation and propagation of *NATM* with ground breaking and courageous applications, the most common belief is that *NATM* represented “conventional tunnel heading with use of shotcrete lining” not the shotcrete lining itself.

In conclusion, probably the best definition of *NATM* belongs to Lauffer (1958):

NATM is a tunneling method in which excavation and support procedures, as well as measures to improve the ground that should be distorted as low as possible, depend on observations of deformation and are continuously adjusted to the encountered conditions. Consequently, *NATM* contrasts the design and construct principle, where the construction has to proceed as originally designed.

This method is intended to comply with the “build as you go” approach. The following cautions should be kept in mind when applying *NATM*: Not too stiff, nor too flexible. Not too early, nor too late (Bhawani Singh, 2006).

The *NATM* takes utmost advantage of controlled/monitored stress release to provide the tunnel stability. Applying the support system, which consists of shotcrete lining and rock bolts, within the stand-up time of the surrounding rock (temporary support) and alterations based on the measurements (permanent support), is the essence of this method. *NATM* is outlined as follows (Rabcewicz and Golser, 1973; Bhawani Singh, 2006):

- Turning rock mass strength to good advantage:
The surrounding rock mass is aimed to support itself partially. This intention is satisfied through implementation of shotcrete lining together with systematically arranged rock bolts.
- Dynamic and pliable support system:
Although loosening is not allowed in *NATM*, the installed support system (rock bolts and shotcrete lining) permits small deformations. That is on the ground that a certain amount of deformation is necessary for a stable stress redistribution to

form after excavation. Moreover, preventing the ground from falling in requires less force initially, but when loosening arises, it takes too much force to stop.

- Closing the invert: In this method, the tunnel is considered as a thick-wall load bearing closed ring. Open rings, particularly in the formations with lower support capacity, are not desirable. As a result, the tunnel invert is an indispensable part of *NATM*.
- This method favours full-face excavation over drivage in different stages. The reason is that in comparison with partial face excavation, a full-face excavation yields a less complicated stress redistribution. However, there are some cases in which full-face excavation is not an option due to little stand-up time and chances of rock falling. With those cases, steel ribs and rock bolts are the only available options for tunnel support.
- Hiring shotcrete in order to maintain the load bearing capacity of the excavated mass: In water containing grounds, shotcrete cover should include radial gaps in order to properly drain the water content.
- Watching the deformations in the excavated rock: In *NATM*, monitoring is the key factor that dictates timing and capacity of secondary support system. Double extensometers, convergence meters, pressure pads, and electronic theodolites are the equipment used for measuring the deformations.

3. GEOLOGY

3.1 Geology of Istanbul

Istanbul District is located on Çatalca Peninsula in the west, the Kocaeli Peninsula in the east separated by a waterway (the Bosphorus) between these peninsulas. Furthermore, the region is one of the two linking points of Asia and Europe. It only covers 0.7% of the country's territories and the shape of the district resembles a rectangle with the long edge in the E-W direction (approximately 100 km) and short edge in the N-S direction (approximately 50-60 km). The Paleozoic lithostratigraphic units in the Kocaeli and Çatalca peninsulas are described in Table 3.1 and Figure 3.1 (Özgül, 2012).

Table 3.1: Palaeozoic stratigraphic units of the Istanbul unit (Özgül, 2012).

Formation	Member	Symbol	Age
Trakya Formation	undifferentiated	Ct	Early Carboniferous
	Küçükköy Member	Ctk	Early Carboniferous
	Kartaltepe Member	Ctk	Early Carboniferous
	Cebeciköy Member	Ctc	Early Carboniferous
	Acıbadem Member	Cta	Early Carboniferous
Denizli Köyü Formation	undifferentiated	Dcd	Middle Devonian- Early Carboniferous
	Baltalimanı Member	DCdb	Early Carboniferous
	Ayineburnu Member	DCda	Late Devonian-
	Yörükali Member	DCdy	Early Carboniferous
	Tuzla Member	DCdt	Middle-Late Devonian Middle-Late Devonian
Pendik Formation	undifferentiated	DP	Middle-Late (?) Devonian
	Kartal Member	Dpk	Early-Middle (?) Devonian
	Kozyatağı Member	Dpkz	Early-Middle (?) Devonian
Pelitli Formation	undifferentiated	SDp	Late Silurian-Early Devonian
	Soğanlık Member	SDpsğ	Early Devonian
	Sedefadaşı Member	SDps	Late Silurian-Early Devonian
	İçmeler Member	SDpi	Late Silurian-Early Devonian
	Dolayoba Kireçtaşı	SDpd	Late Silurian
	Member Mollafenari	SDpm	Late Silurian
	Member		

Table 3.1 (continued): Palaeozoic stratigraphic units of the Istanbul unit (Özgül, 2012).

Yayalar Formation	undifferentiated	OSy	Late Ordovician-Early Silurian
	Şeyhli Member	OSyş	Late Ordovician-Early Silurian
	Umur Deresi Member	Osyu	Late Ordovician-Early Silurian
	Gözdağ Member	OSyg	Late Ordovician-Early Silurian
Aydos Formation	undifferentiated	OSa	Late Ordovician-Early Silurian
	Ayazma Kuvarsit Member	OSaa	Late Ordovician-Early Silurian
	Başıbüyük Member	Osab	Late Ordovician-Early Silurian
	Kısıklı Member	OSak	Late Ordovician-Early Silurian
Kınalıada	Manastır Tepe Member	Okm	Middle-Late Ordovician
	Gülsuyu Member	Okg	Middle-Late Ordovician
Kurtkoy Formation	undifferentiated	Opk	Early Ordovician
	Süreyyapaşa Üyesi	Opks	Early Ordovician
	Bakacak Member	Opkb	Early Ordovician
Kocatöngel Formation	undifferentiated	Opkc	Early Ordovician

SYSTEM	SERIES	FORMATION	MEMBER	Approximate thickness (m)	LITHOLOGY	Explanation
CARBONIFEROUS	LOWER CARBONIFEROUS	TRAKYA	Küçükköy	> 1000		turbiditic sandstone, siltstone and shale
			Kartaltepe	30		lydite-shale
			Acıbadem	400		shale and siltstone
			Cebeciköy			Cebeciköy Member: limestone
DEVONIAN	UPPER DEVON.	DENİZLİ KÖYÜ	Baltalimanı	40		lydite; radiolarian cherts with phosphatic nodules
			Ayineburnu	40		nodular limestone with shale intercalations
			Yörükali	30		lydite-shale with rare limestone intercalations
			Tuzla	60		limestone and shaley limestone
	LOWER AND MIDDLE DEVONIAN	PENDİK	Kartal Kozyatağı	650	max 100	micaceous shale and siltstone
						limestone and shaley limestone
						micaceous shale and siltstone with rare sandstone and limestone intercalations, very rich in macrofossils
		PELİTLİ	Soğanlık	60		nodular limestone with subordinate shale
			Sedefadaşı	270		micritic limestone
			İçmeler	40		laminated limestone with shale
SILURIAN – DEVONIAN	U. SILURIAN – U. DEVONIAN		Dolayoba	60		reefal limestone
			Mollafenari	70		limestone, marn, sandstone
			Şeyhli / Umurdere	110 / 40		Şeyhli M.: feldspathic quartz-arenite, quartz-wacke Umurderesi M.: shale, siltstone with chamositic oolites
			Gözdağ	250		sandstone and siltstone
	UPPER SILURIAN	YAYALAR	Ayazma	70		quartzite
			Başbüyük / Kısıklı	30		Başbüyük Member: conglomerate Kısıklı Member: mudstone and shale
			Manastır Tepe	50		feldspathic quartz-arenite
			Gülsuyu	200		quartz-wacke and siltstone unconformity
ORDOVICIAN – SILURIAN	MIDDLE-UPPER (?) UPPER ORDOVICIAN + LOWER SILURIAN	AYDOS	KINALIADA	2200		
ORDOVICIAN	LOWER ORDOVICIAN	KURTKÖY	Süreyyapaşa	1500		
POLONEZKÖY GROUP	KOCATÖNGEL		Bakacak	500		

Figure 3.1: Generalized stratigraphic section of the Istanbul Palaeozoic sequence (Özgül, 2012).

3.1.1 Stratigraphy

The general geology of the Istanbul District is formed by Paleozoic, Mesozoic, Cenozoic, Quaternary and actual sedimentary materials with soils, according to the IECR (2009). Boundary relations of these rock formations are mostly unconformities that are sourced from tectonic activities. Paleozoic deposits are observed in Çatalca Peninsula, the Bosphorus shores, and the Asian (Kocaeli Peninsula) continuation of linked formations, whereas Cenozoic and Quaternary deposits are examined mostly in the western side of the district. Alluvial formations are mostly encountered at the Bosphorus coast and valley bottoms. Antique and actual artificial fillings (made ground) can be seen at the Marmara Sea coasts apart from these natural deposits. In the northern side of Çatalca Peninsula a rock unit called the “Istranca Group” is observed in vast areas. The Istranca Group is composed of metamorphic rocks such as schist, quartzite and magmatites. The group is located in large areas between Tekirdağ and Edirne and it enters the Istanbul District from the west and northern side. Outcrops of this metamorphic group are observed in the Çatalca region with names such as Kızılağaç Metagranites, Şermat Quartzites, and Mahya Schists. The other main unit which can be observed at both sides of the Bosphorus is called as the “Istanbul Group”. This group does not show any metamorphism related with Paleozoic and Mesozoic times. The oldest rock formation in this group is Lower Ordovician continental rock and it is present at the near side of the metropolitan area. The basal part of this Lower Ordovician stacks is called the Kurtköy Formation but it is not observed in the district. These units are located with unconformities in Infracambrian aged schists, gneisses, and meta-magmatites at Armutlu Peninsula.

In the Early-Middle Ordovician, the Istanbul region accumulated quartzite from a beach environment named the “Aydos Formation” and this accumulation was sourced due to transgression. The region was covered with a tectonically stable and deepening sea in Silurian and Devonian periods. In this process, deposition of Yayalar Formation (Sandstone – Lower Ordovician), Pelitli Formation (shelf type reef and shallow sea carbonate deposit – Lower Ordovician – Silurian), Kartal Formation (low energy deep-sea environment representative limestone & mica schist intercalation containing large amount of macrofossils - Lower – Middle Devonian), and Denizli Village Formation (deep sea shelf deposit representative nodular limestone – Upper Devonian & Lower Carboniferous) occurred (IECR, 2009).

The Denizli Village Formation member called Baltalimanı, which has Lower Carboniferous siliceous deposits, is thought to be the reason for the presence of large amount siliceous material due to volcanic activity around this marine basin. The region is presented as a tectonically stable period from the Ordovician to the start of the Carboniferous and it shows the characteristic behavior of turbidity current deposits. Therefore, turbiditic flysch type sandstone shale intercalation called as “Trakya Formation” has been deposited with more than 1,000 m thickness (IECR, 2009).

North-South strike and East-West dip low angle reverse faults are developed in the region due to tectonic activities which occurred in the Carboniferous – Permian period. To illustrate this, the Çamlıca Thrust, which is the reason of Aydos Quartzites movement over younger formations and eventually forming of Çamlıca Hills, is believed to have developed throughout this period. Magmatic intrusions present within the Sancaktepe Granite (Permian) west of Gebze are also thought to have formed in this period and finally this region formed the continental surface. This continental transformation period in the Permian – Early Triassic is represented with reddish sandstone and pebblestone called the “Kapaklı Formation”. Basaltic volcanic rock intercalations in Kapaklı Formation could be interpreted as the starting of rift formations in the region. In the Middle – Late Triassic, a transgressive sea formed a secondary marine environment and this transgression was followed by deposition of Demirciler Formation (tidal deposits), Ballıkaya Formation (shelf carbonates), and Tepeköy Formation – Bakırlıkıran Formation (slope deposits) (IECR, 2009).

There is no indication or outcrop of any rock units from Jurassic – Early Cretaceous within the Istanbul District boundaries and this condition is the sign of erosion in this time interval. In the Late Cretaceous, another transgressive movement occurred in whole region and deposition of Sarıyer Formation (Upper Cretaceous volcano sediments) and Akveren Formation (Upper Cretaceous – Paleocene clastics with shallow carbonates) occurred in this marine environment. Andesitic volcanic rocks of the Sarıyer Formation, which are believed to be indicative of island arc volcanism in the closure of the Tethys Ocean, covered the northern side of the region. Upper Cretaceous Çavuşbaşı Granodiorites and volcanic dykes in Paleozoic successions also developed in this period (IECR, 2009).

There was intense folding and faulting in the Marmara Basin at Lutetian due to major compressive impacts on Anatolia during the Eocene and this folding and faulting genesis becomes effective in Istanbul District. During deposition of Paleozoic and Mesozoic rock units in the Early Eocene, the Sarıyer-Şile Fault with NNW-SSE strike intruded into the Upper Cretaceous – Early Eocene rock units. Another transgressive movement occurred in the Middle Eocene in the region. In the Middle Eocene – Early Oligocene interval, deposition of beach and reefal units (Koyunbaba Formation, Yunuslubayır Formation, and Soğucak Formation) near coasts and clayey mud (Ceylan Formation) in deeper sides occurred and spread. The region became a continental depositional field again due to tectonic activities affecting Trakya Basin starting from the Middle – Late Oligocene to the present day. In this interval, deposition of river deposits representing Late Oligocene – Late Miocene (Kıraç Formation) and lagoon – lake deposits (Danişmen Formation & Çekmece Formation) developed. Within these formations intensive shear fault and joint systems can be observed with NW-SE and NE-SW orientations, developed with N-S direction compaction. These shear zone fractures developed weak zones and these weak zones are the explanation for the zigzag geometry of the Istanbul and Çanakkale Strait coasts as well as the large river valleys and Golden Horn coasts (IECR, 2009).

3.1.2 Tectonism

Istanbul District is situated in a tectonically active and intricate region. The northern branch of the North Anatolian Fault (*NAF*) is located to the south of the proposed Project area. This branch is the reason for a deformation zone that includes NE-SW directed normal faults and similar basin series development to 30-40 km width. In addition, some of these fault segments' northern parts reach south of the metropolitan area. Here there exists a normal fault system in the north and this system could be the continuation of the Srednogorie zone of Bulgaria. Furthermore, there exists a NE-SW directed Trakya (Istranca) Fault parallel to the Black Sea coasts in the northwest part of the region and this fault reaches closer to Lake Terkos. There is an assumption that this fault may split into small parts to the east of Lake Terkos. In addition to that, there are smaller scale faults between the main fault zones. Büyükdere Fault becomes prominent in these smaller faults and it is an E-W trending fault to the north of Aydos Mountain (IECR, 2009).

3.2 Geology of The Project Area

Paleozoic, Mesozoic and Cenozoic Period formations were recognized at Istanbul. There are generally Paleozoic rocks in the city. From the Ordovician to the Carboniferous Periods, comprising several thousand meters of rock, a concordant rock sequence is observed. This stratigraphic sequence generally consists of clastic rocks and limestone in different faces (Önalın, 1981; Eroskay, 1985) . This study was carried out on the Carboniferous Trakya Formation, a sequence that is unconformably overlain by Neogene sediments.

3.2.1 Trakya formation

The Trakya Formation consists of intercalated sequences of sandstone (greywackes), shale, siltstone and mudstone. They are typically dark grey-green or greyish-brown due to weathering. Sandstone is the most abundant rock type in this formation, and limestone and conglomerate interbeds or lenses are found between layers. The thickness of the Trakya formation varies between 600-1700 metres (Eroskay, 1985). They are generally of marine origin and are believed to have been deposited by submarine turbidity currents (Pettijohn and Porter, 1972).

The Trakya formation is commonly exposed in the west of İstanbul, especially in İkitelli, Cebeciköy, Şişli, Beşiktaş, Levent and Gaziosmanpaşa. Greenish brown coloured andesite dykes, up to 10 m thick, are common in the study area, and generally follow a NW-SE direction. When they were fresh, they could be easily identified in the field. But in the highly weathered conditions, dykes which were yellowish brown coloured could only be differentiated with difficulty from the greywackes (Eroskay, 1985).

The Trakya formation is very intensely folded, faulted, fractured, and is also weathered which is well developed along discontinuities. The major structural features of the area are NW-SE and NE-SW trending faults. Dense crack surface developments are observed and rock masses are completely fractured from place to place. Usually, three or four clearly defined major sets of joints are found. Minor sets or random joints also occur in study area. The strike directions of joints are almost NW-SE and NE-SW. Trakya Formation is subdivided into the Acıbadem, Cebeciköy Limestone, Kartaltepe and Küçükköy members (Figure 3.2).

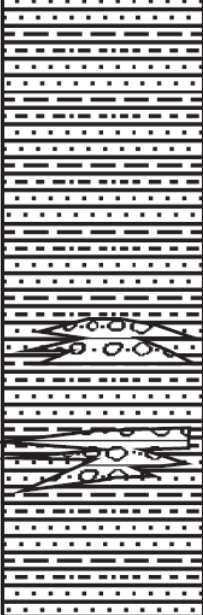
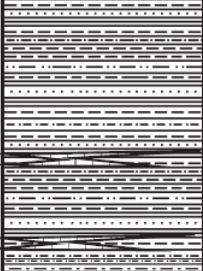
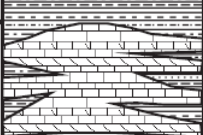
SYSTEM	SERIES	GROUP	FORMATION	MEMBER	Cumulative Thickness (m)	Thickness (m)	LITHOLOGY	EXPLANATIONS
CARBONIFEROUS	Lower Carboniferous	Visean	Trakya	Küçükköy	> 1400			flysch turbiditic sandstone and shale with rare conglomerate lenses, parallel, cross and convolute bedding and lamination, grading, Bouma sequences sandstone – black, dark grey, reddish brown alteration colour, thin to thickly bedded, rich in clastic mica, plant fragments, feldspathic and lithic greywacke shale – black, dark grey, micaceous conglomerate – rounded, medium to weakly sorted quartz, chert, black lydite clasts in a coarse sandy matrix, forms lenses with lateral and vertical transitions to the sandstones
				Kartaltepe	400	~30		shale and siltstone with lydite intercalation, greenish, dark grey with yellowish brown alteration colour
				Acıbadem	200-400			shale, silty shale greenish black, grey, micaceous with intercalation of sandstone, siltstone and rare limestone
				Cebeciköy	100	~ 100		limestone black, dark grey, medium to thickly bedded, rich in organic matter, local dolomitization and recrystallization, black chert beds and nodules in the upper levels, forms lenses within the Küçükköy Member
					0	0		shale with intercalation of siltstone, fine-grained sandstone, limestone and lydite

Figure 3.2: Generalized stratigraphic section of the Trakya Formation.

3.2.2 The Küçükköy member

The fine-grained clastic rocks of the Acıbadem Member, mainly shales and siltstones, are overlain by a thick turbiditic sequence of micaceous coarse-grained sandstone and shale. Kaya and Mamet (1971) named the outcrops of this facies around Küçükköy west of Bosphorus the Küçükköy Member and those around Gümüşdere village the Gümüşdere Formation. As these stratigraphic units do not have any marked lithological differences, Özgül (2005) considered them as a

member within the Trakya Formation. As the outcrops around Küçükköy, especially those around the stadium are clean and extensive and unlikely to be covered in the foreseeable future, the name Küçükköy Member is used for the unit. The turbiditic sandstones and shales east of the quay at Harem are also part of the Küçükköy Member.

The Küçükköy Member consists of a turbiditic sandstone and shale intercalation with conglomerate lenses. The sandstones are greenish, dark grey with a reddish brown alteration color, thinly to very thickly regularly bedded (between 5 and 50 cm) and locally laminated. The Küçükköy Member locally comprises conglomerate lenses representing channel fills. These conglomerates, which interfinger with coarse sandstones are brown, greenish grey and contain well rounded, medium sorted, 1–30 mm large clasts of quartz, quartzite and black lydite in a coarse sandy matrix. As the Küçükköy Member is overlain by Triassic to Neogene units, its full thickness is not known. Furthermore, the Küçükköy Member is strongly deformed and possibly repeated. Its thickness is thought to exceed 1000 m.

4. PROJECT DESCRIPTION

Mini-metro having length of 3104 m is a part of underground transportation project which is situated between Levent and Hisarüstü in the European part of Istanbul. The project have been built within two years and connects the Aşıyan neighborhood, which is along the Bosphorus, to the main Istanbul metro line (Yenikapı-Hacıosman) via a 730 m funicular that connect to the end of the mini-metro line at Hisarüstü, outside Boğaziçi University. The mini-metro is set to have five stations. The new metro will be able to transport up to 10,000 passengers per hour. The route of the metro line is shown in Figure 4.1.

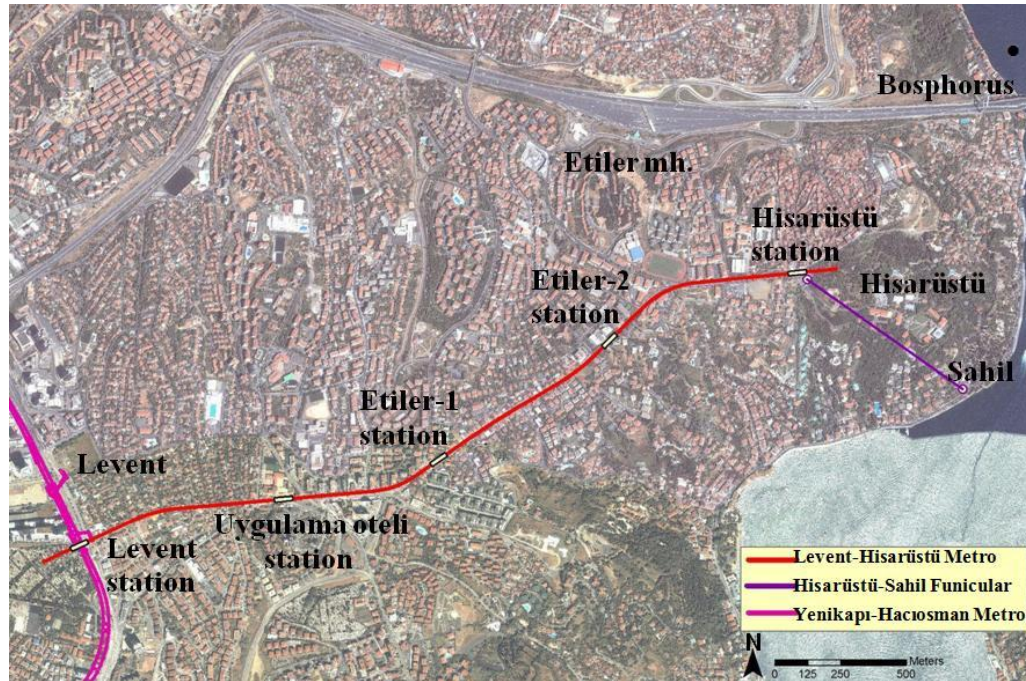


Figure 4.1: The route of Levent-Hisarüstü metro tunnel.

5. FIELD AND LABORATORY STUDIES

5.1 Field Studies

In Levent-Hisarüstü metro project, single track tunnel (type-A) has 34.72 m^2 of vertical cross sectional area as seen in Figure 5.1 and is excavated in two steps. The upper bench of 27.3 m^2 is excavated first and the lower bench of 7.42 m^2 is excavated later. The lower bench is 25-30 m behind the upper bench. A JCB excavator were used with MTB 120 hydraulic hammer having 1,200 kg of hammer

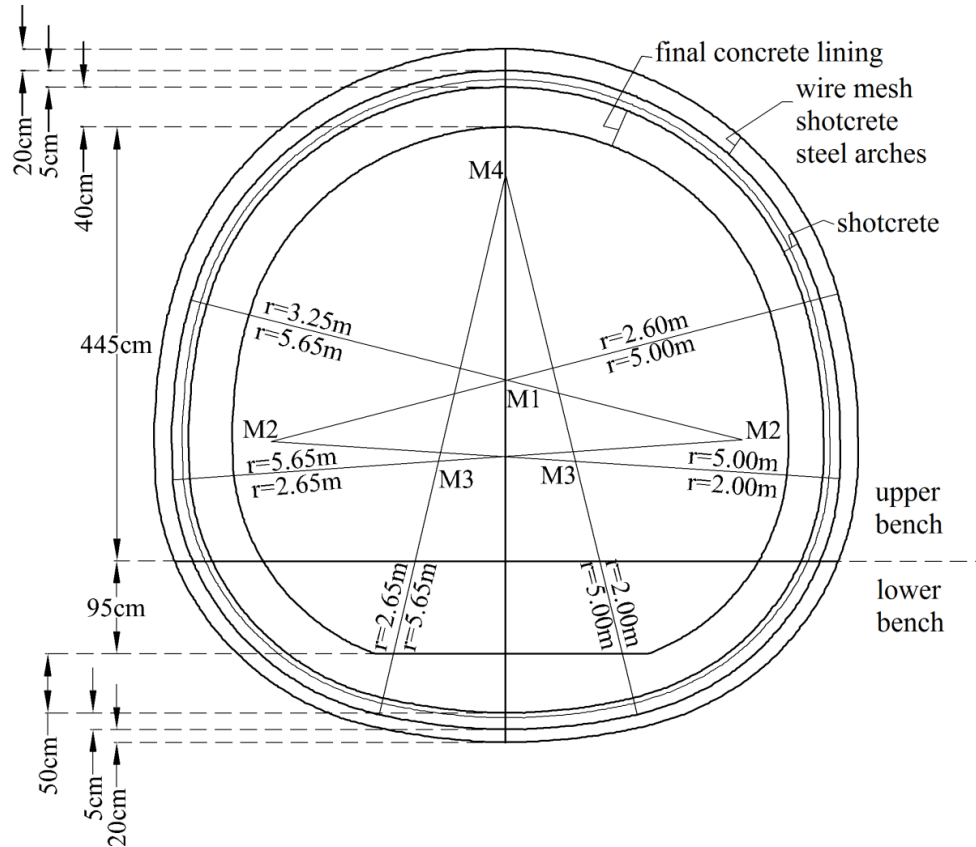


Figure 5.1: Typical cross section of tunnel, type-A (Tuncdemir, 2008).

weight, 1,880 J of impact energy, and 400-700 blow/min frequency. Since the tunnel is excavated under the city, blasting is restricted. As stated by Tuncdemir (2008), Trakya formation allows excavation without blasting because Rock Mass Rating

(*RMR*) values of Trakya Formation are low. Rock bolts, steel arches, wire mesh, shotcrete and final concrete lining are used as support and reinforcement elements (Figure 5.2). The thickness of shotcrete is 20 cm and the length of rock bolts is 4 m. The intervals of steel arches vary between 1.15m and 1.25m.

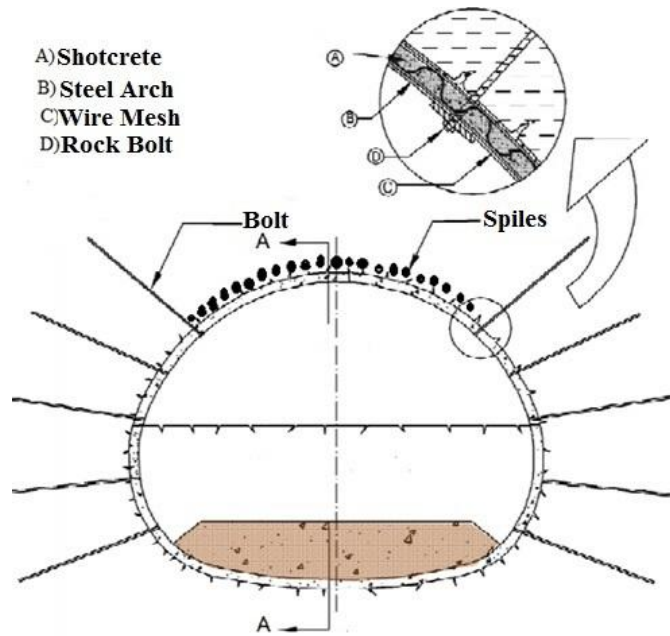


Figure 5.2: Support elements.

In *NATM* tunneling, information or rock data can be collected along the tunnel alignment. The technique described by Poole and Farmer (1978) was used in defining zones for detailed site investigations. The criteria used to separate these zones were according to the obtained geological data and totally independent of any statistical tests used in order to assess correlations between zones. Volumetric joint count (J_v) was realized by summing the number of joints per meter and *RQD* values were calculated using the relationship between J_v and *RQD* described by Brown (1981).

For each zone data about tunnel geology, rock mass structure, intact rock properties, and machine performance were carefully collected. Along the tunnel alignment, where the detailed impact hammer performance analysis was carried out, sandstone is the main rock (60%) encountered with compressive strength values ranging from 68.6 to 145 MPa and *RQD* values from 40 to 60%. Siltstone is met in 20% of the tunnel with compressive strength from 45.8 to 123.3 MPa and *RQD* 38-44%. In the tunnel route, 10% of the rock formations are composed of diabase with compressive

strength ranging from 158.7 to 195.6 MPa and *RQD* 45-60%. Mudstone and shale are met in 10% of the tunnel with compressive strength from 8.9 to 40.1 MPa and *RQD* of 10-40%. The overall performance of the tunnel drive is summarized in detail and given in Figure 5.3. A photo of highly fractured tunnel face can be seen in Figure 5.4.

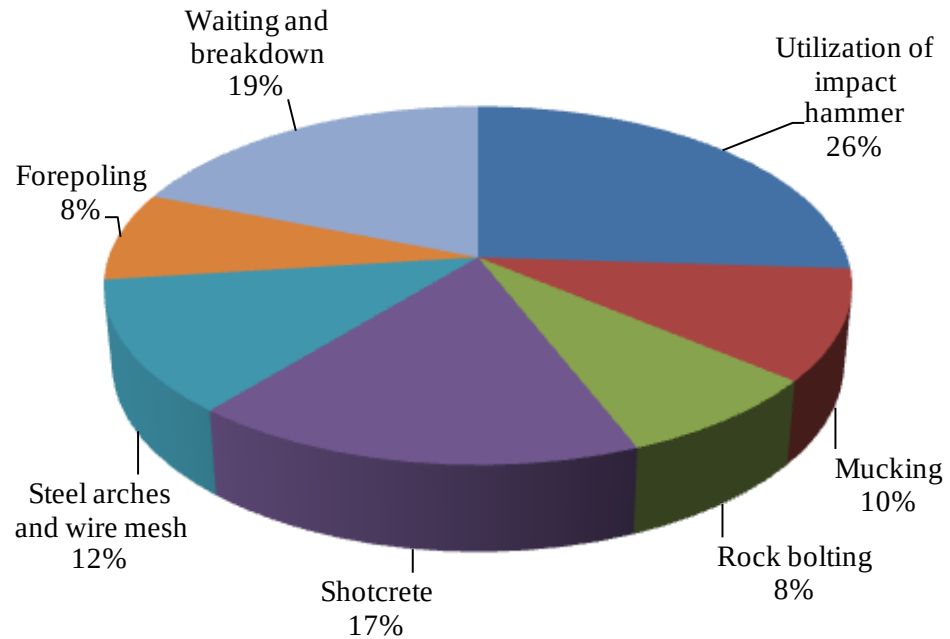


Figure 5.3: Overall performance of tunnel drive in Levent-Hisarüstü metro tunnel.



Figure 5.4: A photo of highly fractured tunnel face.

Instantaneous breaking rate (*IBR*) of MTB 120 impact hammer in m³/h, mounted on JCB excavator, was recorded for each experimental tunnel face. *IBR* is defined excluding all wanted and unwanted machine stoppages as suggested by Bilgin et al. (2002). The performance of impact hammer was recorded continuously during tunnel excavation. *IBR* of impact hammer found to be ranging from 5.35 to 35.00 m³/hour. Daily advance rates changed between 1.15 and 2.5 m.

5.1.1 Technical features of the impact hammer

The following Table 5.1 summarizes the technical features of the hydraulic impact hammer used in this project:

Table 5.1: Technical features of the hydraulic impact hammer.

Specifications	Values
Operating weight (kg)	1200
Impact energy (J)	1880
Operating pressure (bar)	135
Maximum pressure for safety (bar)	175 – 185
Oil flow (l/min)	70 – 130
Back pressure (bar)	10
Hammer diameter (mm)	110
Oil temperature (°C)	-20 +80
Hydraulic oil viscosity (cSt)	15 – 1000
Accumulator pressure (bar)	40
Maximum blow frequency (bpm)	400/700
Truck weight (ton)	14-20
Machine's input power (<i>Hp</i>)	30
Machine's output power (<i>Hp</i>)	23

5.1.2 Types of bolts used in the project

The bolts used in this project are of the SN type. They have a 500 KN tensile strength, are 4 m long, ribbed, and made of T26 special steel. Thread length was 10 cm. An Atlas Copco Rocket Boomer 282 was used for installing the bolts. Base plates were of 150×150×10 mm dimensions. 24 nuts were used to fix the bolts. The minimum hole diameter was 45mm. The mortar contained only cement and water

with water/cement ration of 0.45. Schematic view of the SN bolt is given in Figure 5.5. Figure 5.6 shows the torque application on the SN bolts.

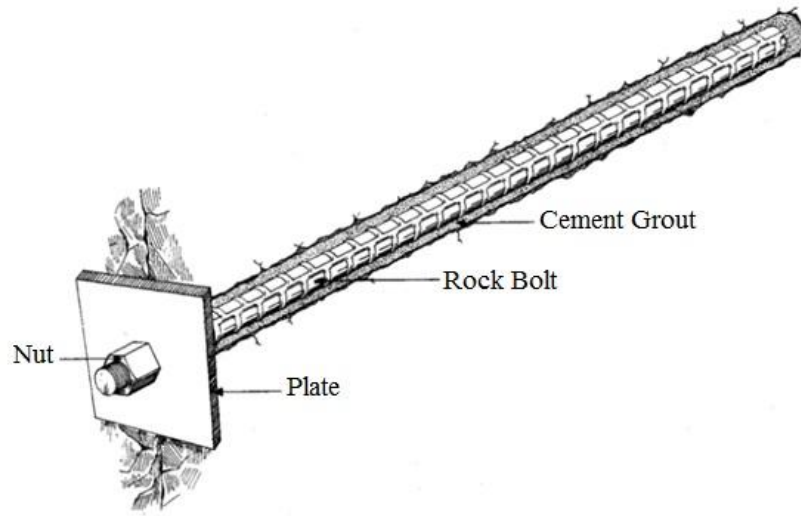


Figure 5.5: Schematic view of the SN bolt.



Figure 5.6: Torque application on bolts.

5.1.3 Wire meshes used in the project

Wire meshes are installed with a 30 cm overlap along the tunnel alignment. Size of the wire mesh segments is 5m×2.15m with 15 cm× 15 cm of grid dimensions. The

wire mesh is of type Q221/221 produced by BMS Çelik Hasır. Rod diameter is 6.5 mm. The weight of the mesh is 3.48 kg/m². A photo of the wire meshes used in this project is given in Figure 5.7.



Figure 5.7: Steel wire mesh.

5.1.4 Shotcrete used in the project

The details of the wet shotcrete used in this project are given below:

- Cement % 15–17,
- Water % 5 – 7,
- Natural Sand (+0-2 mm) % 17-20,
- Crushed Sand (+2-5 mm) % 20-25,
- Crushed Rock (+5-12 mm) % 35-40.

In practice, the largest particle diameter of the spray mixture should be 19 mm.

Figure 5.8 shows the shotcrete application in the tunnel.



Figure 5.8: Shotcrete spraying machine and its application.

5.1.5 Steel arches (lattice girders) used in the project

The arches are used in the A2 -type arc-shaped tunnel project consists of two parts (Figure 5.9) . In these arches ST- 37 type steel is used. In each arch there are one outer and two inner rod bar . The weight of an outer rod is 29.30 kg , while the weight of inner rod is 16.78 kg. These rods are connected to each other by connecting rods with a diameter of 10 mm. There are a total of 44 units in a cage strut tie bar which are connected with retaining lug nuts the mx24 . Size of the base plate 10/200/420 mm. Total weight of type A2 arch with combination of other materials used is 183.11 kg.



Figure 5.9: Steel arches.

5.1.6 Umbrella arches used in the project

In the flowing and squeezing grounds and in the formations containing water particularly suitable time to practice the umbrella arches is before the start of the excavations carried out. In the excavation of Hisarüstü A type tunnel, there is gravel in each 2 rings above one of the umbrella arches. To cope with, between 10 and 20 umbrella arches are reinforced in each 4m length of umbrella arches. This is dependent on the experience of the jumbo operator (Figure 5.10). The outer diameter of rods was 48.3 mm and the thickness was 3.7mm. After mounting the umbrella, arches grout was injected through the arches. Injection fills the gaps completely and this reinforcement application helps rock stabilization.



Figure 5.10: Spile application.

5.2 Laboratory Studies

The most important parameters affecting the performance of impact hammer are physical and mechanical properties of rocks. The intact rock samples are obtained along the tunnel lines in Istanbul in which impact hammer was used. The physical and mechanical properties of the rock samples are determined according to the International Society for Rock Mechanics (*ISRM*)(Ulusay and Hudson, 2007) and American Society for Testing and Materials (*ASTM*) standards. The unshaped rock samples were collected from the tunnel face and sharpened using the preliminary instruments such as small diameter saw and core drill machine. Physical and mechanical property tests include uniaxial compressive strength, Brazilian tensile strength, Shore scleroscope hardness, Schmidt hammer rebound values, point load index, Cerchar abrasivity index, and density. The physical and mechanical tests were performed on 60 samples. Each sample was obtained from an individual ring.

5.2.1 Physical and mechanical property tests

5.2.1.1 Uniaxial compressive strength tests

The compressive strength is probably the most widely used and quoted rock engineering parameter. Under uniaxial load conditions the maximum stress that the rock sample can bear is referred to as uniaxial compressive strength (*UCS* or σ_c). Usually, NX sized (54.7 mm in diameter) cores with length to diameter ratio of 2 to 3 are used as rock samples in this test. Figure 5.11 and Figure 5.12, and show typical core sample preparation machines. *UCS* usually is calculated according to *ISRM* or *ASTM D2938* test standards. For each rock, a minimum of three to five samples should be tested in order to achieve the statistical significance. Equation 5.1 is used to calculate *UCS*:

$$UCS = \frac{F}{A} \quad (5.1)$$

where, *UCS* is the uniaxial compressive strength (MPa), *F* is the failure load (N), and *A* is the cross section area of the core (mm²).



Figure 5.11: Typical core drilling machine.



Figure 5.12: Typical core diamond sawing machine.

Rock foliations have an important impact on *UCS* test results. Foliations, joints, fractures, and beddings perpendicular or parallel to the loading direction produce misleading crack propagations in samples (Figure 5.13). This type of failure is called “Structural Failure” and it does not represent the strength of the rock. As a result, it is necessary to check whether the failure is parallel or perpendicular to the structural weaknesses (Bilgin et al., 2013).

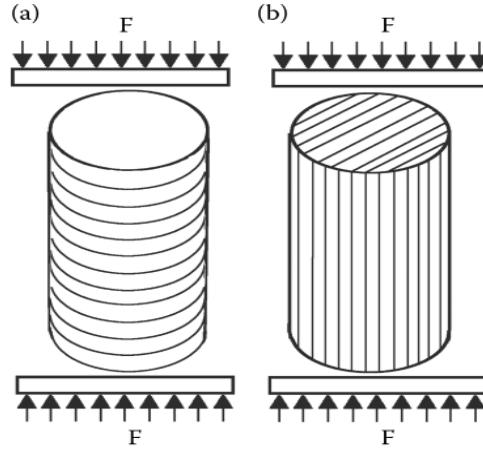


Figure 5.13: Foliation effects of the loading direction. (a) perpendicular to bedding and (b) parallel to bedding.

In this research ELE- Autotest 3000 model machine was used (Figure 5.14). Uniaxial compressive strength tests were carried out on grinded core samples with a length to diameter ratio of 2. The stress rate applied to core samples was 0.5 kN/s. Image of a tested sample is shown in Figure 5.15.



Figure 5.14: ELE- Autotest 3000 model *UCS* testing machine.

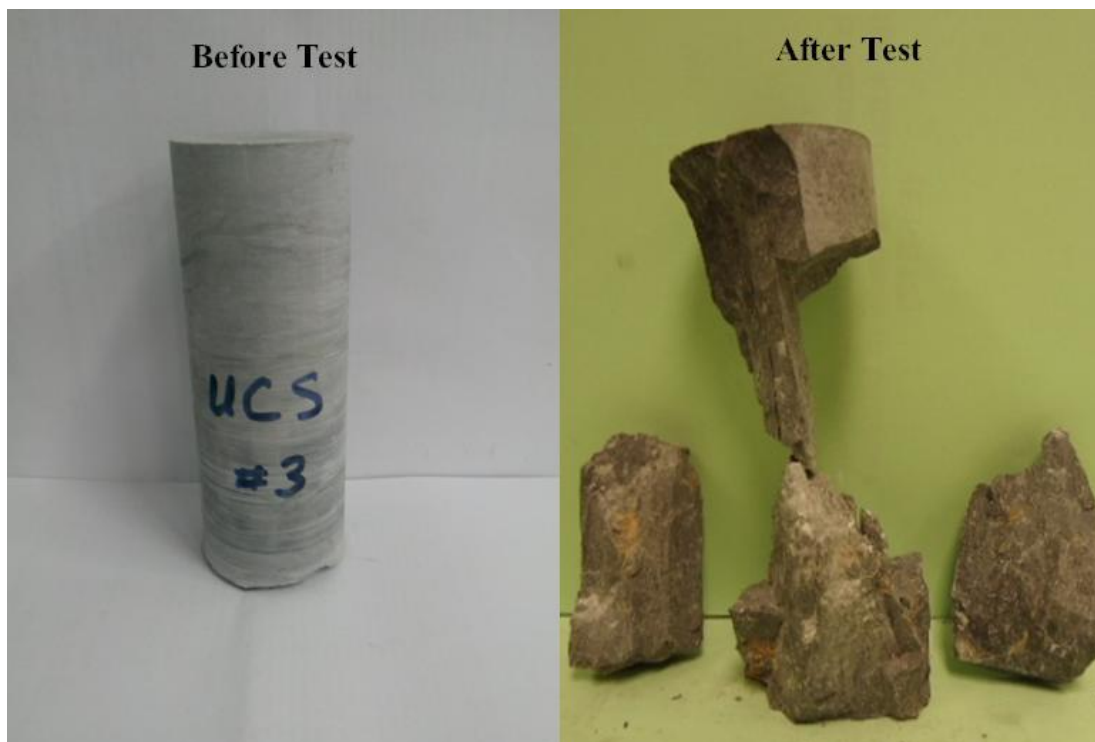


Figure 5.15: Image of a tested sample.

5.2.1.2 Brazilian tensile strength tests

Brazilian Test is a geotechnical laboratory test for indirect measurement of tensile strength of rocks. Due to its simplicity and efficiency, it is almost the most commonly used laboratory testing method in geotechnical investigation of rocks. This mechanical property is measured using NX core samples with length to diameter ratio of 0.5. ASTM D3967 and ISRM standards are commonly used to measure this parameter. It can be calculated as given in equation 5.2:

$$BTS = \frac{2.F}{\pi.d.h} \quad (5.2)$$

where, *BTS* is the Brazilian tensile strength (MPa), *F* is the collapsing force (N), *d* is the diameter of the sample (mm), and *h* is the height of the sample (mm).

In this test, like *UCS* test, failure type and foliation are of great importance in this test as the failures across the structural weak planes are not a reliable index of rock's tensile strength (Bilgin et al., 2013). Figure 5.16 shows a normal failure under *BTS* test performed in this study.

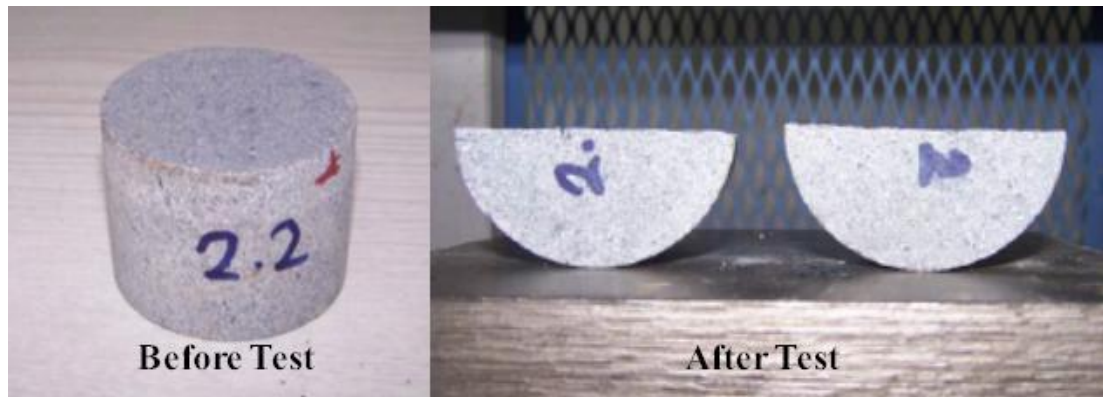


Figure 5.16: An example of the normal failure type of *BTS* testing.

In this study, Brazilian tensile tests were performed on core samples with 0.25 kN/s stress rate and length to diameter ratio of 1 using an ELE- Autotest 3000 machine.

5.2.1.3 Schmidt hammer tests

The Schmidt hammer is a cost friendly and easy to handle equipment which is capable of estimating rock surface hardness (Bilgin et al., 2013). It was originally developed for estimating the in situ strength of concrete. During the past years, numerous research works have been carried out in order to find correlation between

Schmidt hammer and different properties of intact rock and rock mass. Using statistical models, Unconfined Compressive Strength and Plasticity Index can be estimated based on Schmidt hammer rebound values (Bilgin et al., 2013). The Schmidt hammer rebound value can be used as an index value or converted into unconfined compressive strength value based on the statistical relationships. Plasticity index can also be estimated using rebound values (Bilgin et al., 2013).

The mechanism of operation is simple: a plunger released by a spring impacts against the rock surface and then the rebound distance of the plunger is read directly from the numerical scale changing from 10 to 100. Schmidt hammers are available in several different energy ranges, which include Types L, N, M having 0.735, 2.207, and 29.43 Nm impact energies, respectively. Hammer should be calibrated prior to testing. A core sample (block sample in any size larger than $20 \times 20 \times 20$ cm or an excavation face) can be used to apply the Schmidt hammer test. The rock surface should be flat and clean. The test is usually applied in a horizontal direction and correction should be applied for angled or vertical rebound readings (Bilgin et al. 2002).

ASTM D5873 and *ISRM* standards are mostly used for Schmidt hammer rebound test. A typical L-type Schmidt Rebound Hardness device is seen in Figure 5.17.



Figure 5.17: A Typical L-type Schmidt rebound hardness device.

There are four reading procedures developed by different researchers/organizations for testing and reading the results:

Procedure-1(Poole and Farmer, 1978): Taking the peak rebound value from five continuous impacts at a point and averaging the peaks of the three sets of tests conducted at three separate points.

Procedure-2 (Hucka, 1965): Taking the peak rebound value from 10 continuous impacts at a point and averaging the peaks of the three sets of test conducted at three separate points.

Procedure-3(Ulusay and Hudson, 2007): Recording 20 rebound values from single impacts separated by at least a plunger diameter and averaging the highest 10 values.

Procedure-4 (ASTM, 2013): Recording 10 rebound values from single impacts separated by at least the diameter of the piston. Only one test may be taken at any one point and discard readings differing from the average of 10 readings by more than 7 units and determine the average of the remaining readings (Bilgin et al., 2013).

5.2.1.4 Shore scleroscope tests

Shore scleroscope is another simple way of determining surface hardness of the rock. The rebound height of a diamond or tungsten-carbide tipped hammer from a horizontal smooth rock surface determines the value of Shore scleroscope hardness. The instrument used for this test is available in two main models; model C and model D. Model C-2 is comprised of a barrel with a glass tube which is graded from 0 to 140. Figure 5.18 shows a typical C-2 Shore scleroscope hardness device. In accordance with *ISRM* (Ulusay and Hudson, 2007), a test specimen should at least have 10 cm² of surface area and be at least 1 cm thick. The distance between the measurement points should be equal or greater than 5 mm and only one test can be performed on one point. To obtain statistical significance, each rock sample should be tested at least 20 times.



Figure 5.18: Typical Shore scleroscope hardness device.

5.2.1.5 Point load tests

The point load test is one of the most common tests in rock engineering. Benefits of it: The size and the shape of the specimen could be varied in a wide range; therefore it can be performed when cylindrical specimen is not available. This test can easily be performed on field as well, so it gives result very quickly. The uniaxial compressive strength can be estimated by the point load strength. Equation 5.3 is used in point load index calculation.

$$I_s = \frac{F}{D_e^2} = \frac{\pi.F}{4.W.D} \quad (5.3)$$

where, I_s is the point load index value, F is the collapsing force (N), D_e is the equivalent diameter of the sample. The machine used in point load tests is given in Figure 5.19. Before and after test photos are given in Figure 5.20.



Figure 5.19: Point load test equipment.

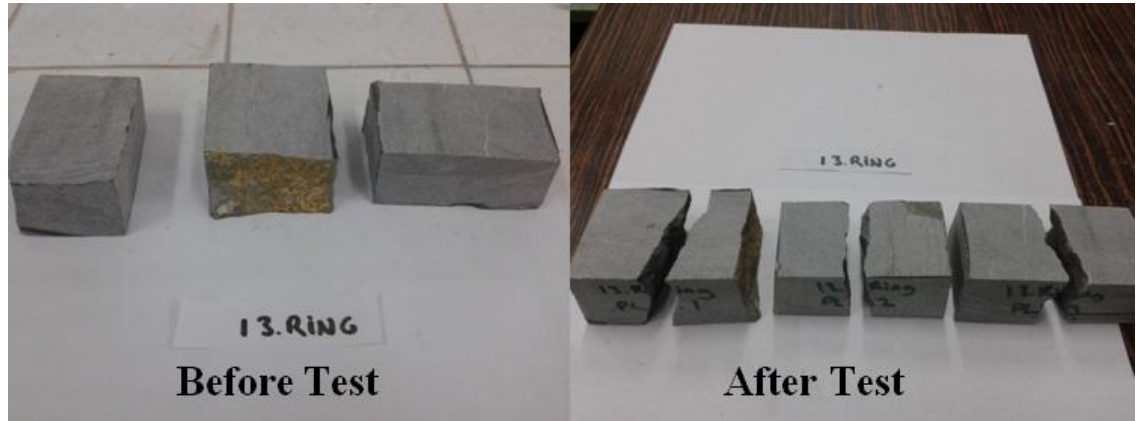


Figure 5.20: Point load test photo.

5.2.1.6 Cerchar abrasivity index tests

Cerchar abrasivity index (CAI) is a test for determination of rock abrasivity. This index is used for classification and prediction of cutter wear rate and cost. The test is performed on a fresh rock surface which has not been exposed to alteration based on ASTM D7625-10 standard. The residual pieces of rock from *BTS* test can be used in this test. Samples are fixed in vise with the fresh surface facing upward. A conical,

hardened still pin with a 90° tip angle is set up in a 7 kg head in a way that when the head axis is parallel to the surface of the sample, the tip of the pin touches the surface. The pin should be drawn on the surface for the distance of 1 cm over 1 second (Figure 5.22). For each sample, the whole process should be repeated for 5 times. Next, the minimum and maximum wear diameter and the shape of the pins were investigated and recorded under the microscope (Figure 5.21). Figure 5.22 shows the device used for *CAI* test.

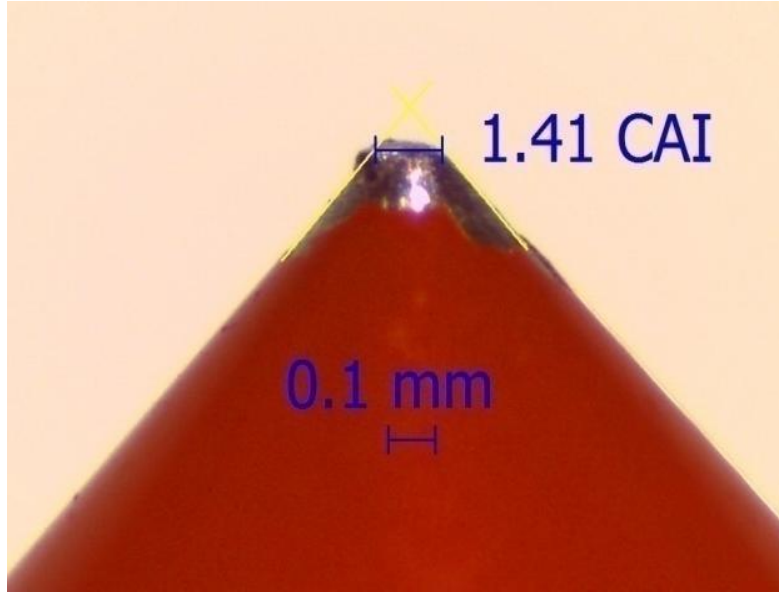


Figure 5.21: Reading of *CAI* under microscope.

Then, under a netted microscope, the two perpendicular diameters of the wear are measured and recorded. The *CAI* is calculated using equation 5.4:

$$CAI = \frac{1}{10} \sum_{i=1}^{i=10} d_i \quad (5.4)$$

where d_i is the pin wear diameter in 0.1 mm. Lower *CAI* values represent softer and less abrasive rocks.

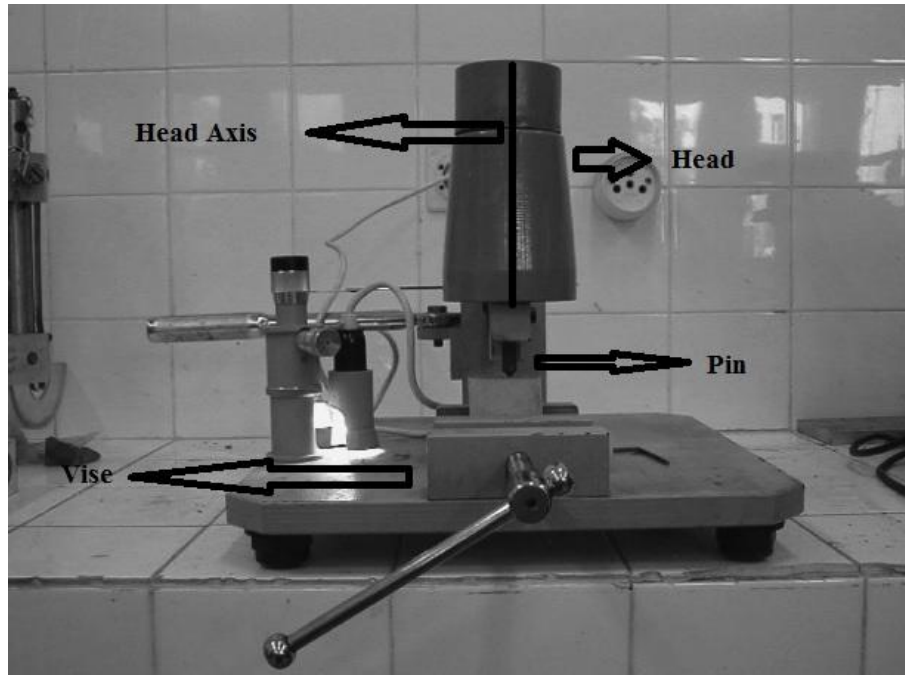


Figure 5.22: Typical Cerchar abrasivity device.

5.2.1.7 Density

Density is the most common physical property of rocks. It is defined as the mass per unit volume of rock and usually ranges from 2.2 to 2.8 gr/cm³. In this project, the density of the samples was measured using ASTM standard.

5.2.1.8 The results of the physical and mechanical property tests

The results are summarized in Table 5.2.

Table 5.2: Physical and mechanical test results.

Observation number	<i>UCS</i> [*] (MPa)	<i>RQD</i> (%)	<i>BTS</i> (MPa)	Density (gr/cm ³)	<i>SH</i> hardness	<i>SS</i> hardness	<i>CAI</i>	<i>IBR</i> (m ³ /h)
1	150.0	43	14.0	2.65	54	59	4.92	12.56
2	10.3	13	2.1	2.09	12	34	2.13	34.13
3	40.1	33	3.7	2.32	45	24	2.32	17.06
4	59.9	40	6.3	2.41	48	45	1.98	14.12
5	45.0	26	4.1	2.34	44	45	1.83	17.87
6	93.6	30	8.3	2.68	42	59	2.36	18.72
7	97.2	31	11.0	2.68	39	65	2.11	17.04
8	78.0	43	12.0	2.63	61	41	2.11	13.65

Table 5.2 (continued): Physical and mechanical test results.

9	8.9	20	2.7	2.13	21	40	1.81	29.25
10	39.2	39	4.0	2.42	41	69	2.30	17.87
11	15.5	24	2.9	2.21	19	28	3.30	27.30
12	123.3	38	9.8	2.69	41	29	3.14	17.06
13	22.2	25	3.6	2.53	37	49	2.41	24.09
14	36.9	40	5.0	2.53	55	58	2.09	14.20
15	44.3	25	9.0	2.53	39	61	3.39	18.72
16	100.3	36	11.3	2.69	41	29	5.11	16.38
17	145.0	41	9.2	2.74	63	49	4.26	12.29
18	179.1	31	13.0	2.71	51	68	2.14	14.63
19	123.6	42	11.0	2.71	47	32	2.36	12.56
20	122.0	25	11.0	2.71	38	49	1.52	17.06
21	58.3	35	6.0	2.49	35	45	1.32	19.66
22	43.6	34	4.0	2.49	35	59	0.97	18.84
23	42.1	40	7.0	2.51	42	64	1.36	15.12
24	41.0	36	4.3	2.49	43	59	2.35	17.06
25	38.7	40	3.2	2.51	41	56	1.08	15.17
26	24.3	25	2.8	2.18	41	59	0.84	22.75
27	39.6	38	3.8	2.21	41	47	2.10	17.06
28	45.8	32	3.2	2.61	44	49	2.89	18.61
29	40.3	41	4.1	2.61	45	25	3.21	14.63
30	39.4	40	3.7	2.58	43	31	2.36	15.17
31	39.3	41	3.7	2.58	49	51	2.41	16.38
32	45.3	43	4.5	2.58	51	68	2.36	13.65
33	44.3	40	4.4	2.57	55	36	3.21	15.75
34	68.6	37	8.0	2.77	68	45	3.21	14.63
35	158.7	46	10.3	2.65	51	48	4.52	10.24
36	144.8	44	9.6	2.65	57	48	3.65	11.38
37	122.5	40	13.0	2.65	63	54	2.41	15.17
38	124.0	38	10.3	2.71	54	67	2.65	15.17
39	195.6	49	11.0	2.71	41	39	3.21	9.75
40	75.0	41	6.3	2.41	42	23	1.95	14.12
41	74.3	38	7.1	2.41	48	47	1.31	14.20

Table 5.2 (continued): Physical and mechanical test results.								
42	89.3	41	8.3	2.45	49	57	1.65	11.83
43	130.0	43	12.9	2.45	50	60	1.52	9.75
44	9.9	10	2.3	2.14	11	38	1.55	35.00
45	45.0	41	8.8	2.54	43	45	1.61	11.90
46	89.8	44	12.0	2.68	36	69	1.35	9.90
47	23.9	60	8.3	2.47	39	56	2.50	15.10
48	63.0	40	8.1	2.65	65	47	1.24	13.30
49	54.1	50	9.1	2.65	63	68	1.35	12.40
50	51.0	50	6.1	2.78	38	59	3.71	11.03
51	51.0	50	6.0	2.65	54	47	2.91	14.10
52	25.0	55	3.0	2.31	36	49	0.81	13.20
53	99.0	54	7.0	2.69	39	38	3.68	11.90
54	71.3	46	9.0	2.55	47	61	1.15	11.30
55	20.0	48	11.0	2.47	65	66	0.94	15.82
56	50.0	47	9.1	2.51	63	67	3.77	10.50
57	45.0	46	14.3	2.54	60	54	0.79	8.20
58	65.2	51	9.0	2.54	54	41	0.77	13.30
59	40.0	55	3.1	2.31	53	45	1.39	16.01
60	80.2	50	9.3	2.71	54	48	3.61	8.20

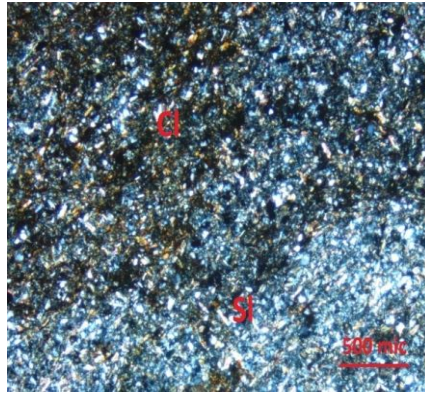
UCS: Uniaxial compressive strength, *RQD*: Rock quality designation, *BTS*: Brazilian tensile strength, ρ : Density, *SHH*: Schmidt hammer hardness, *SSH*: Shore scleroscope hardness, *CAI*: Cerchar abrasivity index, *IBR*: Instantaneous breaking rate. *observations No. 1 to No. 29 were calculated using values obtained from point load test.

5.2.2 Mineralogical and petrographical studies

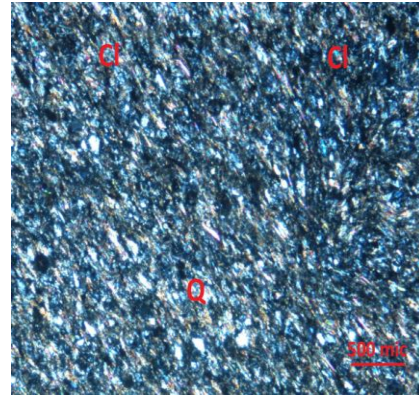
Petrographic analysis provides a detailed description of the texture (grain size, sorting, and grain contacts), framework grain composition, authigenic minerals, sedimentary structures (laminations and bioturbation), and types and distribution of macro-porosity seen in a thin section. Thin section petrographic analysis was also studied to describe the rock textures. Thin section photographs of rocks taken by using plane polarized light are seen in Figure 5.23. Brief petrographic descriptions of the tested rock varieties are given in Table 5.3.

Table 5.3: Petrographic descriptions of the studied rock samples.

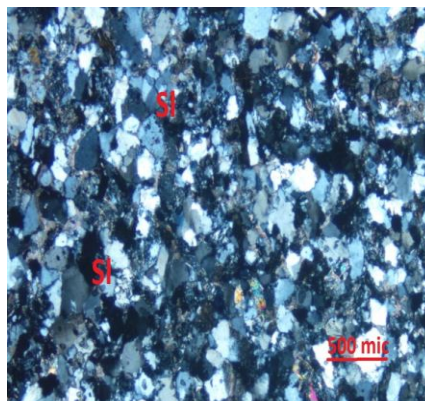
Rock Name	Petrographical Properties	Mineral Content	Grain Size (mic)
Mudstone	Fine grained clay and silt	-	2-6
Shale	Fine grained clay and quartz	-	5-20
Siltstone	Containing very little sand or clay	-	5-75
Diabase	Fine-medium grained, equigranular with a green to dark green and brown weathered surface. It consists of relatively fresh plagioclase, pyroxene, abundant magnetite and a small amount of olivine	85% Feldspar, 10% olivine, 5% Other min.	100-500
Sandstone	Quartz, feldspar (plagioclase and K-feldspar), mica, chlorite, opaque minerals and clay-silt cement. Feldspar minerals generally are altered also biotite is partly chloritized	65% Quartz, 10% Muscovite, 8% Feldspar, 17% rock fragments	20-150



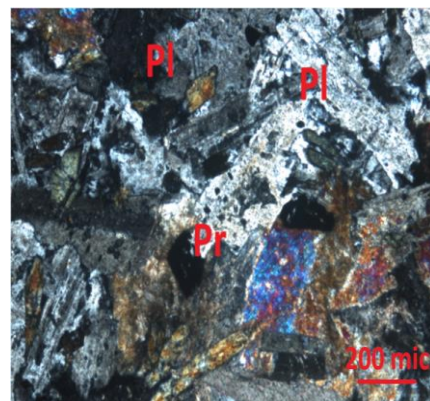
(a) Mudstone



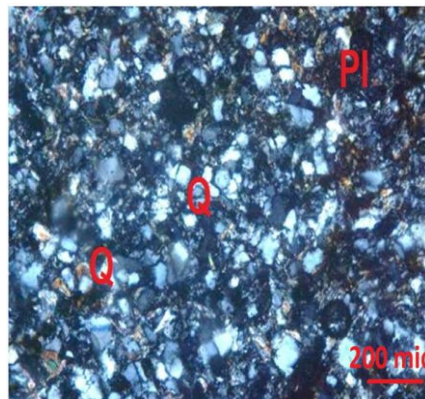
(b) Shale



(c) Siltstone



(d) Diabase



(e) Sandstone

Figure 5.23: Microphotography of a) Mudstone b) Shale c) Siltstone d) Diabase e) Sandstone (Q: Quartz, Pl: Plagioclase, Pr: Pyroxene, Sl: Silt, Cl: Clay).

6. MODEL SUGGESTION

6.1 Regression Modeling

“Rock mass properties” and “physical and mechanical properties of intact rock” are often the major factors that affect the excavation performance. Estimating the impact hammer’s performance, which is affected by many parameters and variables, is a very complex problem. Thus, a practical and empirical equation including machine’s specifications, physico-mechanical properties of the intact rock, and rock mass properties can be very useful for practitioners in terms of prediction performance for impact hammer.

The very simplest case of a single scalar predictor variable (X) and a single scalar response variable (Y) is known as simple regression. The extension to multiple valued predictor variables (denoted with a capital X) is known as multiple regressions. Nearly all real-world regression models involve multiple predictors, and basic descriptions of linear regression are often phrased in terms of the multiple regression model.

6.1.1 Single regression analysis

Firstly, simple regression analyses are carried out to find relations between instantaneous breaking rate (IBR) and physical and mechanical properties of rocks individually. The coefficient of determination (R^2) is used in trend analysis. It is computed as a value between 0 (0 percent) and 1 (100 percent). It is an important tool in determining the degree of correlation of variables in regression analysis. It is square of the coefficient of correlation (r). The higher correlation value gives better fitting.

The relationship between rock quality designation (RQD) and instantaneous breaking rate (IBR) is presented in Figure 6.1. A moderate relationship ($R^2=0.67$) between RQD and IBR is determined in a power function. However, this relation is limited to RQD values less than 60 %. The results indicate that, while RQD increases, IBR

decreases. The importance of *RQD* on impact hammer performance was previously mentioned by Bilgin et al. (1996); Bilgin et al. (1997).

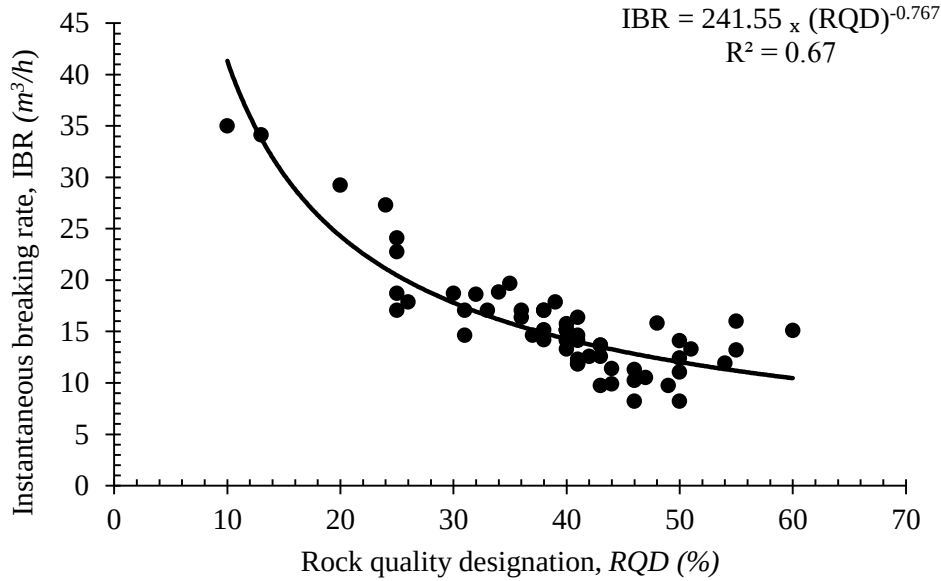


Figure 6.1: Relationship between rock quality designation and instantaneous breaking rate.

Uniaxial compressive strength (*UCS*) has been extensively used by researchers in order to determine its relation with the performance of mechanical excavators and the other mechanical properties of rocks (Copur et al., 2001; Copur, 2010; Copur et al., 2011; Balci and Tumac, 2012; Copur et al., 2014). The relationship between *IBR* and *UCS* is presented in Figure 6.2. A moderate relationship ($R^2=0.68$) between *IBR* and *UCS* is determined in a power function. However, the model is limited to *UCS* values of up to 195.6 MPa and *IBR* values of up to 35 m³/h. The results indicate that, while *UCS* increases, *IBR* decreases.

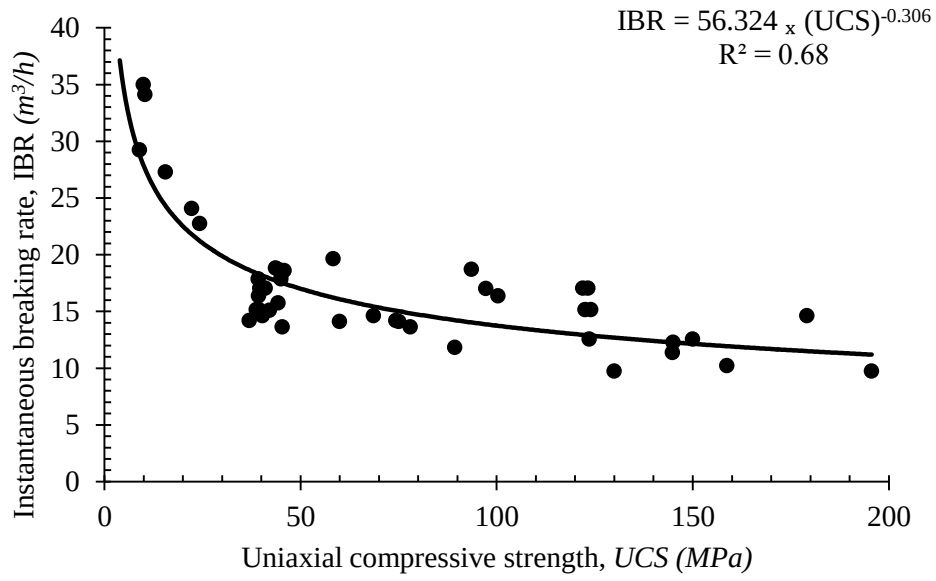


Figure 6.2: Relationship between uniaxial compressive strength and instantaneous breaking rate.

The importance of Brazilian tensile strength (*BTS*) on the estimation of the performance of mechanical excavators and prediction of other physical and mechanical properties of rocks/stones has been previously mentioned by many researchers (Chen et al., 1998; Kahraman et al., 2003; Yagiz, 2009; R. Altindag, 2010). Evans (1974) stated that the susceptibility of the rock to impact breakage was a function of not only the compressive strength, but of tensile strength also. However, there is a weak correlation ($R^2=0.45$) between *BTS* and *IBR* in this study. The relationship between *IBR* and *BTS* is presented in Figure 6.3.

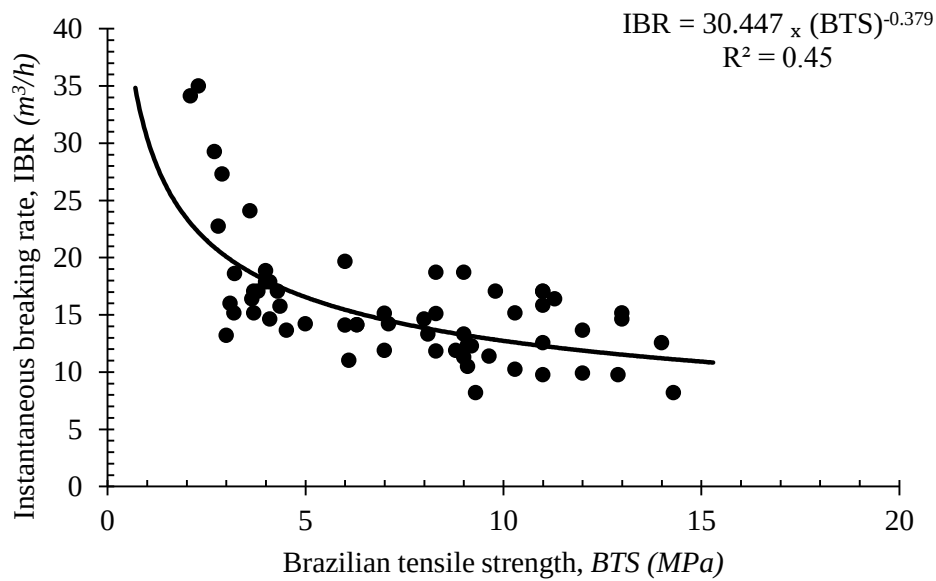


Figure 6.3: Relationship between Brazilian tensile strength and instantaneous breaking rate.

The density of a rock is a function of the rock's properties, such as porosity, mineral composition, etc. Thus, the mechanical properties of rock are highly influenced by density. Moderately good relations are determined between density and mechanical properties, such as, *UCS* and *BTS*. On the other hand, there is a weak correlation ($R^2=0.38$) between density and *IBR* in this study (Figure 6.4).

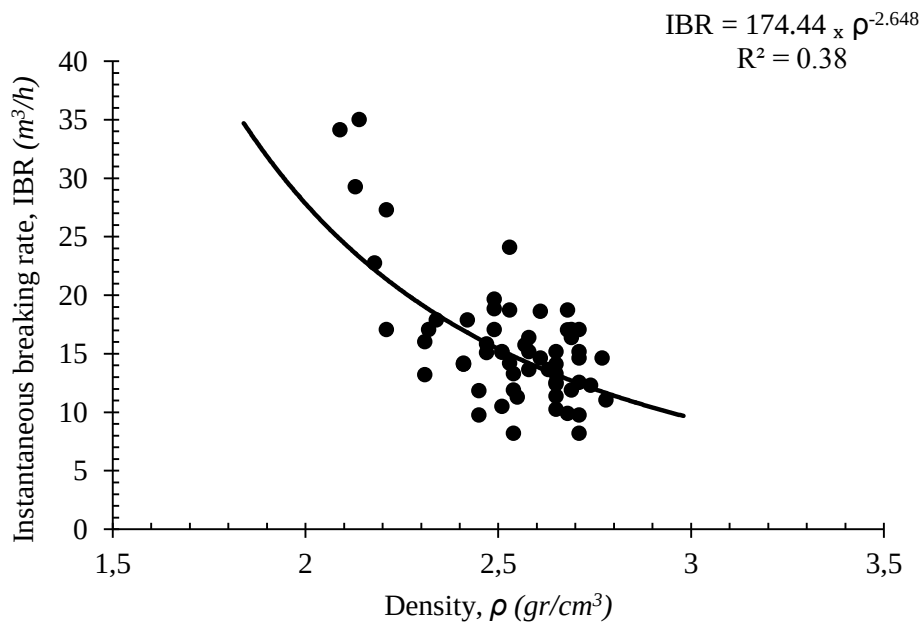


Figure 6.4: Relationship between density and instantaneous breaking rate.

A portable and cost effective instrument, Schmidt hammer (*SH*), has been previously used by researchers for predicting the performance of mechanical excavators and estimating the other physical and mechanical properties of rocks (Hucka, 1965; Deere, 1966; Fowell and McFeat-Smith, 1976). The relationship between *IBR* and *SH* hardness is presented in Figure 6.5. A moderate relationship ($R^2=0.51$) is determined between *IBR* and *SH* hardness when the *RQD* is less than 60%. On the other hand, Bilgin et al. (2002) pointed out that *SH* rebound values were a good indicator of rock characteristics and they stated that these values had a significant correlation with *IBR* of impact hammers when the rock formation is grouped based on *RQD* values. They also found a correlation with R^2 of 0.42 between *IBR* of impact hammer and all values of *RQD* ranging from 2% to 90%. Goktan and Gunes (2005) also stated that *SH* rebound values had a better representation of overall rock hardness and hence a better performance prediction.

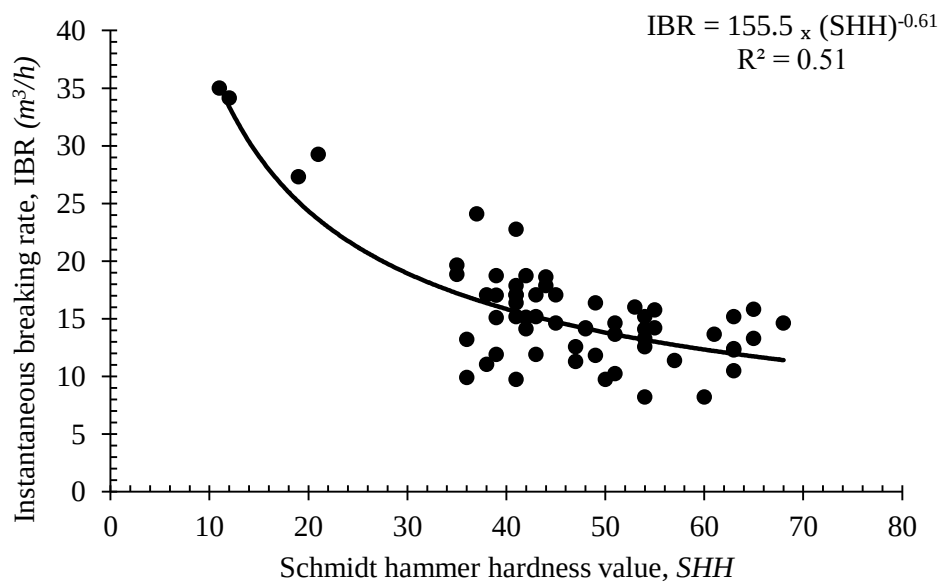


Figure 6.5: Relationship between Schmidt hammer harness value and instantaneous breaking rate.

Shore scleroscope (*SS*) has also been previously used by researchers for predicting the performance of mechanical excavators and estimating the other physical and mechanical properties of rocks (McFeat-Smith, 1977; Tiriyaki, 2006). Tumac et al. (2007) determined significant relations between *SS* hardness and roadheader performance. Tumac (2014) developed chain saw performance prediction models

based on SS hardness. However in this study, poor relationship ($R^2=0.06$) between *IBR* and SS hardness is determined (Figure 6.6).

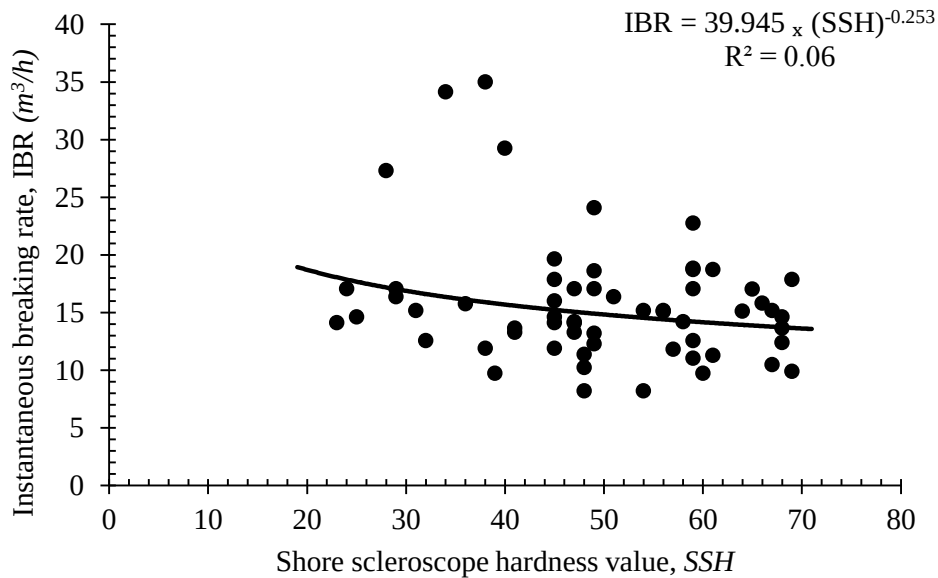


Figure 6.6: Relationship between Shore scleroscope hardness value and instantaneous breaking rate.

Aleman (1983), Howarth (1987), and West (1989) pointed out the importance of Cerchar abrasivity (*CAI*) in excavation engineering. This study indicates that there is no significant relationship between *CAI* and *IBR* (Figure 6.7).

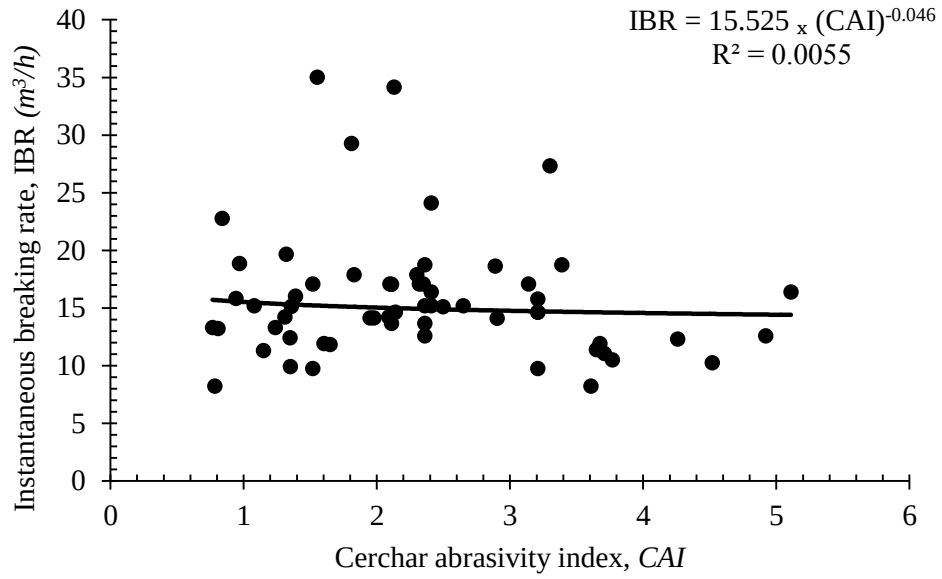


Figure 6.7: Relationship between Cerchar abrasivity index and instantaneous breaking rate.

6.1.1.1 Collinear and non-collinear rock properties

When there exist many potential predictors, identifying the important ones is a very critical task. Collinearity is a concept that is used to identify the unnecessary variables. Based on this concept, one of every linearly dependent pair of predictors can be omitted from the prediction model. In other words, between two predictors (X_1 and X_2), one should be excluded from the model if the Equation (6.1) holds true:

$$X_2 = c_0 + c_1 X_1 \quad (6.1)$$

Where c_0 and c_1 are constants.

Equation (6.1) shows the exact collinearity between X_1 and X_2 . However, exact collinearity is very rare when it comes to statistics. As a result, another concept called “approximate collinearity” is usually used as an alternative. Approximate collinearity is shown in Equation (6.2):

$$X_2 \approx c_0 + c_1 X_1 \quad (6.2)$$

Approximate collinearity is measured by correlation coefficient (r). The higher values of r represent stronger approximate collinearity (Weisberg, 2005). Approximately collinear predictors are explained by each other. Therefore, only one of a pair of collinear predictors is enough for a prediction model.

Knowing the non-collinear properties of rock can benefit the future researches by narrowing down the number of tests required for prediction of a specific parameter. For instance, if X_1 and X_2 are two approximately collinear predictors, the analyst will measure either X_1 or X_2 , not both of them. In the current research, an effort was made to spot non-collinear and collinear properties of rocks by finding the correlation coefficient between each possible pair of the available rock properties. (SPSS®v.21) was hired as a means of calculation. Table 6.1 shows the results of correlation between pairs of rock properties. The obtained results were statistically tested for significance by 0.01 and 0.05 levels.

Table 6.1: Results of correlation between rock properties.

		UCS (MPa)	RQD (%)	BTS (MPa)	ρ (gr/cm3)	SHH	SSH	CAI
UCS (MPa)	<i>r</i>	1	0.214	0.730**	0.636**	0.335**	0.064	0.408**
	P value (2-tailed)		0.100	0.000	0.000	0.009	0.629	0.001
	N	60	60	60	60	60	60	60
RQD (%)	<i>r</i>	0.214	1	0.330**	0.433**	0.581**	0.167	0.077
	P value (2-tailed)	0.100		0.010	0.001	0.000	0.203	0.557
	N	60	60	60	60	60	60	60
BTS (MPa)	<i>r</i>	0.730**	0.330**	1	0.626**	0.502**	0.279*	0.188
	P value (2-tailed)	0.000	0.010		0.000	0.000	0.031	0.151
	N	60	60	60	60	60	60	60
ρ (gr/cm3)	Pearson's Correlation	0.636**	0.433**	0.626**	1	0.555**	0.195	0.424**
	P value (2-tailed)	0.000	0.001	0.000		0.000	0.136	0.001
	N	60	60	60	60	60	60	60
SHH	Pearson's Correlation	0.335**	0.581**	0.502**	0.555**	1	0.283*	0.106
	P value (2-tailed)	0.009	0.000	0.000	0.000		0.028	0.420
	N	60	60	60	60	60	60	60
SSH	Pearson's Correlation	0.064	0.167	0.279*	0.195	0.283*	1	-0.219
	P value (2-tailed)	0.629	0.203	0.031	0.136	0.028		0.093
	N	60	60	60	60	60	60	60

Table 6.1(continued): Results of correlation between rock properties.

CAI	Pearson's Correlation	0.408**	0.077	0.188	0.424**	0.106	-0.219	1
	P value (2-tailed)	0.001	0.557	0.151	0.001	0.420	0.093	
	N	60	60	60	60	60	60	60

** Correlation is significant at the 0.01 level (2-tailed), * Correlation is significant at the 0.05 level (2-tailed).
N: Number of samples, r: Correlation coefficient. UCS: Uniaxial compressive strength, RQD: Rock quality designation, BTS: Brazilian tensile strength, ρ : Density, SHH: Schmidt hammer hardness, SSH: Shore scleroscope hardness, CAI: Cerchar abrasivity index.

In Pearson's correlation method, which was the correlation method used in this study, the null and alternative hypotheses are defined as in Eq.(6.3) and Eq. (6.4)(O'Rourke et al., 2005):

$$H_0 : r = 0 \quad (6.3)$$

$$H_A : r \neq 0 \quad (6.4)$$

where H_0 represents null hypothesis, H_A represents the alternative hypothesis and r is Pearson's correlation coefficient (Usually, Pearson's correlation coefficient is simply referred to as correlation coefficient).

In Table 6.1, the correlations with p-value lower than 0.05 are statistically significant with 0.01 or 0.05 confidence intervals. That is, there is strong evidence against null hypothesis. On the other hand, the correlations with p-values higher than 0.05 represent weak or no evidence against null hypothesis.

In other words, the pairs with low correlation coefficient and p-value higher than 0.05 can be assumed as either statistically unrelated ($r=0$) or weakly related. Higher p-values correspond to stronger assumptions.

Determining the limits of r for diagnosing collinearity depends on the researcher. In this research, the pairs with correlation coefficient of higher than 0.50 and p-values lower than 0.05 are considered as collinear, and the pairs with correlation coefficient of lower than 0.20 and p-values greater than 0.05 are considered as non-collinear.

Table 6.2 shows the collinearity between rock properties.

Table 6.2: Collinear and non-collinear pairs of rock properties.

Collinear	Non-collinear
(UCS, BTS)	(UCS, SSH)
(UCS, Density)	(RQD, CAI)
(RQD, SHH)	(RQD, SSH)
(BTS, Density)	(BTS, CAI)
(BTS, SHH)	(SHH, CAI)
(Density, SHH)	

6.1.1.2 Data transformation

Simple regression analyses were carried out to find relations between instantaneous breaking rate (*IBR*) and physical and mechanical properties of rocks in this study. The coefficient of determination (R^2) was used in trend analysis which is computed as a value between 0 (0 percent) and 1 (100 percent). Coefficient of determination is an important tool in determining the degree of correlation of variables in regression analysis. R^2 is square of the coefficient of correlation (r). The higher value of correlation between response and predictor gives better fitting. In case the correlation between response and predictor is not satisfying, one may consider transformation of the predictor(s) in order to achieve better fitting. The objective of data transformation is to establish a linear relationship between the response and the *transformed* predictor that has a higher coefficient of determination compared to the relationship between the response and *non-transformed* predictor. In other words, R_T^2 should be greater than R^2 in the following equations (Weisberg, 2005):

$$Y = \beta_0 + \beta_1 X, \quad R^2 \quad (6.5)$$

$$Y = \beta'_0 + \beta'_1 X_T, \quad R_T^2 \quad (6.6)$$

Where β_0 and β'_0 are intercepts, β_1 and β'_1 are constant coefficients, Y is the response value, X_T is the *transformed* predictor, and X is the *non-transformed* predictor.

Table 6.3 shows the coefficient of determination for linear relationships between the response and each predictor.

Table 6.3: Coefficient of determination between response and non-transformed predictors.

	Non-transformed UCS (MPa)	Non-transformed RQD (%)	Non-transformed BTS (mpa)	Non-transformed Density (ρ) (gr/cm ³)	Non-Transformed SH hardness (SHH)	Non-transformed SS hardness (SSH)	Non-transformed CAI
<i>IBR</i> (m ³ /h)	$R^2 = 0.2472$	$R^2 = 0.6729$	$R^2 = 0.3431$	$R^2 = 0.4323$	$R^2 = 0.5213$	$R^2 = 0.0666$	$R^2 = 0.0194$

Any combination of mathematical operations can be used as a transformation function. Since it is not feasible to check every possible transformation function, using the trend line options offered by Microsoft Excel was chosen as an alternative approach. “Exponential, linear, logarithmic, polynomial (up to 6th order), and power” are the available trend line options in Microsoft Excel. In order to find the appropriate transformation for each predictor, the predictor was plotted against the response (measure *IBR*) in Microsoft Excel. All the available options for trend line were tested to find the best fitting line. Table 6.4 shows the transformations chosen for each predictor.

Table 6.4: Transformation functions chosen for each predictor.

Non-transformed Predictor	Transformed Predictor*
<i>UCS</i>	$UCS_T = 45.944 \times UCS^{-0.279}$
<i>RQD</i>	$RQD_T = 69.322 - 14.49 \times \ln(RQD)$
<i>BTS</i>	$BTS_T = (-0.0625 \times (BTS^3)) + (1.6991 \times (BTS^2)) - (14.602 \times BTS) + 52.774$
Density (ρ)	$\rho_T = (-249.89 \times (\rho^3)) + (1898.5 \times (\rho^2)) - (4806.3 \times \rho) + 4069$
<i>SHH</i>	$SHH_T = (0.0102 \times (SHH^2)) - (1.1785 \times SHH) + 46.896$
<i>SSH</i>	Transformation yielded no significant improvement in R^2 .
<i>CAI</i>	Transformation yielded no significant improvement in R^2 .

*for all polynomial transformations, all the possible orders (from 2nd to 6th) were checked. In case an increase in order did not make a difference more than 5% in R^2 , the higher orders were rejected in favor of simplicity in calculations.

Table 6.5 shows the coefficient of determination for relationships between the response and each transformed predictor.

Table 6.5: Coefficient of determination between response and transformed predictors

	UCS_T MPa	RQD_T %	BTS_T MPa	ρ_T gr / cm ³	SHH_T
IBR (m ³ /h)	$R^2 = 0.4364$	$R^2 = 0.7832$	$R^2 = 0.605$	$R^2 = 0.6503$	$R^2 = 0.7109$

6.1.2. Multiple regression analysis

Multiple linear regression (*MLR*) analyses were carried out to find relations between instantaneous breaking rate (*IBR*) and physical and mechanical properties of rocks. *MLR* is the most widely used of all statistical techniques. It is the study of linear, additive relationships between variables, usually under the assumption of independently and identically normally distributed errors. The model for *MLR*, given n observations, is Eq.(6.7). This formula has the property that the prediction for response (Y) is a straight-line function of each of the predictors (X_i), holding the others fixed, and the contributions of different X variables to the predictions are additive. The slopes of their individual straight-line relationships with Y are the constants $b_1, b_2, \dots, b_i$, the coefficients of the variables. b_i is the change in the predicted value of Y per unit of change in X_i , other things being equal. The additional constant b_0 , the “intercept”, is the prediction that the model would make if all the X ’s were zero (if that is possible). The coefficients and intercept are estimated by least squares, i.e., setting them equal to the unique values that minimize the sum of squared errors within the sample of data to which the model is fitted.

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_iX_i \quad (6.7)$$

The regression analysis is performed using SPSS®.v.21 statistical software, where the stepwise regression selection procedure is used to determine the best fitting regression model. Stepwise regression can be achieved either by adding one independent variable at a time and including it in the regression model if it is statistically significant, or by including all potential independent variables in the model and eliminating those that are not statistically significant, or by a combination of both methods.

Regression models can only generalize well within the range of inputs (interpolation). Hence, it is immensely significant to cover the whole range of inputs

for developing the model (Priddy and Keller, 2005; Mark Hudson Beale, 2014). On the other hand, it was decided to preserve 15% of the available data for testing the resulting model. In order to reach the suitable set of test data, the samples associated with the extreme values for each input parameter were excluded from the data base (the whole tunnel was divided into 60 rings and each sample is associated to one individual ring). From the remaining samples, the data associated with sample numbers 6, 12, 18, ..., 54 were selected to be used for testing the model. The reason behind selecting an evenly distributed set of test data over the whole tunnel, was to cover the maximum possible conditions of excavated rock.

In this study, to develop the instantaneous breaking rate ($IBR, m^3/h$) model based on the studied data set, transformed rock quality designation ($RQD_T, \%$), transformed uniaxial compressive strength (UCS_T, MPa), transformed Brazilian tensile strength (BTS_T, MPa), transformed density ($\rho_T, g/cm^3$), transformed Schmidt hammer hardness (SHH_T), Shore scleroscope hardness (SSH), and Cerchar abrasivity index (CAI) were used as independent variables, with IBR as the dependent variable. Empirical prediction models were developed by means of stepwise regression. Among all the produced models by the software, Eq.(6.8) is the one that provided a considerably high accuracy ($r=0.94, R^2=0.89$) while requiring a small number of the most commonly used rock properties as predictors.

$$IBR = 0.774 \times RQD_T + 0.608 \times UCS_T - 5.679 \quad (6.8)$$

The analysis of variance technique, F-test and student's t-test statistics, were implemented to assess the reliability of the suggested model. In the analysis of variance, if the significance of F-value within the 95% confidence interval is lower than 0.05 while the F-ratio is greater than the F-tabulated value obtained from the F distribution table, then it can be said that the regression is statistically significant (Stoodley et al., 1980). The t-test compares a calculated t-ratio with tabulated t-value in order to check the validity of the null hypothesis. If the absolute value of the calculated t-ratio is greater than the tabulated t-value, the null hypothesis can be rejected. The null hypothesis in this test indicates that the investigated predictor does not have any effect on the prediction of the response for the whole population (as opposed to "sample") (Montgomery and Runger, 2010). The results of the analysis of variance for the selected model are summarized in tabular form as shown in Table

6.6. The statistical results of the suggested equation are shown in Table 6.7. Since a 95% confidence level was chosen in the regressions, a corresponding tabulated t-value of 2.01 for Eq. (6.8) was obtained. As it is seen in Table 6.8, the computed t-ratios are greater than the tabulated t-value. Analysis indicates that the Eq. (6.8) is statistically meaningful with high confidence level and considerably low significance value (p-value less than 0.05) in two-tail analysis. As it is seen in Table 6.6, significance of F-value (0.000) within the 95% confidence interval is lower than 0.05 for Eq.(6.8). The F-ratio is 190.657 for Eq.(6.8) while the F-tabulated value is 3.197 within the 95% confidence interval. Since the F-ratio is greater than the F-tabulated value, it could be inferred that the model is statistically meaningful. According to the statistical results, Eq.(6.8) may be suggested in order to reliably and practically predict the instantaneous breaking rate of impact hammers.

Table 6.6: The results of the analysis of variance for the selected multiple regression model.

Model	Anova	Sum of squares	Mean square	F-ratio	F-tabulated	Significance F
	Regression	1290.560	645.280			
Eq.(6.8)	Residual	162.456	3.385	190.657	3.197	0.000
	Total	1453.016				

Table 6.7: Statistical results of the selected multiple regression model.

Model	Eq. (6.8)		
Independent variables	Constant	Transformed <i>RQD</i> (%)	Transformed <i>UCS</i> (MPa)
Coefficient	-5.679	0.774	0.608
Standard error	1.293	0.062	0.095
t-ratio	-4.392	12.486	6.432
p-value<0.05	0	0	0
Tabulated t-value		± 2.01	

Table 6.7 (continued): Statistical results of the selected multiple regression model.

Correlation coefficient (r)	0.942
Determination coefficient (R^2)	0.888
Adjusted correlation coefficient (R^2_{adj})	0.884

Figure 6.8 illustrates the performance of the proposed model. The perfect model would have been fitted exactly on the $y=x$ line (dotted line).

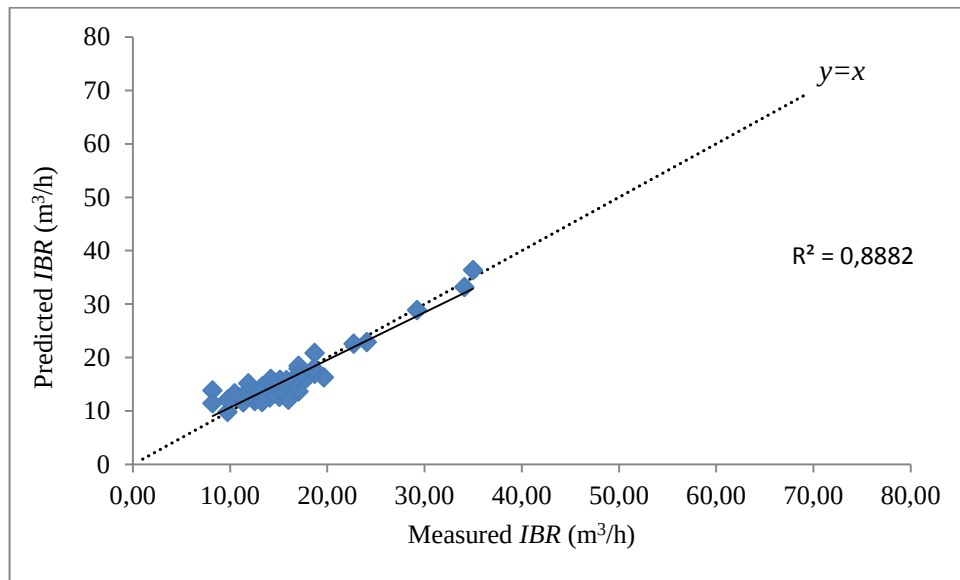


Figure 6.8: Performance illustration for Eq.(6.8).

6.2 Artificial Neural Network Modeling

Terminologically, all the terms “neural network”, “artificial neural network”, and “Parallel Distributed Processing” refer to the same concept and can be used interchangeably (Munakata, 2008). In the current study, “Artificial Neural Network (ANN)” was chosen to be used.

ANN is an abstract computer model of the human brain. The human brain comprises an estimated number of 10^{11} neurons interconnected by nearly 10^{15} links. Currently, neural network is admitted to be the basic functional source of intelligence for all the living creatures including humans (Munakata, 2008). Analogous with the brain,

neural network consists of artificial neurons and interconnections (Munakata, 2008). ANNs are widely used as a means of nonlinear system modeling and identification. An ANN does not have any judgment about physical properties of the exposed data base. It simply implements different learning/training algorithms/methods to find a model by which the behavior of the inserted numbers are best described (Avunduk et al., 2014).

Artificial neural networks are divided into two large groups (Teshnehlab and Kyoko, 2013):

- Recurrent networks: neurons are interconnected in a manner that there are feedback loops of signal flow and the network bears dynamic properties (Figure 6.9). Hopfield and the Bidirectional Associative Memory (BAM) networks are the most popular recurrent neural networks (Priddy and Keller, 2005). Recurrent neural networks are usually used to solve pattern recognition problems. Figure 6.10 shows an example of pattern recognition problem solved by a BAM network (Priddy and Keller, 2005).

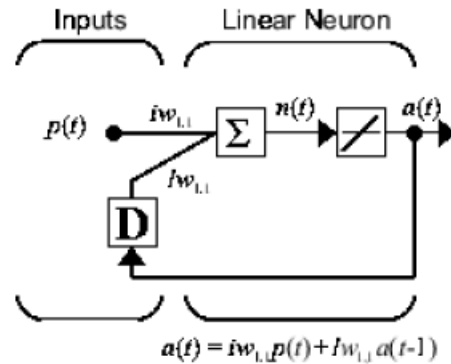


Figure 6.9: Schematic view of a simple recurrent network.

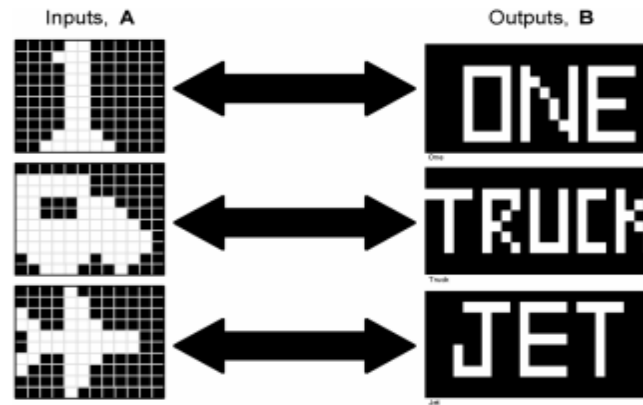


Figure 6.10: Example of the inputs and outputs encoded by a *BAM* network.

- Feedforward networks: comprises three layers with a certain number of neurons in hidden and output layers. In this type, there is no interconnection between neurons of the same layer and the signals flow from the input layer, through the hidden layer(s), to the output layer in solely one direction. Figure 6.11 shows schematic view of a multilayered neural network with two neurons in the hidden layer and one neuron in input and output layers. The feedforward neural network can be trained for either function approximation or pattern recognition. With sufficient number of neurons in the hidden layer, a network like the one shown in Figure 6.11 can approximate any function arbitrarily well (Mark Hudson Beale 2014).

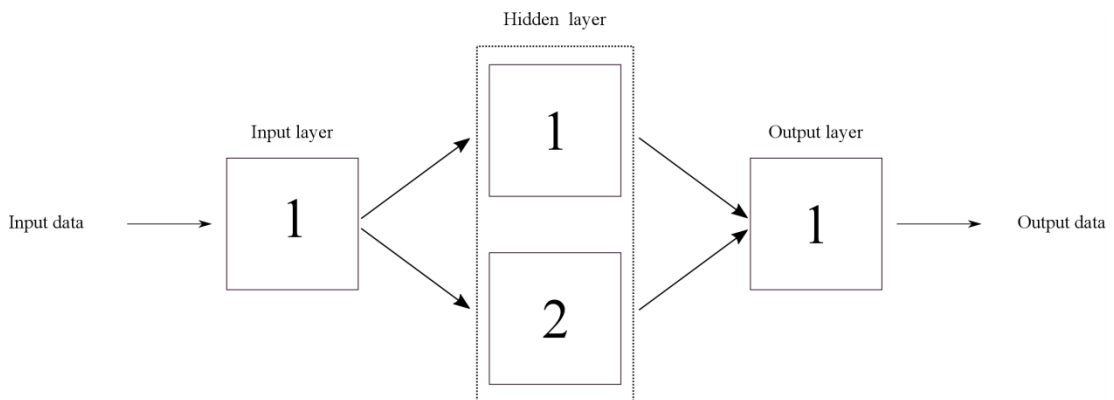


Figure 6.11: Schematic view of a feedforward network.

Since the objective of the current study was to fit a function on the obtained data, feedforward network was selected to form the architecture of the network. Neural network toolbox of the MATLAB R2014b package was used to develop the desired network.

6.2.1 Creating the network

6.2.1.1 Learning architecture

A neural network is formed by taking three main steps including training, validation, and testing. To divide the data into “training data”, “validation data”, and “test data” is the prerequisite for taking those steps. Generally, the portion of the training data is greater than that of validation and test data. While it is constantly checking the validation data to find out when to stop training, the network deploys training data along with a specified learning algorithm to learn how to relate the input parameters to the output. When the training process finishes, test data are used to find out how good the network performs (Mark Hudson Beale, 2014).

The previous paragraph implies that the next step is to choose a proper learning algorithm for the network. Among all the formerly proposed neural network learning algorithms, backpropagation is the most dominant in terms of practical applications (Neaupane and Achet, 2004; Teshnehlal and Kyoko, 2013). Moreover, backpropagated neural networks have demonstrated a creditable performance in prediction problems of geotechnical engineering (Neaupane and Achet, 2004). A network which uses backpropagation algorithm, is called a backpropagation model (Munakata, 2008). The backpropagation algorithm is designed to minimize the performance (or cost) function (Eq. (6.9)) ,the inputs of which are the network outputs (a) and the target outputs (t) (measured values), using the gradient descent method (Teshnehlal and Kyoko, 2013).

$$F = mse = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2 \quad (6.9)$$

For the current study, based on the mentioned grounds, backpropagation was the selected learning algorithm.

Batch mode and incremental mode are the two modes under which the learning process can occur. In batch mode, all the inputs in the training set are applied to the network before weights are updated. In incremental mode, the gradient is computed and the weights are updated after each input is applied (Mark Hudson Beale, 2014). With static/feedforward networks, both batch and incremental modes can be used. Making a decision on which mode to use depends on the format of the input data. If the data is a matrix of concurrent vectors, batch training is the choice. If the

data is a sequence, incremental training will be selected. However, the train function, which was used to train the selected network, always uses batch training regardless of the format of the input data.

6.2.1.2 Neuron model

Figure 6.12 shows simple view of a single neuron with R inputs. The transfer function (f) is a function fed by sum of weighted inputs ($\sum_{i=1}^R p_i \times w_i$) and bias (b) and returns the neuron's output (a). Any differentiable function can be used as transfer function in neurons (Mark Hudson Beale, 2014).

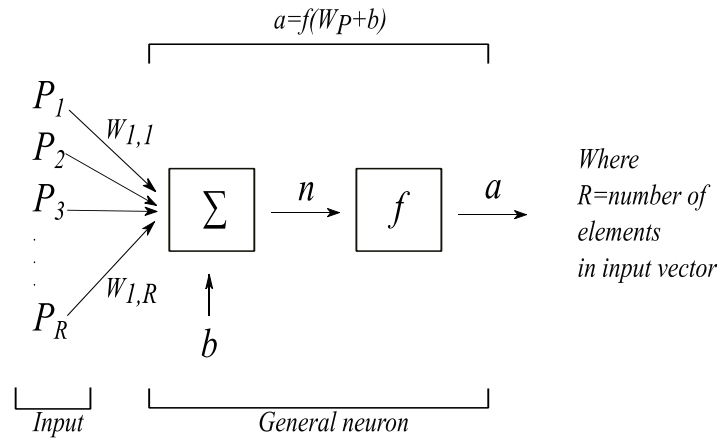


Figure 6.12: Simple view of a single neuron.

Multilayer networks generally implement three types of transfer functions:

- log-sigmoid transfer function:

$$f(x) = \frac{e^x}{e^x + 1} = \frac{1}{1 + e^{-x}} \quad (6.10)$$

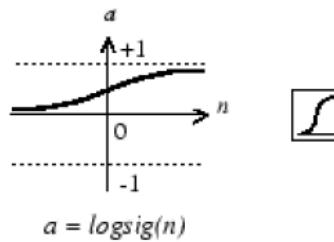


Figure 6.13: Log-Sigmoid transfer function.

As it is illustrated in Figure 6.13, *logsig* transfer function returns the outputs ranging from 0 to 1 while the inputs can vary between plus and minus infinity.

- tan-sigmoid transfer function (Figure 6.14):

$$\sigma(t) = \tanh(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}} \quad (6.11)$$

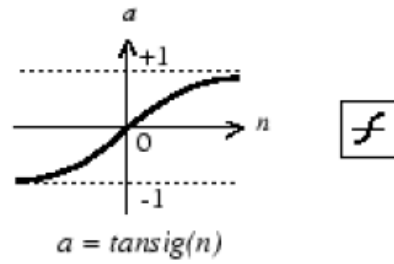


Figure 6.14: Tan-Sigmoid transfer function.

- linear transfer function (Figure 6.15):

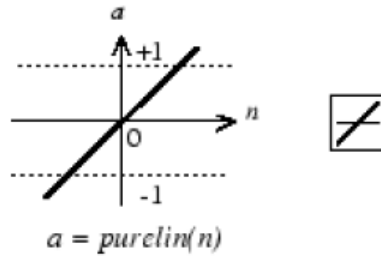


Figure 6.15: Linear transfer function.

Multilayer networks with nonlinear transfer functions are designed to model nonlinear relationships between input and output. Linear output transfer functions are more handy for function fitting problems (nonlinear regression) (Mark Hudson Beale, 2014).

In the current study, based on the above explanations, “tan-sigmoid” and “linear” functions were respectively assigned for the “hidden layer” and “output layer”.

6.2.1.3 Choosing neural network input-output processing functions

Before training the network, the data set (input and target data) should be processed and divided into training, validation, and test subsets. Processing can provide the network with a more efficient training process. For instance, sigmoid transfer

functions, which are usually used in the hidden layer, become saturated for input values greater than 3. In such cases, the gradient of the performance function will be very small. As a result, since the training function uses performance gradient to modify the weights, the training process will be remarkably slow. It may not always be the case, but if the randomly selected initial weights are not small enough, it is extremely likely. Normalizing the input data is the standard practice to avoid such problems (Mark Hudson Beale, 2014).

Processing the output data is also very common. The output values are usually normalized too. In this fashion, the network output will fall into a normalized range. This helps decreasing computational burden off the *CPU*. The normalized output data will be transformed back before being compared to target values (Mark Hudson Beale, 2014). To summarize, the data are processed before entering the input layer and after leaving the output layer (Figure 6.16).

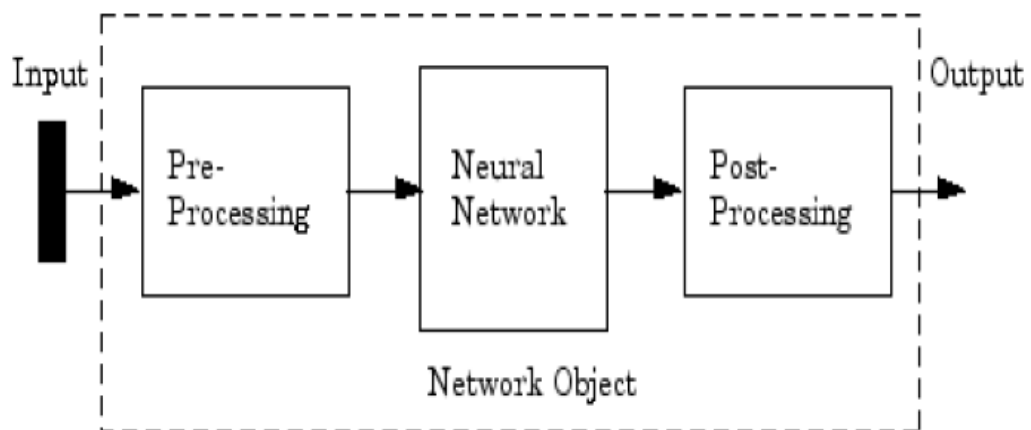


Figure 6.16: Stages of input and output data processing in neural networks.

Multilayer network creation functions such as `feedforwardnet` in MATLAB, assign processing functions to both input and output layers by default. Although the user can change the pre-assigned processing functions through adjusting network properties, the defaults have the best performance in most cases. For multilayer network creation functions such as `feedforwardnet`, the default input processing functions are “`mapminmax`” and `removeconstantrows`. “`removeconstantrows`” spots and removes the constant rows in input matrices. “`mapminmax`” processes input data by finding minimum and maximum values in each row of the input matrix. First, the function assigns -1 and +1 to minimum and maximum values of each row

respectively. Then, the it updates the remaining values accordingly. For example, in a row of the input data (Table 6.8), the “mapminmax “ function changes 150 to 1 and 2.65 to -1 and converts the rest correspondingly (Table 6.8).

Table 6.8: An instance for the effect of "mapminmax" function.

	<i>UCS</i> (MPa)	<i>RQD</i> %	<i>BTS</i> (MPa)	<i>Density</i> (gr/cm ³)	<i>SH</i> hardness	<i>SS</i> hardness	<i>CAI</i>
Original Data	150.0	43	14.0	2.65	54	59	4.92
Processed by “mapminmax”	1.0000	-0.4523	-0.8459	-1.0000	-0.3030	-0.2352	-0.9692

In the current research, “mapminmax” and “removeconstantrows” functions were used for both pre- and post- data processing.

6.2.1.4 Dividing data for optimal neural network training

Multiple regression analysis showed that transformed *RQD* and *UCS* can linearly predict *IBR* to a high degree of correlation. They are also such commonly used rock properties that in most cases they are already determined before the design process of the projects. As a result, they do not require performing individual laboratory tests. On the other hand, as explained under the title “neuron model”, the mathematical operations in and between neurons are the same as in multiple linear regression analysis. Hence, *RQD* and *UCS* were selected as input parameters for the neural network. Since very good results were achieved using non-transformed *RQD* and *UCS*, there was not any need to elevate the level of sophistication by applying data transformation process.

Before training the multilayer networks, the data set should be divided to three subsets. The first subset, training set, is used for gradient computing through which the network updates the randomly selected initial weights and biases. The second subset, validation set, is used in order to avoid “overfitting”. “Overfitting” is a term referring to a state in which the network memorizes the training examples instead of learning to generalize to new situations. During the training process, the error on validation set is monitored constantly. At the beginning phase of training, validation error normally decreases along the side of training error. Nonetheless, when the

network starts memorizing, the validation error ascends while training error is still decreasing. The final weights and biases are corresponding to the least validation error. The third subset, test data, is not used during training. It is a means of comparing different models with each other. It can also be used as an indicator of poor data division. If the test error reaches its minimum long before validation error, revision on the data division should be considered (Mark Hudson Beale, 2014). Four functions are available for performing data division in multilayer networks (Table 6.9). They are dividerand (the default), divideblock, divideint, and divideind. The data division is normally performed automatically when you train the network.

Table 6.9: Data dividing functions and their algorithms.

Function	Algorithm
Dividerand	Divides the data randomly
Divideblock	Divides the data into contiguous blocks
Divideint	Divides the data using an interleaved selection
Divideind	Divides the data by index

Multilayer feedforward neural networks can only generalize well within the range of inputs (interpolation) they have been trained with. Hence, it is immensely significant to cover the whole range of inputs in the training data (Priddy and Keller, 2005; Mark Hudson Beale, 2014). In order to reach to the suitable set of training data, a combination of Microsoft Excel (2010) functions and “divideind” function were used. First, the extreme values for each input parameter were found. Then, the data were reorganized in a way that maintained the paste of the record while putting the extreme values on specific rows (rows 1, 4, 7, ...) in .xls file. Finally, the “divideind” function was used to divide the input data into training, validation, and test datasets with standard ratio of %70, %15, and %15 for each set respectively.

6.2.1.5 Training algorithms

Although any standard numerical optimization algorithm can be used to optimize the performance function, there are some certain algorithms that proved to be

exceptionally suitable for neural network training. Those algorithms implement either gradient or Jacobian of the network errors with respect to the weights.

As an instance on how the training process works, the simplest optimization algorithm, gradient descent, is considered. It adjusts the weights and biases towards the direction that provides the most decrease in the performance function (negative gradient). Eq. (6.12) shows one iteration of this algorithm.

$$x_{k+1} = x_k - \alpha_k g_k \quad (6.12)$$

where x_{k+1} is a vector of current weights and biases, g_k is the current gradient, and α_k is the learning rate. This equation is iterated until the network converges.

A list of the training algorithms that are available in the Neural Network Toolbox and use gradient- or Jacobian-based methods, is shown in the following table (Table 6.10).

Table 6.10: Training algorithms that are available in the neural network toolbox software.

Function	Algorithm
trainlm	Levenberg-Marquardt
Trainbr	Bayesian Regularization
Trainbfg	BFGS Quasi-Newton
Trainrp	Resilient Backpropagation
Trainscg	Scaled Conjugate Gradient
Traincgb	Conjugate Gradient with Powell/Beale Restarts
Traincgf	Fletcher-Powell Conjugate Gradient
traincgp	Polak-Ribière Conjugate Gradient
Trainoss	One Step Secant
Traingdx	Variable Learning Rate Gradient Descent
Traingdm	Gradient Descent with Momentum
Traingd	Gradient Descent

“Levenberg-Marquardt”, which is the default optimization algorithm in Neural Network Toolbox, is generally considered to be the fastest training function. In general, on function approximation problems, for networks that contain up to a few

hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. This advantage is especially noticeable if a very accurate training is required. It is also the fastest method of function approximation when the number of weights and biases does not exceed a few hundreds (Mark Hudson Beale, 2014). Thus, Levenberg-Marquardt was selected as training algorithm for the current study. Meanwhile, other algorithm were kept in mind as alternative in case Levenberg-Marquardt does not satisfy the expectations.

There are many criteria that can be used to stop network training (Table 6.11). Each of them can be a measure of how good the network has converged. Although their values are assigned by default, they can also be manually set.

Table 6.11: List of criteria that can be used to stop Levenberg-Marquardt training.

Parameter	Stopping Criteria
Gradient	minimum gradient magnitude
Time	maximum training time
Performance	minimum performance value
Epochs	maximum number of training epochs (iterations)
Validation checks	Maximum number of validation increases

For the current study, all the default values for stopping criteria were accepted at first. When the network failed to achieve the desired correlation factor (R greater than 0.98 for training and test) in a reasonable time, “Validation checks” was increased from six to 10.

When the training process stops, a training window will pop up. In that window, the user can have access to four plots including “performance”, “training state”, “error histogram”, and “regression”. The performance plot shows the value of performance versus iteration number for each data subset (training, validation, and test). The training state plot shows the state of other training variables, such as validation check fails and gradient magnitude. The error histogram plot shows the distribution of the network errors. Finally, the regression plot shows the linear relation between network outputs and network targets (Mark Hudson Beale, 2014).

6.2.1.6 Number of neurons

At this stage, all the required parameters for creating a network were decided, except the “number of the neurons” in the hidden layer. Try and error is the only available method of determining the appropriate number of the neurons (Mark Hudson Beale, 2014). Hence, a “for loop” was used to determine different number of neurons that have the potential of providing the desired prediction accuracy. In other words, it finds the neuron numbers between one and 100 (upper limit can be changed if necessary) that produced correlated output and target data with accuracy of higher than 0.98 for test and training data sets. Table 6.12 shows the potential neuron numbers.

Table 6.12: Potential number of neurons in the hidden layer.

5	11	12	16	29
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Number of potential neuron numbers can be narrowed down by setting the accuracy on higher values (greater than 0.95). Since “Levenberg-Marquardt” algorithm uses randomly selected initial weights and biases, the presented numbers of neurons in Table 6.12 were not the only options. However, since they had shown good results once, it was certain that they could regenerate the same or better results with enough retraining. Thus, two “while loops” were used to find the appropriate neuron number among them. The appropriate neuron number is the one that provides the high regression between output and target for train, validation, test, and all data. Finally, a network with eleven neurons in the hidden layer provided highly satisfying results ($R=0.98$ for training data set, $R=0.99$ for test data set).

```

i=1;j=1;
upperlimit=size (NumberOfNeurons);
while j<=upperlimit(1,2)
    regressionTrain=0;
    regressionTest=0;
    regressionVal=0;
    regressionAll=0;
    NumberOfRetrain=0;
    while (regressionTrain<0.98 || (regressionTest<0.98)) ||
        regressionVal<0.90)
        % Train the network with the following number of neurons in the hidden
        % layer:
        NumberOfRetrain=NumberOfRetrain+1;
        hiddenLayerSize = NumberOfNeurons(1,j);
    end;
    j=j+1;
end

```

Figure 6.17: "While loop" used to determine the number of the neurons.

“upperlimit” is a 1*2 matrix as (1, “number of potential neuron numbers” or “number of cells in Table 6.12”), “NumberOfNeurons” is a matrix filled by the same numbers as in Table 6.12, “regressionTrain” is the correlation factor between predicted and target (measured) *IBR* for training data set, and “regressionTest” is the correlation factor between predicted and target (measured) *IBR* for test data set.

6.2.1.7 Final network

Finally, a network with the properties shown in Table 6.13 was created. Figure 6.18 shows a schematic view of the final network. Figure 6.19, Figure 6.20, Figure 6.21 and Figure 6.22 show the “Target-Output” regression for training, test, validation, and all data respectively. The network is saved in a .mat file and can be accessed using a MATLAB compiler. Moreover, in case MATLAB compiler is not available, the final weights and biases can be used for prediction in any software or calculator that can handle matrices. In such a case, it should be kept in mind that the data should pass through a process analogous to *mapminmax* function before entering the network and a reversed process after leaving the output layer (Table 6.8). Table 6.14, Table 6.15, and Table 6.16 show the input layer final weights, final biases, and hidden layer final weights respectively.

Table 6.13: Final network properties.

Network property	Assigned function, algorithm, or value
Learning architecture	Feedforward
Transfer function in input layer	Tan-sigmoid

Table 6.13 (continued): Final network properties.	
Transfer function in hidden layer	Linear
Input and output processing functions	“Mapminmax” and “removeconstantrows”
Data division function	Divideind
Training algorithm	Levenberg-Marquardt
Number of neurons	11

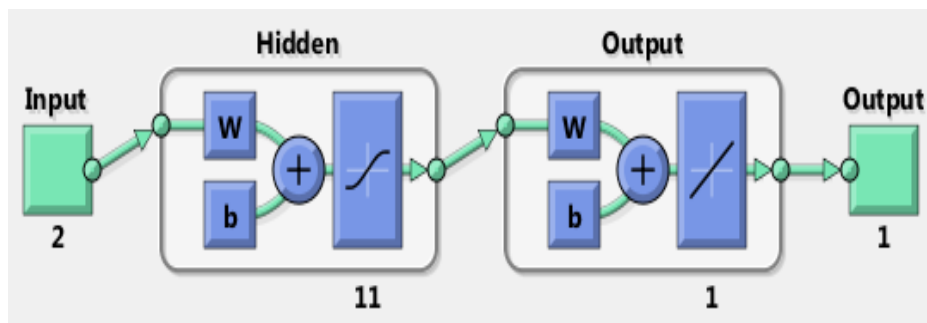


Figure 6.18: A schematic view of the final network (generated by MATLAB R2014b).

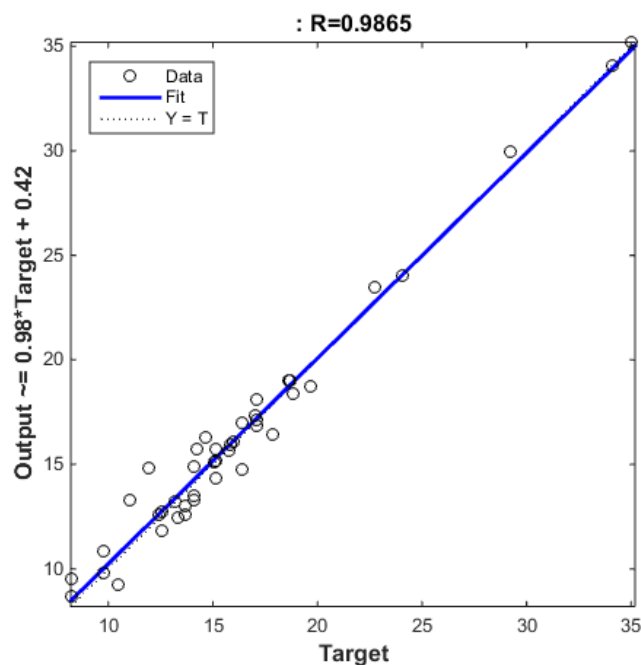


Figure 6.19: Regression plot for training data (generated by MATLAB R2014b).

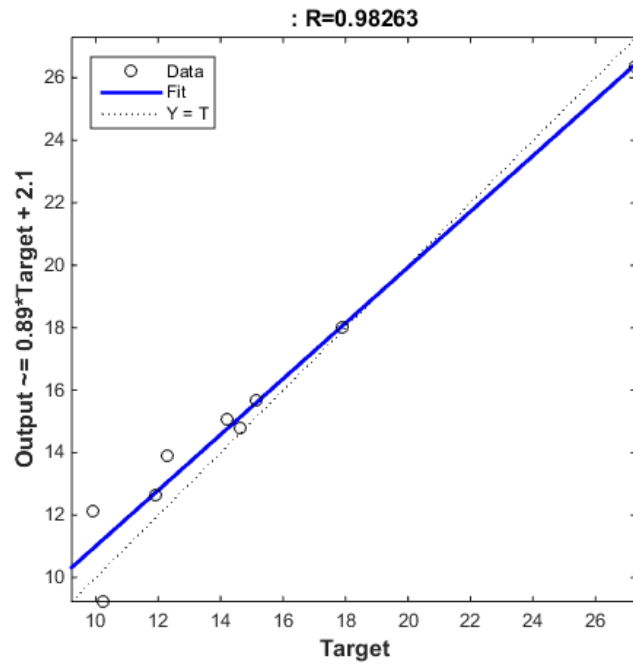


Figure 6.20: Regression plot for test data (generated by MATLAB R2014b).

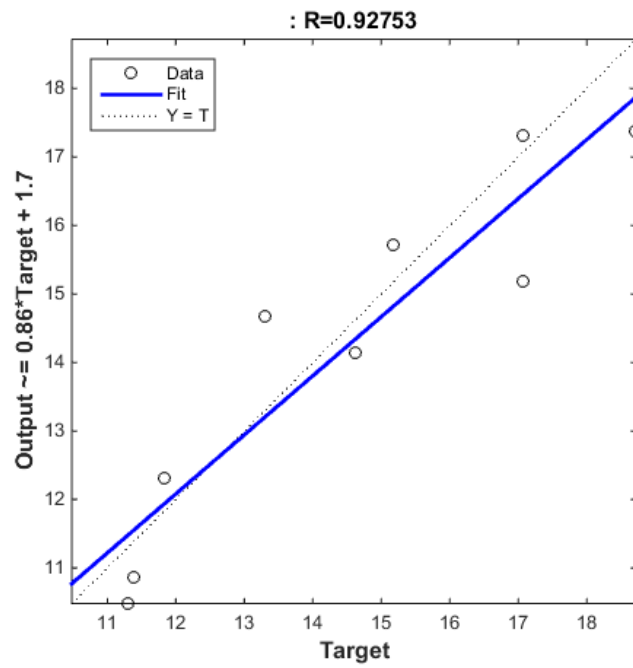


Figure 6.21: Regression plot for validation data (generated by MATLAB R2014b).

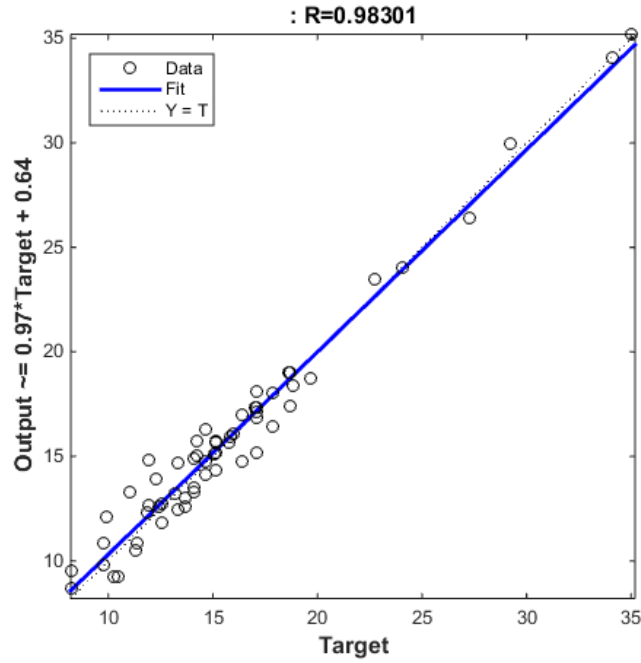


Figure 6.22: Regression plot for all data (generated by MATLAB R2014b).

Table 6.14: Final weights for hidden layer.

	Weights	
	UCS	RQD
Neuron No. 1	0.2214	3.576685
Neuron No. 2	-1.66754	6.038528
Neuron No. 3	-2.33709	4.602427
Neuron No. 4	-0.55765	3.274783
Neuron No. 5	-2.95471	6.789109
Neuron No. 6	3.222422	8.403589
Neuron No. 7	0.52823	2.291988
Neuron No. 8	-1.25429	4.332985
Neuron No. 9	-0.11867	-1.39641

Table 6.14 (continued): Final weights for hidden layer.

Neuron No. 10	1.933153	-4.84729
Neuron No. 11	-1.29976	2.934281

Table 6.15: Final biases for hidden layer.

	Biases
Neuron No. 1	-5.3497
Neuron No. 2	-5.7726
Neuron No. 3	-1.04153
Neuron No. 4	-2.9288
Neuro No. 5	-1.35393
Neuron No. 6	2.9522
Neuron No. 7	1.35013
Neuron No. 8	-2.62439
Neuron No. 9	-6.34327
Neuron No. 10	4.16969
Neuron No. 11	-5.88565

Table 6.16: Final weights for output layer.

	Weights
Neuron No. 1	-1.00642
Neuron No. 2	-2.32875
Neuron No. 3	1.644826
Neuron No. 4	2.442228
Neuron No. 5	-1.3932

Table 6.17 (continued): Final weights for output layer.

Neuron No. 6	0.42291
Neuron No. 7	-1.35089
Neuron No. 8	-1.51793
Neuron No. 9	0.526251
Neuron No. 10	-1.62541
Neuron No. 11	-0.52143

And the final bias for the output layer is -0.3101.

7. INCORPORATING “POWER”

It is unanimously accepted that the breaking/cutting rate of mechanical excavators is linearly proportional to the power of the machine (Rostami et al., 1995; Copur et al., 2001; Balci et al., 2004; Copur et al., 2011). Thus, the power can be incorporated into the suggested models in form of a first order coefficient. To find the proper coefficient, both input and output power have the potential to be used. Considering the effect of hammer efficiency (Tuncdemir, 2008), output power seems to be a more promising choice. Therefore, the following coefficient was introduced as an indicator of power effect on the machine's performance:

$$C = \frac{P_{output}}{17.23} \quad (7.13)$$

where P_{output} is the power of the machine performance of which is going to be estimated in kW (or Hp) and 17.23 is the power of the machine used for the studied project in kW (or Hp).

In order to include the effect of the machine's power in the performance prediction, C should multiply the output of the proposed models. Therefore, the multiple linear regression model will be justified as follows:

$$IBR = \frac{P_{output}}{17.23} \times (0.774 \times RQD_T + 0.608 \times UCS_T - 5.679) \quad (7.14)$$

8. TEST AND COMPARISON

To realize how well the proposed models will perform, the performance of the previously presented prediction models were compared to that of multiple linear regression (*MLR*) and artificial neural network (*ANN*) models. There are two previously developed models that required parameters for which are available. The models were proposed by Bilgin et al. (1997) (Eq.(8.15) and Eq. (8.16)) and Bilgin et al. (2002) (Eq.(8.17)):

$$IBR = 4.24 \times P \times RMCI^{-0.567} \quad (8.15)$$

$$RMCI = \sigma_c \times \frac{RQD}{100}^{\frac{2}{3}} \quad (8.16)$$

$$IBR = -1.05 \times SHRV + 70.1 \quad (8.17)$$

where *IBR* is the Instantaneous cutting rate of an impact hammer in m³/hour, *P* is the input power of the machine in Horse Power (*Hp*), *RMCI* is the Rock Mass Cuttability Index in *MPa*, σ_c is the uniaxial compressive strength of rock in *MPa*, *RQD* is the rock quality designation, and *SHRV* is the Schmidt hammer rebound values associated with the excavated section of tunnel.

Before testing the models, a test data set should be selected. The test data used for testing the neural network has not been used for developing any of the models. Thus, it is the best available option to be used as testing data.

The proposed model by Bilgin et al. (2002) is developed only for a Montabert 625 hammer with input power of 33 *Hp*. To make the model applicable for the impact hammer used in the current study (MTB 120), the produced results by this model should be multiplied by a coefficient that applies the effect of power. The breaking/cutting rate of mechanical excavators is linearly proportional to the power of the machine (Rostami et al., 1995; Copur et al., 2001; Balci et al., 2004; Copur et al., 2011). Although it is better to use the output power of the machines in defining the coefficient, the output power of the Moontabert 625 was neither accessible nor

calculable. Hence, the input powers of the machines were used to define the coefficient as follows:

$$C = \frac{30}{33}$$

where C is the coefficient, 30 is the input power of the machine used to obtain the test data for this study in Hp , and 33 is the input power of the machine used to develop Eq. 8.17 in Hp .

Table 8.1 shows the test data used for testing the prediction models. Table 8.2 and Table 8.3 show the comparison between the models based on mean squared error (MSE), correlation factor (R), and coefficient of determination (R^2).

Table 8.1: Data used to test and compare the models.

Ring No.	UCS	RQD
6	45	26
12	15.5	24
18	145	41
24	42.1	40
30	40.3	41
36	158.7	46
42	74.3	38
47	89.8	44
54	99	54

Table 8.2: Performance comparison for test data.

	<i>ANN</i> model	<i>MLR</i> model	Bilgin et al. (1997)	Bilgin et al. (2002)
<i>MSE</i>	1.856	2.868	56.832	120.3572
Correlation factor (<i>R</i>)	0.983	0.946	0.974	0.674
R^2	0.966	0.896	0.945	0.455

Table 8.3: Performance comparison for all data.

	<i>ANN</i> model	<i>MLR</i> model	Bilgin et al. (1997)	Bilgin et al. (2002)
<i>MSE</i>	0.755	3.185	127.950	87.706
Correlation factor (<i>R</i>)	0.983	0.942	0.880	0.722
R^2	0.966	0.888	0.778	0.5213

As is shown in Table 8.2 and Table 8.3, the developed *ANN* and *MLR* models provide better correlations of all the available data along with considerably lower *MSE* values. For the test data, although the proposed model by Bilgin et al. (1997) shows surprisingly good correlation, it carries a considerably high *MSE* compared to the developed *ANN* and *MLR* models.

9. CONCLUSION AND RECOMMENDATIONS

The main goal of this study is to suggest performance prediction models for impact hammers. An accurate and reliable model is of a high value for the stages of project design and planning. The obtained models are interpreted as follows (Equation (6.8) and the artificial neural network):

- The developed prediction models contribute to reliable and accurate prediction of instantaneous breaking rate of impact hammer requiring the least number of the most commonly used and versatile rock properties as predictors.
- Equation (6.8) shows that an increase in RQD , UCS causes the IBR to decrease. As a result, one may say that higher rates of breaking can be achieved when the mentioned factors have lower values.
- This study also showed that the relationship between IBR as predicted value and CAI and SSH as predictors is extremely weak. This indicates that CAI and SSH do not contribute to prediction of IBR for impact hammers.
- This research reapproved the belief that increasing the number of the samples will result in an increase in accuracy of the model.
- Among all the recorded data, collinear pairs of parameters were identified. Knowing linearly parallel parameters can lead into better test design and significant cost reduction for the future studies.
- An ANN model was developed to increase the prediction accuracy even further. It provided extremely high correlation between predicted and target data. Meanwhile, the MSE is significantly low.
- The associated final weights and biases of the network were reported in order to make the network more handy and transcend the technical limitations.

Since the effect of machine's power on the performance of the impact hammer is not investigated in this study, it is highly recommended to perform future studies on this subject. In addition, by gathering more data the range of application for the future

models will be extended. Finally, incorporating the operator's effect will increase accuracy and reliability of the future models.

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