TUNNEL BORING MACHINE PERFORMANCE PREDICTION IN TROPICALLY WEATHERED GRANITE THROUGH EMPIRICAL AND COMPUTATIONAL METHODS

DANIAL JAHED ARMAGHANI

UNIVERSITI TEKNOLOGI MALAYSIA

TUNNEL BORING MACHINE PERFORMANCE PREDICTION IN TROPICALLY WEATHERED GRANITE THROUGH EMPIRICAL AND COMPUTATIONAL METHODS

DANIAL JAHED ARMAGHANI

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Civil Engineering)

Faculty of Civil Engineering
Universiti Teknologi Malaysia

JULY 2015

DEDICATION

Specially Dedicated To…

My Beloved Father, Mother

and Sister

Thanks for all the love, support, motivation and always being there whenever I need you.

My Supervisor

Assoc. Prof. DR. Edy Tonnizam Bin Mohamad

For his guidance and assistance throughout the whole thesis.

ACKNOWLEDGMENT

First and foremost, gratitude and praises to Allah, The Most Gracious and The Most Merciful for his blessing in completing this thesis. Pursuing a Ph.D. thesis is just like climbing a high peak, step by step, accompanied with hardships as well as encouragement, trust and countless help from many people. Though it will not be enough to express my gratitude in words to all those people who helped me, I would still like to give my many, many thanks to all these people.

First of all, I would like to express my sincere gratitude to my honorific supervisor Assoc. Prof. Dr. Edy Tonnizam Bin Mohamad who accepted me as his Ph.D. student without any hesitation when I presented him my research proposal. I am extremely grateful for his continuous support in my Ph.D. study and research, patience, motivation, enthusiasm and immense knowledge. His guidance helped me throughout the research and writing of this thesis.

Special thanks are also given to my co-supervisor Dr. Mogana Sundaram Narayanasamy from AURECON Pty Ltd., company, Australia for his encouragement and insightful comments. His flexibility, concern and faith in me during the dissertation process enabled me to attend to life while also earning my Ph.D.

I would like to extend my sincere gratitude to the Pahang-Selangor Raw Water Transfer Project team, especially to Ir. Dr. Zulkeflee Nordin, Ir. Arshad and contractor and consultant groups for facilitating this study. Also, I appreciate SNUI JV company as contractor of PSRWT tunnel project and Malaysian Ministry of Energy, Green Technology, and Water (KeTTHA), for giving me opportunity to conduct this research. I would also like to express my appreciation to Universiti Teknologi Malaysia for support and making this study possible.

Last but not least, I am greatly indebted to my parents. Their love and support without any complaint or regret has enabled me to overcome all difficulties during my studies. I love you so much and you are my hero.

ABSTRACT

Many works highlight the use of effective parameters in Tunnel Boring Machine (TBM) performance predictive models. However, there is a lack of study considering the effects of tropically weathered rock mass in these models. This research aims to develop several models for predicting Penetration Rate (PR) and Advance Rate (AR) of TBMs in fresh, slightly weathered and moderately weathered zones in granite. To achieve these objectives, an extensive study on 12,649 m of the Pahang- Selangor Raw Water Transfer (PSRWT) tunnel in Malaysia was carried out. The most influential parameters on TBM performance in terms of rock (mass and material) properties and machine specifications were investigated. A database consisting the tunnel length of 5,443 m, 5,530 m and 1,676 m representing fresh, slightly weathered and moderately weathered zones, respectively was analysed. Based on field mapping and laboratory study, a considerable difference of rock mass and material characteristics has been observed. In order to demonstrate the need for developing new models for prediction of TBM performance, two empirical models namely Q_{TBM} and Rock Mass Excavatability (RME) were analysed. It was found that empirical models could not predict TBM performance of various weathering zones satisfactorily. Then, multiple regression (i.e. linear and non-linear) analyses were applied to develop new equations for estimating PR and AR. The performance capacity of the multiple regression models could be increased in the mentioned weathering states with overall coefficient of determination (R^2) of 0.6. Furthermore, two hybrid intelligent systems (i.e. combination of artificial neural network with particle swarm optimisation and imperialism competitive algorithm) were developed as new techniques in field of TBM performance. By incorporating weathering state as input parameter in hybrid intelligent systems, performance capacity of these models can be significantly improved (R^2 = 0.9). With a newly-proposed systems, the results demonstrate superiority of these models in predicting TBM performance in tropically weathered granite compared to other existing and proposed techniques.

ABSTRAK

Pengaruh iklim tropika panas lembab mengakibatkan kesan luluhawa yang berbeza sifat jasad batuannya dengan kebanyakan model menilai jangka prestasi mesin pengorekan terowong (TBM) sedia ada. Kajian ini bertujuan membangunkan beberapa model untuk menilai jangka Kadar Penembusan (PR) dan Kadar Kemajuan Pengorekan (AR) TBM terbaru dalam zon luluhawa tropika rencam batuan granit. Bagi mencapai objektif ini, kajian yang menyeluruh terhadap prestasi pengorekan terowong Penyaluran Air Mentah Pahang-Selangor sepanjang 12,649 m telah dijalankan. Parameter jasad dan bahan batuan yang berpengaruh terhadap prestasi TBM telah dikaji di lapangan dan makmal. Di samping itu, prestasi TBM juga telah direkodkan pada sela panjang terowong tertentu. Analisa terhadap prestasi pengorekan terowong sepanjang 5443 m, 5530 m dan 1676 m yang dikategorikan sebagai zon segar, sedikit terluluhawa dan sederhana terluluhawa telah dilaksanakan. Hasil daripada kajian lapangan dan makmal, mendapati bahawa terdapat pengaruh luluhawa terhadap prestasi PR dan AR adalah signifikan. Keputusan menilai jangka prestasi TBM melalui dua model empirikal iaitu Q_{TBM} dan *Rock Mass Excavatability* (RME) didapati kurang memuaskan bila dibanding dengan prestasi sebenar TBM. Di samping itu, penilaian jangka TBM juga telah diuji dengan kaedah regresi linear dan tidak linear. Hasilnya, mendapati model empirik juga tidak dapat menilai jangka prestasi TBM dalam zon luluhawa tropika rencam dengan memuaskan. Dengan analisis regresi berganda, keupayaan prestasi model menilai jangka prestasi TBM dipertingkatkan dengan pekali tentuan (R^2) 0.6. Menyedari tentang kepentingan jangkaan yang lebih jitu, sistem hibrid pintar yang menggabungkan rangkaian neural tiruan dengan pengoptimuman (PSO) dan algoritma kompetitif imperialisme (ICA) telah dibangunkan bagi tujuan menilai jangka AR dan PR untuk prestasi TBM. Berdasarkan keputusan di lapangan dan analisis makmal tentang pengaruh luluhawa terhadap prestasi TBM, tahap luluhawa tropika telah digabungkan sebagai parameter input dalam sistem pintar hybrid. Melalui pendekatan dan pembangunan model ini, tahap keboleh nilai jangka prestasi TBM dalam batuan granit terluluhawa tropika telah dapat dipertingkatkan dengan signifikan (R^2 = 0.9) berbanding dengan model terdahulu.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

TBM	-	Tunnel Boring Machine
PR	-	Penetration Rate
AR	-	Advance Rate
RME	-	Rock Mass Excavatability
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
UCS	-	Uniaxial Compressive Strength
Rn	-	Schmidt Hammer Rebound Value
DTSS	-	Deep Tunnel Sewerage System
PSRWT	-	Pahang Selangor Raw Water Transfer
KeTTHA	-	Malaysian Ministry of Energy, Green Technology, and Water
TD	-	Tunnel Distance
UI	-	Utilisation Index
ISRM	-	International Society of Rock Mechanics
T_b	-	Time in Operation
T_{sh}	-	Shift Time
T_d	-	Wasted Time
RPM	-	Revolution Per Minute
SE	-	Specific Energy
P_{rev}	-	Penetration Per Revolution
n_c	-	Number of Cutters
r_c	-	Cutter Distance from Center of Rotation
F_r	-	Cutter Rolling Force
D	-	TBM Diameter
S/P	-	Spacing to Penetration Ratio
F_N	-	Normal Force
d	-	Disc Diameter
P	-	Penetration

ϕ	-	One-Half of Cutter Tip Angle
θ	-	Tip Wedge Angle
σ_0	-	Hydrostatic Pressure in the Crushed Zone
F_N	-	Rolling Force
F	-	Force
k	-	Coefficient of Cutting
a	-	Penetration Coefficient
S	-	Cutter Spacing
b	-	Spacing Coefficient
F_R/F_N	-	Rolling Coefficient
CSM	-	Colorado School of Mines
F_t	-	Total Resultant Force
T	-	Cutter Ttip Width
R	-	Cutter Radius
P_c	-	Pressure of Crushed Zone
Ψ	-	Power of Pressure Function
P^o	-	Base Pressure in the Crushed Zone
C	-	Constant
σ_t	-	Tensile Strength
HP	-	Installed Cutterhead Power
η	-	Mechanical Efficiency Factor
A	-	Tunnel Cross Sectional Area
σ_{cf}	-	Compressive Strength
P_{rev}	-	Penetration Per Revolution
P_d	-	Thrust Per Disc Periphery
N	-	Speed of Cutting Head
h	-	Average Number of Disc Per Kerf
r	-	Average Radius of Disc
N_c	-	NCB Cone Indenter Index
H_A	-	Taber Abrasion Hardness
FPI	-	Field Penetration Index
SRn	-	Schmidt Hammer Rebound Hardness
H_T	-	Total Hardness
DRI	-	Drilling Rate Index
RMi	-	Rock Mass Index

NTNU	-	Norwegian Institute of Technology
CLI	-	Cutter Life Index
RQD	-	Rock Quality Designation
F	-	Average Cutter Load
σ_{cm}	-	Compressive Rock Mass Strength
σ_{tm}	-	Tensile Rock Mass Strength
q	-	Quartz Content
σ_{θ}	-	Biaxial Stress on the Tunnel Face
RMR	-	Rock Mass Rating
$I_{s(50)}$	-	Point Load Index
γ	-	Density
T_s	-	Signifies Time
m	-	Negative Gradient
L	-	Length of Tunnel
ARA	-	Average Rate of Advance
ARA_T	-	Theoretical Average Rate of Advance
R	-	Correlation Coefficient
ARA_R	-	Real Average Rate of Advance
F_A	-	Factor of Team Adaptation to the Terrain
F_D	-	Factor of Tunnel Diameter
F_E	-	Factor of Crew Efficiency
R^2	-	Coefficient of Determination
GSI	-	Geological Strength Index
LMR	-	Linear Multiple Regression
NLMR	-	Non-Linear Multiple Regression
BTS	-	Brazilian Tensile Strebgth
PSI	-	Peak Slope Index
DPW	-	Distance between Plane of Weakness
α	-	Angle between Tunnel Axis and the Planes of Weakness
BI	-	Rock Brittleness
J_C	-	Joint Condition
J_s	-	Joint Spacing
RTc	-	Rock Type Code
RQDc	-	RQD Code
J_v	-	Volumetric Joint Count

PR_{blocky}	-	Signifies Penetration Rate in Blocky Rock Mass
AR_{blocky}	-	Signifies Advance Rate in Blocky Rock Mass
FPI_{blocky}	-	FPI in Blocky Rock Mass
TF	-	Thrust Force
CP	-	Cutterhead Power
CT	-	Tutterhead Torque
FIS	-	Fuzzy Inference System
PSO	-	Particle Swarm Optimization
ELM	-	Extreme Learning Machine
LSSVM	-	Least Square Support Vector Machine
PLS	-	Partial Least Square
GPML	-	Gaussian Processes for Machine Learning
SVR	-	Support Vector Regression
CFF	-	Core Fracture Frequency
ANFIS	-	Adoptive Neuro-Fuzzy Inference System
TPC	-	Thrust Per Cutter
RMW	-	Rock Mass Weathering
WTS	-	Water Table Surface
LCM	-	Linear Cutting Machine
RMCI	-	Rock Mass Cuttability Index
RSR	-	Rock Structure Rating
UAI	-	United Alteration Index
Ch	-	Chainage
EL	-	Elevation Level
UTM	-	Universiti Teknologi Malaysia
E	-	Young’s Modulus
LVDT	-	Linear Variable Differential Transformer
ρ_{dry}	-	Dry Density
Vp	-	P-Wave Velocity
SI	-	Site Investigation
Kpr	-	Alkali Feldspar
Plg	-	Plagioclase
Bi	-	Biotite
NATM	-	New Austria Tunnelling Method
ICA	-	Imperialism Competitive Algorithm

JH	-	Japan Highway Public Corporation
J_r	-	Joint Roughness Number
J_a	-	Joint Alteration Number
J_w	-	Joint Water Reduction Factor
J_n	-	Joint Set Number
SRF	-	Stress Reduction Factor
GP	-	Grade Point
p_z	-	Vertical Virgin Stress
Z	-	Depth of Excavation
VAF	-	Value Account For
RMSE	-	Root Mean Square Error
BP	-	Back-Propagation
FF	-	Feed-Forward
CMAC	-	Cerebellar Model Articulation Control
MLP	-	Multi-Layer Perceptron
LVQ	-	learning vector quantization
GMDH	-	Group Method of Data Hhandling
W	-	Weight
OA	-	Optimisation Algorithm
OT	-	Optimisation Technique
GA	-	Genetic Algorithm
$N_{country}$	-	Number of Country
N_{imp}	-	Number of Imperialist
Dc	-	Cutter Diameter
WZ	-	Weathering Zone
N_{decade}	-	Number of Decade

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The tunnel boring machine (TBM) which has been developed in recent decades, is a machine that is designed to excavate a safer and more economical tunnels. This method has become a standard technique for excavation of tunnels with lengths over 1.5–2 km (Hassanpour *et al*., 2011). The use of TBMs in construction of civil and mining projects, is controlled by several factors such as economic considerations and schedule deadlines (Girmscheid and Schexnayder, 2003). This machine has been extensively-utilised in different ground conditions ranging from hard and massive to broken and blocky grounds.

Since James S. Robbins constructed the first TBM in 1954, many improvements have been made on the TBM design to be applicable to ever-wider ranges of rock conditions at higher performances. These changes have led to the improvement of more powerful and efficient TBMs that can be effectively employed in a variety of rocks, from those that are very hard to those that are soft. One of the challenging issues is predicting the performance of TBM in difficult rock mass. Geological documentation provides valuable information about the geological conditions ahead of the tunnel face and the response of the rock mass to excavation progress. Rock mass weathering, strength, geological structures and other conditions affect TBM performance in tunnelling project. Prediction of TBM performance is a critical task for planning the tunnel projects and selecting the suitable construction methods. It can decrease the risks related to high capital costs, which are very common for the tunnel excavation (Yagiz, 2002; Yagiz *et al*., 2009).

Many classifications and models have been developed for estimation of TBM performance. To estimate penetration rate (PR) and advance rate (AR), Barton (1999) developed Q_{TBM} model based on Q-system (Barton *et al*., 1974). Q_{TBM} has additional parameters to the existing Q-system in order to be utilised for TBM applications. In addition, rock mass excavatability (RME) was proposed by Bieniawski *et al*. (2006) to predict AR. The development of RME index was according to the case histories that have been gathered from more than 400 tunnel sections. This index has been already updated many times (Bieniawski, 2007; Bieniawski *et al*., 2006, 2007, 2008). These models (Q_{TBM} and RME) have been applied by several researchers to predict TBM performance in their case studies. Goel (2008) found that the actual TBM performance parameters are less than the estimated values obtained by Q_{TBM} and RME models. In addition, Palmstrom and Broch (2006) mentioned that Q_{TBM} is a complex model and cannot be utilised in its current form. As a result, empirical models could not perform well in predicting TBM performance.

Apart from empirical models, in order to propose more accurate models, statistical methods have been utilised by various scholars considering rock mass and material properties and machine characteristics (e.g. Yagiz, 2008; Khademi Hamidi *et al*., 2010; Hassanpour *et al*., 2011; Oraee *et al*., 2012; Mahdevari *et al*., 2014). However, several scholars mentioned that these methods are not always robust enough to describe nonlinear and complex problems and their performance capacities are poor in the presence of outliers and extreme values in the data. Besides, the use of artificial intelligence (AI) techniques such as artificial neural network (ANN) in solving geotechnical problems, especially in the field of tunnelling was underlined in many studies (e.g. Benardos and Kaliampakos, 2004; Alvarez Grima *et al*., 2000; Yagiz and Karahan, 2011; Eftekhari *et al*., 2010; Salimi and Esmaeili, 2013). It is due to the fact that such predictive models take advantage of flexible nature where the models can be easily calibrated when new data becomes available. This advantage makes them powerful tools in solving engineering problem more specifically when the problem are highly nonlinear and the contact natures between input and output parameters are unknown (Garret, 1994). As reported by many researchers, AI techniques can provide higher performance capacity in predicting TBM performance compared to statistical and conventional methods.

1.2 Problem Statement

The prediction of TBM performance is one of the complex tasks encountered frequently in mechanised tunnel excavations. Many years after manufacturing the first TBM, different predictive models have been proposed based on both intact and mass rock properties, as well as machine specifications. For selecting the most suitable economic tunnelling methods, it is very important to provide an accurate prediction of TBM performance. According to many researchers (e.g. Alvarez Grima *et al*., 2000; Sapigni *et al*., 2002; Yagiz, 2008; Maidl *et al*., 2012), TBM performance is dependent on the rock material and mass properties as well as machine specifications. Several preliminary studies have been conducted to propose predictive models for TBM performance mainly on the basis of one or two rock (mass and material) parameters and machine specifications such as uniaxial compressive strength (UCS), Schmidt hammer rebound value (Rn), joint condition and average cutter force (e.g. Roxborough and Phillips, 1975; Tarkoy and Hendron, 1975; Graham, 1976; Farmer and Glossop, 1980; Sanio, 1985; Sato *et al*., 1991). Aside from this, many methods and classifications have been developed to predict TBM performance using multiple factors of rock (material and mass) and machine specifications (e.g. Hughes, 1986; Rostami and Ozdemir, 1993; Bruland, 1998; Barton, 1999; Bieniawski *et al*., 2008; Yagiz *et al*., 2009; Khademi Hamidi *et al*., 2010; Farrokh *et al*., 2012; Delisio *et al*., 2013; Mahdevari *et al*., 2014). Most of the effective parameters (as mentioned by many researchers) on TBM performance such as compressive and tensile strengths, plane of rock mass weakness, joint condition, cutter specifications, specific energy and cutterhead torque have been considered as predictors in these methods and classifications. As a result, these models/classifications cannot perform well in predicting TBM performance. This is due to the reason that all influential factors (i.e. rock mass, rock material and machine specifications) on TBM performance have not been employed in these models/classifications.

As highlighted by many researchers, weathering has an enormous impact on TBM performance. While there is an extensive literature exploring the use of influential factors on TBM performance, there is a lack of study considering the effect of rock mass weathering in TBM performance predictive models. Benardos and Kaliampakos (2004) predicted AR of Athens Metro tunnel, in Greece. They introduced and used rock mass weathering as one of the predictors in their predictive model.

To the best of author’s knowledge, only one study has been focused on tropically weathered granite which is carried out by Gong and Zhao (2009). They estimated rock mass boreability of deep tunnel sewerage system (DTSS) project in Singapore. Therefore, as far as the author knows, there is no study focusing on tropically weathered granite for developing the new models/techniques for TBM performance prediction. Hence, proposing TBM performance predictive models for different mass weathering zones is of advantage. Harvesting from the above discussion, this study attempts to propose new models for predicting TBM performance of Pahang-Selangor Raw Water Transfer (PSRWT) tunnel in different rock mass weathering zones.

1.3 Aim and Objectives of the Study

The performance analysis of the TBM and the development of more accurate assessment models for prediction of TBM performance is the ultimate aim in TBM tunnelling research works. Considering rock mass and material parameters as well as machine specifications, this study aims to predict TBM performance (in terms of penetration rate and advance rate) in tropically weathered granite using empirical, statistical and intelligent approaches. This aim is achieved through the following objectives:

1. To determine the rock (mass and material) properties and machine characteristics influencing penetration and advance rate of TBM

2. To examine empirical models namely RME and Q_{TBM} in predicting TBM performance of different rock mass weathering zones

3. To propose statistical models for estimating penetration and advance rate of TBM in different rock mass weathering zones based on rock mass and material properties and machine characteristics

4. To develop intelligent models for predicting penetration and advance rate of TBM in different rock mass weathering zones based on rock mass and material properties and machine characteristics

1.4 Significance of the Study

The prediction of TBM performance in a specified rock mass is a longstanding research topic. TBM performance has a major impact on tunnel completion time and cost. To plan the tunnel projects and select proper construction methods, there is a need to estimate TBM performance parameters with high degree of accuracy. Due to existing complex interaction between rock mass and TBM, prediction of TBM performance is too difficult theoretically. Therefore, developing more accurate predictive models of TBM performance is of advantage. Models with higher capability in estimating TBM performance can help designers to construct TBMs with different performance capacities. This issue will be highlighted when TBMs face various ground conditions. Results of this study can be utilised to design TBMs (with various capacities) in different mass weathering zones (from fresh to moderately weathered). Furthermore, they can be used to estimate project construction time with minimum error in tropical areas.

1.5 Study Area

The PSRWT tunnel project is located in central area of Peninsula Malaysia and has been proposed for transferring raw water (1890 million litre/day) from Pahang state to Selangor state. This project aims to address appropriately the future water demand shortfalls in Selangor and Kuala Lumpur states. The Pahang State that is located in the east of Selangor State and possesses abundant water resources in comparison with their local demand and it possesses adequate reserve for the interstate transfer. The tunnel project is owned by Malaysian Ministry of Energy, Green Technology, and Water (KeTTHA). The location of PSRWT tunnel project is shown in Figure 1.1.

Figure 1.1 Location of PSRWT tunnel project

PSRWT tunnel is crossing under the Main Range between Pahang and Selangor states. This mountain range forming the backbone of Peninsular Malaysia has a general elevation ranging from 100 m to 1400 m. The main rock type is granite with typical intact rock strength of 100 MPa to 200 MPa. The tunnel is 44.6 km in length with diameter of 5.23 m and a longitudinal gradient of 1/1,900. The tunnel is designed to operate under free flow conditions with a maximum discharge flow of 27.6 m^3/sec of raw water.

Tunnel excavation primarily is planned using TBM for 34.74 km long the main tunnel route, while the remaining tunnel portions including access work adits are excavated by conventional drill and blast method. Three TBM sections and four conventional drill and blast sections were planned to be excavated in PSRWT tunnel project. The mentioned TBMs were used to excavate various ground conditions in different mass weathering zones from fresh to moderately weathered. In PSRWT tunnel project, mixed ground (11,761 m), very hard ground (11,761 m) and blocky ground (11,218 m) were excavated by TBM 1, TBM 2 and TBM 3, respectively. Table 1.1 shows chainage and overburden details of three TBMs in PSRWT tunnel project. Based on this table, minimum and maximum overburden values exist in TBM 3 and TBM 2, respectively.

Table 1.1: Chainage and overburden details of TBMs in PSRWT tunnel

Section	**Chainage (m)**		**Overburden (m)**	
	From	To	Min	Max
TBM 1	6821	18582	260	1240
TBM 2	18582	30343	194	1390
TBM 3	30343	41561	110	490
All	6821	41561	110	1390

From 34,740 m of PSRWT tunnel which was excavated by TBMs, a total 12,649 m comprising of 5,443 m in fresh, 5,530 m in slightly weathered and 1,676 m in moderately weathered zones, was investigated. Rock (mass and material) properties and machine characteristics of the mentioned tunnel distances (TDs) were recognised and used to develop some new models for predicting TBM performance of different mass weathering zones (from fresh to moderately weathered).

1.6 Limitation of the Study

This study has some limitations which are discussed here. As mentioned before, this study aims to predict hard rock TBM performance namely penetration rate and advance rate using as-built data obtained from PSRWT tunnel in different rock mass weathering zones. Since three rock mass weathering zones ranging from fresh to moderately weathered were observed in PSRWT tunnel, it is obvious that the developed models in this study should be used in the above mentioned rock mass weathering zones. Hence, applying the proposed TBM performance predictive models for other mass weathering zones (highly weathered, completely weathered and residual soil) is not suggested in the present form. Another limitation of this study is related to type of rock. As mentioned earlier, the main rock type in PSRWT tunnel is granite which forms the Main Range granite. Due to the difference in the nature of rock, the models/equations proposed in this study, should be used only in the case of tropically weathered granite. It is worth noting that the proposed TBM performance predictive models are open to further development by other researchers.

1.7 Definition of Key Terms

In this section, the definition of key terms used in this research is explained. This study mainly involves different concepts such as TBM, TBM performance parameters, weathering, statistical models and artificial intelligence techniques.

1.7.1 Tunnel Boring Machine

A TBM is a machine used to excavate tunnels with a circular cross section through a variety of soil and rock strata. TBMs can bore through anything from hard rock to soil.

1.7.2 TBM Performance Parameters

TBM performance is commonly measured in terms of utilisation index (UI), penetration rate (PR, the rate of TBM penetration during boring times) and the advance rate (AR, the rate of TBM progress during a work time period).

1.7.3 Weathering

Weathering is the breaking down of the soil, rock and minerals contact with the earth's atmosphere, biota and waters. In case of rock, weathering is composed of both decomposition and disintegration. Decomposition weathering refers to changes in rock produced by chemical agents such as hydration, oxidation and carbonation. Disintegration is the result of environmental conditions such as wetting and drying, freezing and thawing that break down the exposed surface layer. According to International Society of Rock Mechanics (ISRM) (2007), a typical rock weathering profile is composed of 6 weathering grades namely fresh, slightly weathered, moderately weathered, highly weathered, completely weathered and residual soil.

1.7.4 Statistical Models

Statistical models can be used to recognise the relationships between independent (predictor) and dependent (output) variables. In cases where more than one independent variable exists, these models may be employed in order to achieve the best-fit equation (Khandelwal and Monjezi, 2013).

1.7.5 Artificial Intelligence Systems

Artificial intelligence systems are information processing patterns designed based on the simulation of the biological nervous systems. They are used for predicting existing function from the actual data. It means that they are flexible non-linear function approximation that are capable of figuring out relationships between predictors and output parameters.

tropical areas. In addition, other researchers can use the procedures employed in this study for other rock types such as sandstone and shale in weathered rock mass.

As artificial intelligence systems are a simplified mathematical model inspired by the biological structure, they can be extensively-used in the field of engineering problems. The results of this study can be expanded by future research projects using newly-developed intelligent models such as genetic programming and combination of ICA and fuzzy model to predict PR and AR of TBM with higher performance capacity compared to developed models in this study.

REFRENCES

Abdechiri, M., Faez, K., and Bahrami, H. (2010). Neural network learning based on chaotic imperialist competitive algorithm. In *Intelligent Systems and Applications (ISA), 2010 2nd International Workshop on*, IEEE. 1-5.

Abdull Hamedi, H.N., Shamsuddin, S.M., and Salim, N. (2008). Particle Swarm Optimization for Neural Network Learning Enhancement. *Jurnal Teknologi*, 49: 13-26.

Adhikari, R., and Agrawal, R. K. (2011). Effectiveness of PSO based neural network for seasonal time series forecasting. In: *Proceedings of the indian international conference on artificial intelligence (IICAI)*, Tumkur, India, 232–244.

Ahmadi, M. A., Ebadi, M., Shokrollahi, A., and Majidi, S. M. J. (2013). Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir. *Applied Soft Computing*. 13(2): 1085-1098.

Akcin, N. A., Muftuoglu, Y. V., and Bas, N. (1994). Prediction of drilling performance for electro-hydraulic percussive drills. In: *Proceedings of the Third International Symposium on Mine Planning and Equipment Selection*, Balkema, Istanbul, Turkey, 483–488.

Akun, M. E., and Karpuz, C. (2005). Drillability studies of surface-set diamond drilling in Zonguldak Region sandstones from Turkey. *International Journal of Rock Mechanics and Mining Sciences*. 42: 473–479.

Alber, M. (2000). Advance rates for hard rock TBMs and their effects on project economics. *Tunnelling and Underground Space Technology*. 15(1): 55–64.

Aleman, V. P. (1981). A strata strength index for boom type roadheaders. *Tunnels and Tunnelling International*. 13: 52–55.

Alvarez Grima, M., and Babuska, R. (1999). Fuzzy model for the prediction of unconfined compressive strength of rock samples. *International Journal of Rock Mechanics and Mining Sciences*. 36: 339–349.

Alvarez Grima, M. and P. N. W. Verhoef. (1999). Forecasting rock trencher performance using fuzzy logic. *International Journal of Rock Mechanics and Mining Sciences*. 36(4): 413-432.

Alvarez Grima, M., Bruines, P. A., and Verhoef, P. N. W. (2000). Modeling tunnel boring machine performance by neuro-fuzzy methods. *Tunnelling and underground space technology*. 15(3): 259-269.

Arikan, F., and Aydin, N. (2012). Influence of weathering on the engineering properties of dacites in Northeastern Turkey. *International Scholarly Research Notices*. Article ID 218527 pp. 1-15.

Arikan, F., Ulusay, R., and Aydın, N. (2007). Characterization of weathered acidic volcanic rocks and a weathering classification based on a rating system. *Bulletin of Engineering Geology and the Environment*, 66(4): 415-430.

Atashpaz-Gargari, E., and Lucas, C. (2007). Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: *IEEE Congress on Evolutionary Computation*. 4661–4667.

Azit, R., and Ismail, M. A. M. (2014). Rock Mass Classification System Used for Pahang-Selangor Raw Water Transfer Tunnel. In *InCIEC 2013*. Springer Singapore. 519-529.

Baheer, I. (2000). Selection of methodology for modeling hysteresis behavior of soils using neural networks. *Computer-Aided Civil and Infrastructure Engineering*. 5(6): 445–463.

Bahrami, A., Monjezi, M., Goshtasbi, K., and Ghazvinian, A. (2011). Prediction of rock fragmentation due to blasting using artificial neural network. *Engineering with Computers*. 27(2): 177-181.

Bamford, W. F. (1984). Rock test indices are being successfully correlated with tunnel boring machine performance. In: *Proceedings of the 5th Australian Tunneling Conference*, Melbourne. 9–22.

Bansal, J. C., Singh, P. K., Saraswat, M., Verma, A., Jadon, S.S., and Abraham, A. (2011). Inertia Weight Strategies in Particle Swarm Optimization. *Third World Congress on Nature and Biologically Inspired Computing*, IEEE. 640-647.

Barton, N., Lien, R., and Lunde, J. (1974). *Engineering classification of rock masses for the design of tunnel support*. Oslo: Norwegian Geotechnical Institute.

Barton, N. (1999). TBM performance estimation in rock using QTBM. *Tunnels and Tunneling International*. 31(9): 30–33.

Barton, N. (2000). *TBM tunnelling in jointed and faulted rock*. Rotterdam: Balkema.

Barton, N., and Bieniawski, Z. T. (2008). RMR and Q-setting records. *Tunnels and Tunnelling International*. 26–29.

Bashir, Z.A., and El-Hawary, M.E. (2009). Applying Wavelets to Short-Term Load Forecasting Using PSO-Based Neural Networks. *IEEE Transactions on Power Systems*. 24(1): 20-27.

Beale, R., and Jackson, T. (1998). *Neural computing: an introduction*. Department of Computer Science, University of York. IOP Publishing Ltd.

Beiki, M., Majdi, A., and Givshad, A. D. (2013). Application of genetic programming to predict the uniaxial compressive strength and elastic modulus of carbonate rocks. *International Journal of Rock Mechanics and Mining Sciences*. 63: 159-169

Benardos, A. G., and Kaliampakos, D. C. (2004). Modelling TBM performance with artificial neural networks. *Tunnelling and Underground Space Technology*. 19(6): 597-605.

Bieniawski, Z. T. (1973). Engineering classification of jointed rock masses. *Transactions of the South African Institution of Civil Engineers*. 15: 335–344.

Bieniawski, Z. T. (1974). Geomechanics classification of rock masses and its application in tunneling. *Proceedings of the 3rd International Congress on Rock Mechanics, ISRM*. Denver, Colorado, September 1974. 27–32.

Bieniawski, Z. T. (1976) Rock mass classifications in rock engineering. *Proceedings of the Symposium on Exploration for Rock Engineering*. Johannesburg, November 1976. 97–106.

Bieniawski, Z. T. (1984). *Rock mechanics design in mining and tunneling*. Rotterdam: A. A. Balkema.

Bieniawski, Z. T. (1989). *Engineering Rock Mass Classifications*. New York: John Wiley & Sons.

Bieniawski, Z. T. (1979). The geomechanics classification in rock engineering applications. *Proceedings of the 4th International Congress on Rock Mechanics, ISRM*. Montreux, Switzerland, September 1979. 41–48.

Bieniawski, Z. T. (2007). Predicting TBM excavability. *Tunnels and Tunnelling International*. 32–35.

Bieniawski, Z. T., Caleda, B., Galera, J. M., and Alvares, M. H. (2006). Rock mass excavability (RME) index. *ITA World Tunnel Congress (Paper no. PITA06-254),* April, Seoul.

Bieniawski, Z. T., Celada, B., and Galera, J. M. (2007). Predicting TBM excavability. *Tunnels and Tunnelling International*, September. p. 25.

Bieniawski, Z. T., Celada, B., Galera, J. M., and Tardáguila, I. (2008). New applications of the excavability index for selection of TBM types and predicting their performance. *ITA-AITES World Tunnel Congress & 34th ITA General Assembly, Agra, India*. 1-10

Bilgin, N., Yazici, S., and Eskikaya, S. (1996). A model to predict the performance of roadheaders and impact hammers in tunnel drivages. In: *Prediction and Performance in Rock Mechanics and Rock Engineering*, Torino, 715–720.

Blindheim, O. T. (2005). A critique of Q_{TBM}. *Tunnels and Tunnelling Internatinal*. 32–35.

Boyd, R. J. (1986). Hard rock continuous mining machine: mobile miner MM-120. In: *Howarth, D.F., et al. (Ed.), Rock Excavation Engineering Seminar, Dept. Mining and Met. Eng,* University of Queensland.

Bruland, A., Johannessen, B. E., Lislerud, A., Movinkel, T., Myrvold, K., and Johannessen, O. (1988). *Hard rock tunnel boring*. Project report 1-88:].83 pp. Trondheim: Norwegian Institute of Technology.

Bruland, A. (1998). *Hard rock tunnel boring*. Ph.D. Thesis, Norwegian University of Science and Technology, Trondheim.

Bruland, A. (1999). *Hard Rock Tunnel Boring: Advance Rate and Cutter Wear*. Norwegian Institute of Technology (NTNU), Trondheim, Norway.

Bruines, P. (1998). Neuro-fuzzy modeling of TBM performance with emphasis on the penetration rate. *Memoirs of the Centre of Engineering Geology in The Netherlands, Delft,* no. 173, 202 pp. ISSN: 1386-5072.

Cassinelli, F., Cina, S., Innaurato, N., Mancini, R., and Sampaolo, A. (1982). Power Consumption and Metal Wear in Tunnel-boring Machines: Analysis of Tunnel-Boring Operation in Hard Rock. *Tunneling '82, London, Inst. Min. Metall*. 73–81.

Ceryan, N., Okkan, U., and Kesimal, A. (2012). Prediction of unconfined compressive strength of carbonate rocks using artificial neural networks. *Environmental Earth Science* 68(3), 807-819.

Cheema, S. (1999). *Development of a Rock Mass Boreability Index for the Performance of Tunnel Boring Machines*. PhD Thesis. Department of Mining Engineering, Colorado School of Mines, Golden, CO, USA.

Choobbasti, A. J., Farrokhzad, F., and Barari, A. (2009). Prediction of slope stability using artificial neural network (case study: Noabad, Mazandaran, Iran). *Arabian journal of geosciences*. 2(4): 311-319.

Clerc, M., and Kennedy, J. (2002). The Particle Swarm Explosion, Stability, and Convergence in a Multi-dimensional Complex Space. *IEEE Transaction on Evolutionary Computation*. 6(1): 58-73.

Clerc, M. (2011). *Standard Particle Swarm Optimisation, From 2006 to 2011*. Retrieved from clerc.maurice.free.fr/pso/SPSO_descriptions.pdf (2011-07-13 version).

Crow, S. C. (1975). Jet tunnelling machines: a Guide for Design. *Tunnels and Tunnelling International*. 23–38.

Dalton, F. E., DeVita, L. R., and Macaitis, W. A. (1993). TARP tunnel boring machine performance. In *L. D. Bowerman & J. E. Monsees (Eds.), Proceedings of the RETC Conference*. Boston, MA: SME. 445–451.

Demuth, H., and Beale, M. (2000). *Neural network toolbox user's guide*.

Dearman W.R. (1974). Weathering classification in the characterization of rock for engineering purposes in British practice. *Bulletin of international Association of Engineering Geologists*. 9: 33-42.

Dearman W.R. (1978). Weathering classification in the characterization of rock : a revision. *Bulletin of International Association of Engineering Geologists*, 18: 123-128.

Deere, D. U., Hendron, A. J., Patton, F. D., and Cording, E. J. (1967). Design of surface and near surface construction in rock. P*roceedings of the 8th US Symposium on Rock Mechanics, AIME*. New York, 237–302.

Deketh, H. J. R., Alvarez Grima, M., Hergarden, I., Giezen, M., and Verhoef, P. N. W. (1998). Towards the prediction of rock excavation machine performance. *Bulletin of Engineering Geology and the Environment*. 57: 3-15.

Delisio, A., Zhao, J., and Einstein, H. H. (2013). Analysis and prediction of TBM performance in blocky rock conditions at the Lötschberg base tunnel. *Tunnelling and Underground Space Technology*. 33: 131-142.

Demuth, H., Beale, M., and Hagan, M. (2009). MATLAB Version 7.14.0.739; Neural Network Toolbox for Use with Matlab. The Mathworks.

Deutscher Ausschuss für unterirdisches Bauen (DAUB). (1997). Empfehlungen zur Auswahl und Bewertung von Tunnelvortriebsmaschinen. *Tunnel*. 16(5): 20-35.

Diamantis, K., Gartzos, E., and Migiros, G. (2009). Study on uniaxial compressive strength, point load strength index, dynamic and physical properties of serpentinites from Central Greece: test results and empirical relations. *Engineering Geology*. 108: 199-207.

DiMillo, T. (2000). *U.S. Patent No. 6,017,095*. Washington, DC: U.S. Patent and Trademark Office.

Dreyfus, G. (2005). *Neural Networks: Methodology and Application*. Germany: Springer Berlin Heidelberg.

Ebrahimi, E., Mollazade, K., and Babaei, S. (2014). Toward an automatic wheat purity measuring device: A machine vision-based neural networks-assisted imperialist competitive algorithm approach. *Measurement*. 55: 196-205.

Eftekhari, M., Baghbanan, A., and Bayati, M. (2010). Predicting penetration rate of a tunnel boring machine using artificial neural network. *ISRM International Symposium-6th Asian Rock Mechanics Symposium*. International Society for Rock Mechanics. 1-7.

Engelbrecht, A. P. (2007). *Computational intelligence: an introduction*. John Wiley & Sons.

Engineer Manual. (1997). *Tunnels and shafts in rock: engineering and design*. Washington: Department of the Army, US Army Corps of Engineers.

Erzin, Y., and Cetin, T. (2013). The predıctıon of the crıtıcal factor of safety of homogeneous fınıte slopes usıng neural networks and multıple regressıons. *Computers and Geosciences*. 51: 305–313.

Farmer, I. W., and Glossop, N. H. (1980). Mechanics of disc cutter penetration. *Tunnels Tunnelling International*. 12(6): 22–25.

Farrokh, E., Rostami, J., and Laughton, C. (2012). Study of various models for estimation of penetration rate of hard rock TBMs. *Tunnelling and Underground Space Technology*, 30: 110-123.

Farjallat, I. E. S., Tatam, C. T., and Yodhida, R. (1974). An experimental evaluation of rock weatherability. P*roceedings of 2^{ed} Congress of International Association of Engineering Geologists*, 1-9.

Fausett, L. (1993). *Fundamentals of Neural Networks: Architectures, Algorithms and Applications*. New York: Prentice Hall International.

Finol, J., Guo, Y. K., and Dong Jing, X. (2001). A rule-based fuzzy model for the prediction of petrophysical rock parameters. *Journal of Petroleum Science and Engineering*. 29: 97–113.

Fookes P.G. (1991). Geomaterial. *Quarterly Journal of Engineering Geology*. 24: 3-15.

Fookes P.G., Dearclan W.R. and Franklin, I.A. (1971). Some engineering aspects of rock weathering. *Quarterly Journal of Engineering Geology*. 4: 139-185.

Fu, L. (1995). *Neural Networks in Computer Intelligence*. New York: McGraw-Hill.

Garret, J. H. (1994). Where and why artificial neural networks are applicable in civil engineering. *Journal of Computer in Civil Engineering*. 8: 129–130.

Ghasemi, E., Yagiz, S., and Ataei, M. (2014). Predicting penetration rate of hard rock tunnel boring machine using fuzzy logic. *Bulletin of Engineering Geology and the Environment*. 73(1): 23-35.

Gholamnejad, J, and Tayarani, N. (2010). Application of artificial neural networks to the prediction of tunnel boring machine penetration rate. *Mining Science and Technology (China)*. 20(5): 727-733.

Girmscheid, G., and Schexnayder, C. (2003). Tunnel boring machines. *Practice periodical on structural design and construction*. 8(3): 150-163.

Goel, R. K. (2008). Evaluation of TBM performance in a Himalayan tunnel. *Proceedings of world tunnel congress Underground Facilities for Better Environment and Safety – India*. 1522-1532.

Goel, R. K., and Singh, B. (2011). *Engineering Rock Mass Classification: Tunnelling, Foundations and Landslides*. USA: Elsevier.

Goh, A. T. (1995). Modeling soil correlations using neural networks. *Journal of Computing in Civil Engineering*. 9(4): 275-278.

Goh, A. T. (1996). Pile driving records reanalyzed using neural networks. *Journal of Geotechnical Engineering*. 122: 492–495.

Gokceoglu, C., and Zorlu, K. (2004). A fuzzy model to predict the uniaxial compressive strength and the modulus of elasticity of a problematic rock. *Engineering Applications of Artificial Intelligence*. 17: 61–72.

Gong, Q. M., and Zhao, J. (2009). Development of a rock mass characteristics model for TBM penetration rate prediction. *International Journal of Rock Mechanics and Mining Science*. 46(1): 8–18.

Gori, M., and Tesi, A. (1992). On the Problem of Local Minima in Backpropagation. *IEEE Transactions and Pattern Analysis and Machine Intelligence*. 14(1): 76-86.

Graham P. C. (1976). Rock exploration for machine manufacturers. *Bieniawski ZT, editor. Exploration for rock engineering*. Johannesburg, Balkema. 173–80.

Grandori, R., Lavoie, T. A., Pflumm, M., Tian, G. L., Niersbach, H., Maas, W. K., Fairman, R. and Carey, J. (1995). The DNA-binding domain of the hexameric arginine repressor. *Journal of Molecular Biology*. 254: 150–162.

Grandori, R. (2007). TBM Performances and RME Classification System. *Jornada sobre 'Experiencias recientes con tuneladoras'. CEDEX*, Madrid.

Grimstad, E., and Barton, N. (1993). Updating of the Q-system for NMT. In: *International Symposium on Sprayed Concrete. Fagernes, Proceedings*. 46–66.

Gupta, V. (2009). Non-destructive testing of some Higher Himalayan Rocks in the Satluj Valley. *Bulletin of Engineering Geology and the Environment*. 68: 409-416.

Gurocak, Z., and Kilic, R. (2005). Effect of weathering on the geomechanical properties of the Miocene basalts in Malatya, Eastern Turkey. *Bulletin of Engineering Geology and the Environment*. 64(4): 373-381.

Hajihassani, M. (2013). *Tunneling-Induced Ground Movement and Building Damage Prediction Using Hybrid Artificial Neural Networks*. PhD Thesis. Universiti Teknologi Malaysia.

Hajihassani, M., Jahed Armaghani, D., Marto, A., and Tonnizam Mohamad, E. (2014a). Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. *Bulletin of Engineering Geology and the Environment*. doi: 10.1007/s10064-014-0657-x.

Hajihassani, M., Jahed Armaghani, D., Sohaei, H., Mohamad, E. T., and Marto, A. (2014b). Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Applied Acoustics*. 80: 57-67.

Haskins, D. R., and Bell, F. G. (1995). Drakensberg Basalts: their alteration, breakdown and durability. *Quarterly Journal of Engineering Geology and Hydrogeology*. 28: 287–302.

Hassanpour, J., Rostami, J., and Zhao, J. (2011). A new hard rock TBM performance prediction model for project planning. *Tunnelling and Underground Space Technology*. 26: 595–603.

Hassanpour, J., Rostami, J., Khamehchiyan, M., Bruland, A., and Tavakoli, H. R. (2010). TBM performance analysis in pyroclastic rocks: a case history of Karaj water conveyance tunnel. *Rock Mechanics and Rock Engineering*, 43(4): 427-445.

Hassoun, M. H. (1995). *Fundamentals of Artificial Neural Networks*. MIT Press: Cambridge, MA.

Haykin, S. (1999). *Neural Networks a Comprehensive Foundation, Second Edition*. Prentice Hall.

Hecht-Nielsen, R. (1987). Kolmogorov's mapping neural network existence theorem. In: *Proceedings of the First IEEE International Conference on Neural Networks*, San Diego, CA, USA, 11–14.

Henseler, J. (1995). Backpropagation. In: *Braspenning, P.J., et al. (Eds.), Artificial Neural Networks, an Introduction to ANN Theory and Practice*, Lecture Notes in Computer Science. Springer, Berlin, 37–66.

Hoek, E., and Brown, E. T. (1997). Practical estimates of rock mass strength. *International Journal of Rock Mechanics and Mining Sciences*. 34(8): 1165-1186.

Hoek, E., and Brown, E. T. (1980). Underground excavations in rock. *Institution of Mining and Metallurgy,* London. 527 pp.

Hoek, E. (1981). Geotechnical design of large openings at depth. *Rapid Exc. & Tunn. Conf. AIME 1981*.

Hornik, K., and Stinchcombe, M, and White, H. (1989). Multilayer feedforward networks are universal Approximators. *Neural Networks*. 2: 359-366.

Howarth, D. F. (1986). Review of Rock Drillability and Boreability Assessment Methods. Trans. IMM Sect. A Min. Ind. *The Institution of Mining and Metallurgy, London*. 9: 191–202.

Howarth, D. F., Adamson, W. R., and Berndt, J. R. (1986). Correlation of model tunnel boring and drilling machine performances with rock properties. *International Journal of Rock Mechanics and Mining Sciences*. 23: 171–175.

Huang, S. L., and Wang, Z. W., (1997). The mechanics of diamond core drilling of rocks. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*. 34: 6–12.

Hughes, H. M. (1986). The relative cuttability of coal-measures stone. *Mining Science and Technology*. 3(2): 95–109.

Hush, D. R. (1989). Classification with neural networks: a performance analysis. In: *Proceedings of the IEEE International Conference on Systems Engineering*. Dayton, OH, USA, 277–280.

Iliev, I. G. (1967). An attempt to estimate the degree of ;,weathering of intrusive rock from their physico-mechanical properties. *Proceedings of 1st Congress of International Society for Rock Mechanics*, Lisbon, 109-114.

Innaurato, N., Mancini, R., Rondena, E., and Zaninetti, A. (1991). Forecasting and effective TBM performances in a rapid excavation of a tunnel in Italy. *Proceedings of the Seventh International Congress ISRM*, Aachen, 1009-1014.

Isik, F., and Ozden, G. (2013). Estimating compaction parameters of fine-and coarse-grained soils by means of artificial neural networks. *Environmental Earth Sciences*. 69(7): 2287-2297.

ISRM. (2007). The complete ISRM suggested methods for rock characterization, testing and monitoring: 1974–2006. *Ulusay R, Hudson JA (eds) Suggested methods prepared by the commission on testing methods, International Society for Rock Mechanics. ISRM Turkish National Group*, Ankara, Turkey.

Jahed Armaghani, D., Tonnizam Mohamad, E., Momeni, E., Narayanasamy, M.S., and Mohd Amin, M.F. (2014a). An adaptive neuro-fuzzy inference system for predicting unconfined compressive strength and Young's modulus: a study on Main Range granite. *Bulletin of Engineering Geology and the Environment*. doi:10.1007/s10064-014-0687-4.

Jahed Armaghani, D., Hajihassani, M., Yazdani Bejarbaneh, B., Marto, A., and Tonnizam Mohamad, E. (2014b). Indirect measure of shale shear strength parameters by means of rock index tests through an optimized artificial neural network. *Measurement*. 55: 487-498.

Jahed Armaghani, D., Hajihassani, M., Mohamad, E. T., Marto, A., and Noorani, S. A. (2014c). Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arabian Journal of Geosciences*. 7: 5383–5396.

Jalil, Y. A., Nelson, P. P., and Laughton, C. (1995). TBM performance analysis and rock mass impacts. *2nd Int. Symp. Mine Mechanization and Automation*, Lulea, 201-209.

Kaastra, I., and Boyd, M. (1996). Designing a neural network for forecasting financial and economic time series. *Neurocomputing*. 10: 215-36.

Kahraman, S. (1999). Rotary and percussive drilling prediction using regression analysis. *International Journal of Rock Mechanics and Mining Sciences*. 36: 981–989.

Kahraman, S., Gunaydin, O., Fener, M., and Bilgin, N. (2003). Correlation between Los Angeles abrasion loss and uniaxial compressive strength. In: *Proceedings of International Symposium on Industrial Minerals and Building Stones*, Istanbul, Turkey, 577-581.

Kalatehjari, R., Ali, N., Kholghifard, M., and Hajihassani, M. (2014). The effects of method of generating circular slip surfaces on determining the critical slip surface by particle swarm optimization. *Arabian Journal of Geosciences*. 7(4): 1529-1539.

Kanellopoulas, I., and Wilkinson, G. G. (1997). Strategies and best practice for neural network image classification. *International Journal of Remote Sensing*. 18: 711–725.

Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization* (Vol. 200). Technical report-tr06, Erciyes university, engineering faculty, computer engineering department.

Karpuz, C., and Pa, A. G. (1997). Field characterisation of weathered Ankara andesites. *Engineering Geology*. 46(1): 1-17.

Karpuz, C., Pasamehmetoglu, A. G., Dincer, T., and Muftuoglu, Y. (1990). Drillability studies on the rotary blasthole drilling of lignite overburden series. *International Journal of Mining, Reclamation and Environment*. 4: 89–93.

Kassim, A., and Tonnizam Mohammad, E. (2007). Laboratory study of weathered rock for surface excavation works. *Research Project Report, VOT 75055. University of Technology Malaysia*, p. 61.

Kennedy, J., and Eberhart, R. (1995). Particle Swarm Optimization. IEEE International Conference on Neural Networks. Perth, Australia. 1942-1948.

Kennedy, J., and Clerc, M. (2006). *Standard PSO 2006*. Retrieved from http://www.particleswarm.info/Standard-PSO-2006.c.

Khademi Hamidi, J., Shahriar, K., Rezai, B., and Rostami, J. (2010a). Performance prediction of hard rock TBM using rock mass rating (RMR) system. *Tunnelling and Underground Space Technology*. 25(4): 333–345.

Khademi Hamidi, J., Shahriar, K., Rezai, B., and Bejari, H. (2010). Application of fuzzy set theory to rock engineering classification systems: an illustration of the rock mass excavability index. *Rock mechanics and rock engineering*. 43(3): 335-350.

Khandelwal, M., and Monjezi, M. (2013). Prediction of backbreak in open-pit blasting operations using the machine learning method. *Rock Mechanics and Rock Engineering*. 46(2): 389-396.

Khandelwal, M., and Singh, T. N. (2009). Prediction of blast-induced ground vibration using artificial neural network. *International Journal of Rock Mechanics and Mining Sciences*. 46(7): 1214-1222.

Kim, T. (2004). *Development of a fuzzy logic based utilization predictor model for hard rock tunnel boring machines*. PhD Thesis. Dept Mining Eng, Colorado School of Mines.

Kim, T. (2008). Geological Parameters Affecting Open Hard-Rock Tunnel Boring Machine Performance. In *North America Tunnelling 2008 Proceedings*. 374-380.

Kilic, R. (1999). The Unified Alteration Index (UAI) for Mafic rocks. *Environmental and Engineering Geoscience*. 4: 475–483.

Kosko, B. (1994). Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence. New Delhi: Prentice-Hall.

Kröse, B., and Smagt, P.V.D. (1996). *An introduction to Neural Networks*, Amsterdam, The University of Amsterdam.

Kuok, K.K., Harun, S., and Shamsuddin, S.M. (2010). Particle swarm optimization feedforward neural network for modeling runoff. *International Journal of Environmental Science and Technology*. 7 (1): 67-78.

Lan, H. X., Hu, R. L., Yue, Z. Q., Lee, C. F., and Wang, S. J. (2003). Engineering and geological characteristics of granite weathering profiles in South China. *Journal of Asian Earth Sciences*. 21(4): 353-364.

Lazzús, J.A. (2013). Neural network-particle swarm modeling to predict thermal properties. *Mathematical and Computer Modelling*. 57: 2408–2418.

Lee, Y., Oh, S. H., and Kim, M. W. (1991). The effect of initial weights on premature saturation in back-propagation learning. In: *Proceedings of the International Joint Conference on Neural Networks*. 765–770.

Lin, C. J., and Hsieh M. H. (2009). Classification of mental task from EEG data using neural networks based on particle swarm optimization. *Neurocomputing*. 72: 1121– 1130.

Liou, S. W., Wang, C. M., and Huang, Y. F. (2009). Integrative discovery of multifaceted sequence patterns by frame-relayed search and hybrid PSO-ANN. *Journal of Universal Computer Science*. 15(4): 742-764.

Lislerud, A. (1983). *Hard rock tunnel boring*. Project report 1-83. Trondheim: Norwegian Institute of Technology.

Looney, C. G. (1996). Advances in feed-forward neural networks: demystifying knowledge acquiring black boxes. *IEEE Transactions on Knowledge and Data Engineering*. 8(2): 211–226.

Mahdevari, S., Shahriar, K., Yagiz, S., and Shirazi, M. A. (2014). A support vector regression model for predicting tunnel boring machine penetration rates. *International Journal of Rock Mechanics and Mining Sciences*. 72: 214-229.

Maidl, B., Herrenknecht, M., and Anheuser, L. (1994). *Maschineller Tunnelbau im Schild- vortrieb*. Berlin: Ernst & Sohn.

Maidl, B., Schmid, L., Ritz, W., and Herrenknecht, M. (2012). *Hardrock tunnel boring machines*. Berlin: John Wiley & Sons.

Marto, A., Hajihassani, M., Jahed Armaghani, D., Tonnizam Mohamad, E., and Makhtar, A. M. (2014). A novel approach for blastinduced flyrock prediction based on imperialist competitive algorithm and artificial neural network. *Scientific World Journal*. Article ID 643715.

Masters, T. (1994). *Practical neural network recipes in C++*. Boston MA: Academic Press.

Maulenkamp, F., and Grima, M. A. (1999). Application of neural networks for the prediction of the unconfined compressive strength (UCS) from Equotip hardness. *International Journal of Rock Mechanics and Mining Science*. 36: 29–39.

McCulloch, W.S., and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*. 5: 115-133.

McFeat-Smith, I., and Askilsrud, O.G. (1993). Tunnel boring machines in Hong Kong. In: *Proceedings, Rapid Excavation and Tunneling Conference*. 401–413.

Mckelvey, J. G., Schultz, F. A., Helin, T. A. B., and Blindheim, O. T. (1996). Geotechnical analysis in south African Tunnels. *Tunnel and Tunnelling International*. 29-33.

Mehrotra, K., Mohan, C.K., and Ranka, S. (1997). *Elements of Artificial Neural Networks. Massachusetts*, MIT Press, Cambridge.

Mendes, R., Cortes, P., Rocha, M., and Neves, J. (2002). Particle swarms for feed forward neural net training. In: *Proc IEEE Int Joint Conf on Neural Networks, Honolulu, HI, USA*, 12–17 May 2002, 1895–1899.

Mikaeil, R., Naghadehi, M. Z., and Sereshki, F. (2009). Multifactorial fuzzy approach to the penetrability classification of TBM in hard rock conditions. *Tunnelling and Underground Space Technology*. 24(5): 500-505.

Mogana, S. N., Rafek, A. G., Komoo, I. (1998). The influence of rock mass properties in the assessment of TBM performance. In: *Moore, D., Hungr, O. (eds.), 8th IAEG Congr*, Vancouver, Balkema, Rotterdam, 3553–3559.

Mogana, S. N. (2007). The effects of ground conditions on TBM performance in tunnel excavation – A case history. *Proceedings of the 10th Australia New Zealand conference on Geomechanics 2007*, 442-447.

Mogana, S. N., and Komoo, I. (1997). Geological input as applied to TBMs: A case study of the Kelinchi Transfer Tunnel, Malaysia. In *Environmental and Safety Concerns in Underground Construction, Lee, Yang & Chung (eds)*, Balkema, Rotterdam, 113- 118.

Momeni, A. A., Khanlari, G. R., Heidari, M., Sepahi, A. A., and Bazvand, E. (2015a). New engineering geological weathering classifications for granitoid rocks. *Engineering Geology*. 185: 43-51.

Momeni, E., Armaghani, D. J., Hajihassani, M., and Amin, M. F. M. (2015b). Prediction of uniaxial compressive strength of rock samples using hybrid particle swarm optimization-based artificial neural networks. *Measurement*. 60: 50-63.

Momeni, E., Nazir, R., Jahed Armaghani, D., and Maizir, H. (2014). Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. *Measurement*. 57: 122-131.

Monjezi, M., Ghafurikalajahi, M., and Bahrami, A. (2011). Prediction of blast-induced ground vibration using artificial neural networks. *Tunnelling and Underground Space Technology*. 26(1): 46-50.

Monjezi, M., Khoshalan, H. A., and Varjani, A. Y. (2012). Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. *Arabian Journal of Geosciences*. 5(3): 441-448.

Montana, D. J., and Davis, L. (1989). Training feedforward neural networks using genetic algorithms. *International Joint Conferences on Artificial Intelligence*. 89: 762–767.

Moye, D.G. (1955). Engineering Geology for the Snowy Mountains scheme. *Journal of the Institution of Engineers*. 27: 287-298.

Negnevitsky, M. (2005). *Artificial intelligence: a guide to intelligent systems*. Pearson Education.

Nelson, P. P. (1983). *Tunnel boring machine performance in sedimentary rock*. PhD Thesis. Cornell University, Ithaca, NY.

Nelson, P., O'Rourke, T. D., and Kulhawy, F. H. (1983). Factors affecting TBM penetration rates in sedimentary rocks. In: *Proceedings, 24th US Symposium on Rock Mechanics, Texas A&M, College Station*, TX. 227–237.

Nelson, M., and Illingworth, W. T. (1990). *A Practical Guide to Neural Nets*. Addison-Wesley: Reading MA.

Niknam, T., Taherian Fard, E., Pourjafarian, N., and Rousta, A. (2011). An efficient hybrid algorithm based on modified imperialist competitive algorithm and K-means for data clustering. *Engineering Applications of Artificial Intelligence*. 24(2): 306-317.

Nordin, Z. (2014). Planning and Construction of Pahang-Selangor Raw Water Transfer (PSRWT) Tunnel. *Seminar on Tunnels and Underground Structures*, 2-4 September, Malaysia.

Ocak, I., and Seker, S. E. (2013). Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes. *Environmental Earth Sciences*. 70(3): 1263-1276.

Osman, I., and Laporte, G. (1996). Methaheuristics: A Bibliography. *Annals of Operations Research*. 63: 513-623.

Ozdemir, L. (1977). *Development of theoretical equations for predicting tunnel borability*. Ph.D. Thesis, T-1969, Colorado School of Mines, Golden, CO, USA.

Ozdemir, L., Miller, R., and Wang, F. D. (1978). Mechanical Tunnel Boring Prediction and Machine Design. *Final Project Report to NSF APR73-07776-A03*. Colorado School of Mines, Golden, Co.

Oilier, C. (1984). Weathering (2nd edition). London: Longman.

Okubo, S., Kfukie, K., and Chen, W. (2003). Expert systems for applicability of tunnel boring machine in Japan. *Rock Mechanics Rock Engineering*. 36: 305–22.

Oraee, K., Khorami, M. T., and Hosseini, N. (2012). Prediction of the penetration rate of TBM using adaptive neuro fuzzy inference system (ANFIS). *Proceeding of SME Annual Meeting & Exhibit, From the Mine to the Market, Now It's Global, Seattle, WA*, USA. 297-302.

Oraee, K., and Salehi, B. (2013). Assessing prediction models of advance rate in tunnel boring machines—a case study in Iran. *Arabian Journal of Geosciences*, 6(2): 481-489.

Pal, M., and Deswal, S. (2008). Modeling pile capacity using support vector machines and generalized regression neural network. *Journal of Geotechnical and Geoenvironmental Engineering*. 134: 1021–1024.

Palmstrom, A. (1995). RMi—*a rock mass characterization system for rock engineering purposes*. PhD Thesis. University of Oslo.

Palchik, V., and Hatzor, Y. H. (2004). The influence of porosity on tensile and compressive strength of porous chalks. *Rock Mechanics and Rock Engineering*. 37(4): 331-341.

Palmstrom, A., and Broch, E. (2006). Use and misuse of rock mass classification systems with particular reference to the Q-system. *Tunnelling and Underground Space Technology*. 21: 575–593.

Paola, J. D. (1994). *Neural network classification of multispectral imagery*. MSc thesis, The University of Arizona, USA.

Papworth, F. (2002). Design Guidelines for the use of Fibre-Reinforced Shotcrete in Ground Support. *Shotcrete*. 16–21.

Pelzer, A. (1954). Die Entwicklung der Streckenvortriebsmaschinen im In- und Ausland. *Glückauf*. 90: 1648.1658.

Poli, R., Kennedy, J., and Blackwell, T. (2007). Particle Swarm Optimization an Overview. *Swarm Intelligence*. 1: 33-57.

Priddy, K. L., and Keller, P.E. (2005). *Artificial Neural Networks: An Introduction*. Bellingham, Society of Photo-Optical Instrumentation Engineers (SPIE).

Rafig, M. Y., Bugmann, G., and Easterbrook, D. J. (2001). Neural Network Design for Engineering Applications. *Computers and Structures*.79: 1541-1552.

Ramezanzadeh, A., Rostami, J., and Kastner, R. (2004). Performance Prediction Models for Hard Rock Tunnel Boring Machines. In *Proceedings of Sixth Iranian Tunneling Conference,* Tehran, Iran. 1-15.

Ramezanzadeh, A. (2005). *Performance analysis and development of new models for performance prediction of hard rock TBMs in rock mass*. Ph.D Thesis. INSA, Lyon, France, p. 333.

Rayatdust, H., Shahriar, K., Ahangari, K., and Kamali-Bandpey, H. (2012). A Statistical Model for Prediction TBM Performance using Rock Mass Characteristics in the TBM Driven Alborz Tunnel Project. *Research Journal of Applied Sciences, Engineering and Technology*. 4(23): 5048-5054.

Reynolds, C. (1987). Flocks, Herbs, and Schools, A Distributed Behavioural Model. *Computer Graphics*. 21(4): 25-34.

Ribacchi, R., and Lembo-Fazio, A. (2005). Influence of rock mass parameters on the performance of a TBM in a gneissic formation (Varzo Tunnel). *Rock Mechanics and Rock Engineering*. 38(2): 105-127.

Ripley, B. D. (1993). Statistical aspects of neural networks. In: *Barndoff- Neilsen OE, Jensen JL, Kendall WS, editors. Networks and chaos-statistical and probabilistic aspects*. London: Chapman & Hall, 40-123.

Ritter, W. (1879). *Die Statik der Tunnelgewölbe*. Berlin: Springer.

Robbins, R.J. (1976). Mechanized tunneling, progress and expectations. *Tunnelling × 76*. London: Institution of mining and metallurgy.

Robbins, R. J. (1990). Tunnel machines in hard rock. *Civil engineering for underground rail transport*. London, Butterworth. 365-386.

Rojas, R. (1996). *Neural Networks, a Systematic Introduction*. Berlin: Springer-Verlag.

Rosenblatt, F. (1959). The perceptron: a probabilistic model for information storage and organization in the brain. *Psychological Review*. 65: 386-408.

Rostami, J. (1993). A new model for performance prediction of hard rock TBMs. *Proc. Rapid Excavation and Tunneling Conference (RETC)*. 793-809.

Rostami, J., and Ozdemir L. (1993). A new model for performance prediction of hard rock TBM. *Bowerman, L.D. et al. (Eds.), Proceedings of RETC, Boston, MA*. 793–809.

Rostami, J. (1997). *Development of a Force Estimation Model for Rock Fragmentation with Disc Cutters through Theoretical Modeling and Physical Measurement of Crushed Zone Pressure*. Ph.D. Thesis, Colorado School of Mines, Golden, Colorado, USA.

Roxborough, F. F., and Phillips, H. R. (1975). Rock excavation by disc cutter. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*. 12: 361–366.

Rumelhart. D.E., Hinton. G.E., and Williams, R.J. (1986). Learning representations by backpropagation errors. *Nature*. 323: 533- 536.

Ruxton, B.P., and BERRY, L. (1957). Weathering of granite and associated erosional features in Hong Kong. *Bulletin of Geological Society of America*. 68: 1263-1292.

Salimi, A., and Esmaeili, M. (2013). Utilising of linear and non-linear prediction tools for evaluation of penetration rate of tunnel boring machine in hard rock condition. *International Journal of Mining and Mineral Engineering*. 4(3): 249-264.

Sanio, H. P. (1985). Prediction of the performance of disc cutters in anisotropy rocks. *International Journal of Rock Mechanics and Mining Science, Abstracts*. 22 (3): 153–161.

Sapigni, M., Berti, M., Behtaz, E., Busillo, A., and Cardone, G. (2002). TBM performance estimation using rock mass classification. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*. 39: 771–788.

Sato, K., Gong, F., and Itakura, K. (1991). Prediction of disc cutter performance using a circular rock cutting ring. *Proceedings, The first International Mine Mechanization and Automation Symposium, Colorado School of Mines, Golden, Colorado*, USA.

Shao, C., Li, X., and Su, H. (2013). Performance Prediction of Hard Rock TBM Based on Extreme Learning Machine. In *Intelligent Robotics and Applications*. Springer Berlin Heidelberg. 409-416.

Shahin, M. A., Jaksa, M. B., and Maier, H. R. (2001). Artificial neural network applications in geotechnical engineering. *Australian Geomechanics*. 36(1): 49-62.

Shi, Y., and Eberhart, R. (1998). Parameter selection in particle swarm optimization. In: *Proceedings of the 7th International Conference on Evolutionary Programming VII, LNCS vol. 1447*. Springer, New York, 591–600.

Shinji, M., Akagi, W., Shiroma, H., Yamada, A., and Nakagawa, K. (2002). JH Method of Rock Mass Classification for Tunnelling. In *ISRM International Symposium*-EUROCK 2002.

Simoes, M. G., and Kim, T. (2006). Fuzzy modeling approaches for the prediction of machine utilization in hard rock tunnel boring machines. In *Industry Applications Conference, 2006. 41st IAS Annual Meeting. Conference Record of the 2006 IEEE*. IEEE. 947-954.

Simpson, P. K. (1990). Artificial neural system—foundation, paradigm, application and implementations. NewYork: Pergamon Press.

Singh, V. K., Singh, D., and Singh, T. N. (2001). Prediction of strength properties of some schistose rocks from petrographic properties using artificial neural networks. *International Journal of Rock Mechanics and Mining Sciences*. 38(2): 269-284.

Singh, R., Kainthola, A., and Singh, T. N. (2012). Estimation of elastic constant of rocks using an ANFIS approach. *Applied Soft Computing*. 12(1): 40-45.

Snowdon, R. A., Ryley, M. D., and Temporal, J. (1982). A study of disc cutting in selected British rocks. *International Journal of Rock Mechanics and Mining Sciences*. 19: 107–121.

Socha, K., and Blum, C. (2007). An ant colony optimization algorithm for continuous optimization: application to feed-forward neural network training. *Neural Computing and Application*. 16: 235–247.

Sonmez, H., Gokceoglu, C., Nefeslioglu, H.A., and Kayabasi, A. (2006). Estimation of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation. *International Journal of Rock Mechanics and Mining Science*. 43: 224-235.

Sonmez, H., and Gokceoglu, C. (2008). Discussion on the paper by H. Gullu and E. Ercelebi "A neural network approach for attenuation relationships: An application using strong ground motion data from Turkey. *Engineering Geology*. 97: 91-93.

Sousa, L. M. O. (2013). The influence of the characteristics of quartz and mineral deterioration on the strength of granitic dimensional stones. *Environmental Earth Science*. 69(4): 1333–1346.

Sousa, L. M. O., Suárezdel Río, L. M., Calleja, L., Ruiz de Argandoña, V., and Rey, A. R. (2005). Influence of microfractures and porosity on the physico-mechanics properties and weathering of ornamental granites. *Engineering Geology*. 77: 153–168.

SPSS Inc. (2007). *SPSS for Windows (Version 16.0)*. Chicago: SPSS Inc.

Stack, B. (1982). *Handbook of Mining and Tunnelling Machinery*. Chichester: Wiley.

Stein, R. (1994). Selecting data for neural networks. *AI EXPERT*. 42-47.

Stern, H.S. (1996). Neural networks in applied statistics. *Technometrics*. 38: 205-214.

Sundin, N. O., and Wanstedt, S. (1994). A boreability model for TBMs. In: Nelson, P., Laubach, S.E. (Eds.), Rock Mechanics Models and Measurements Challenges from Industry. *Proceedings of the 1st North American Rock Mechanics Symposium, The University of Texas at Austin*, Balkema, Rotterdam. 311–318.

Suwansawat, S., and Einstein, H. H. (2006). Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunnelling. *Tunnelling and Underground Space Technology*. 21: 133-150.

Swingler, K. (1996). *Applying neural networks: a practical guide*. New York: Academic Press.

Taghavifar, H., Mardani, A., and Taghavifar, L. (2013). A hybridized artificial neural network and imperialist competitive algorithm optimization approach for prediction of soil compaction in soil bin facility. *Measurement*. 46(8): 2288–2299.

Talatahari, S., Farahmand Azar, B., Sheikholeslami, R., and Gandomi, A. H. (2012). Imperialist competitive algorithm combined with chaos for global optimization. *Communications in Nonlinear Science and Numerical Simulation*. 17(3): 1312-1319.

Tarkoy, P.J. (1973). Predicting TBM penetration rates in selected rock types. In: *Proceedings, 9th Canadian Rock Mechanics Symposium*, Montreal.

Tarkoy, P. J., and Hendron, A. J. (1975). Rock hardness index properties and geotechnical parameters for predicting tunnel boring machine performance. *Report to NSF. No. GI-36468/NSF-RA-7-75-030*. USA. p. 347.

Terzaghi K. (1946). *Rock Tunneling with Steel Supports, R.V. Practor and T. White (ed)*. Commercial Sheving Co., Youngstown, Ohio. 296 p.

Tallon, E. M. (1983). Comparison and application of geomechanics classification schemes in tunnel construction. *International Journal of Rock Mechanics and Mining Sciences and Geomechanics Abstracts*. 20: 10-20.

Tonnizam Mohamad, E., Hajihassani, M., Jahed Armaghani, D., and Marto, A. (2012). Simulation of blasting-induced air overpressure by means of artificial neural networks. *International Review on Modelling and Simulations*. 5: 2501–2506.

Tonnizam Mohamad, E., Jahed Armaghani, D., Momeni, E., and Alavi Nezhad Khalil Abad, S. V. (2014). Prediction of the unconfined compressive strength of soft rocks: a PSO-based ANN approach. *Bulletin of Engineering Geology and the Environment*. doi:10.1007/s10064-014-0638-0.

Torabi, S. R., Shirazi, H., Hajali, H., and Monjezi, M. (2013). Study of the influence of geotechnical parameters on the TBM performance in Tehran–Shomal highway project using ANN and SPSS. *Arabian Journal of Geosciences*. 6(4): 1215-1227.

Tugrul, A., and Gurpinar, O. (1997). The effect of chemical weathering on the engineering properties of Basalts, Turkey. *Environmental and Engineering Geoscience*. 2: 225–234.

Tugrul, A., and Zarif, I. H. (1999). Correlation of mineralogical and textural characteristics with engineering properties of selected granitic rocks from Turkey. *Engineering Geology*. 51(4): 303-317.

Van den Bergh, F. (2001). *An analysis of particle swarm optimizers*. Ph.D Thesis. University of Pretoria. South Africa.

Vasumathi, B., and Moorthi, S. (2012). Implementation of hybrid ANN–PSO algorithm on FPGA for harmonic estimation. *Engineering Applications of Artificial Intelligence*. 25: 476–483.

Venkatesan, D., Kannan, K., and Saravanan, R. (2009). A genetic algorithm-based artificial neural network model for the optimization of machining processes. *Neural Computing and Applications*. 18: 135-140.

Verhoef, P. N. W. (1997). *Wear of Rock Cutting Tools: Implications for the site investigation of rock dredging projects.* Rotterdam: Balkema.

Wang, C. (1994). *A theory of generalization in learning machines with neural application*. PhD Thesis. The University of Pennsylvania, USA.

Wang, X. G., Tang, Z., Tamura, H., Ishii, M., and Sun, W. D. (2004). An improved backpropagation algorithm to avoid the local minima problem. *Neurocomputing*. 56: 455–60.

Wickham, G. E., Tiedemann, H. R., and Skinner, E. H. (1972). Support determination based on geologic predictions. *Proceedings of the Rapid Excavation and Tunneling Conference (RETC),* 43-64.

Wilson M. J. (1975). Chemical weathering of some primary rock forming minerals. *Soil Sciences*. 119: 349-355.

Wu, S., Qian, B., and Gong, Z. (2006). The time and cost prediction of tunnel boring machine in tunneling. *Wuhan University Journal of Natural Sciences*. 11(2): 385–398.

Wyhthoff, B. J. (1993). Backpropagation neural networks: a tutorial. *Chemometrics and Intelligent Laboratory Systems*. 18: 115–155.

Wyllie, D. C., and Mah, C. W. (2004). *Rock slope engineering, civil and mining (4th edition)*. USA: Taylor & Francis.

Xie, L., Zeng, J., and Cui, Z. (2009). General Framework of Artificial Physics Optimization Algorithm. *World Congress on Nature and Biologically Inspired Computing, IEEE*. 1321-1326.

Yagiz, S., and Ozdemir, L. (2001). Geotechnical Parameters Influencing the TBM Performance in Various Rocks. I*n Program with Abstracts. 44th Annual Meeting of Association of Engineering Geologists. Technical Session 10; Engineering Geology for Construction Practices.* Saint Louis. MO USA.

Yagiz, S., Gokceoglu, C., Sezer, E., and Iplikci, S. (2009). Application of two non-linear prediction tools to the estimation of tunnel boring machine performance. *Engineering Applications of Artificial Intelligence*, *22*(4): 808-814.

Yagiz, S. (2002). *Development of Rock Fracture and Brittleness Indices to Quantifying the Effects of Rock Mass Features and Toughness in the CSM Model Basic Penetration for Hard Rock Tunneling Machines*. PhD Thesis. T-5605, Colorado School of Mines, CO, USA.

Yagiz, S. (2008). Utilizing rock mass properties for predicting TBM performance in hard rock conditions. *Tunnelling and Underground Space Technology*. 23(3): 326–339.

Yagiz, S., and Karahan, H. (2011). Prediction of hard rock TBM penetration rate using particle swarm optimization. *International Journal of Rock Mechanics and Mining Sciences*. 48(3): 427-433.

Yagiz, S., and Gokceoglu, C. (2010). Application of fuzzy inference system and nonlinear regression models for predicting rock brittleness. *Expert Systems with Applications*. 37(3): 2265-2272.

Yarali, O., and Soyer, E. (2013). Assessment of relationships between drilling rate index and mechanical properties of rocks. *Tunnelling and Underground Space Technology*. 33: 46-53.

Yavari, M., and Mahdavi, S. (2005). Prediction of penetration rate of TBM using ANN. In *national Mining Conference*, 1-3 Feb 2005, Iran. 1-10.

Yilmaz, I., and Yuksek, G. (2009). Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. *International Journal of Rock Mechanics and Mining Sciences*. 46(4): 803-810.

Yildiz, A., Kuscu, M., Dumlupunar, I., Aritan, A.E., and Bagci, M. (2010). The determination of the mineralogical alteration index and the investigation of the efficiency of the hydrothermal alteration on physico-mechanical properties in volcanic rocks from Köprülü, Afyonkarahisar, West Turkey. *Bulletin of Engineering Geology and the Environment*. 69: 51–61.

Zhang J.R., Zhang, J., Lok, T.M., and Lyu, M.R. (2007). A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training. *Applied Mathematics and Computation*. 185: 1026–1037.

Zhao, J. (2007). Tunnelling in rocks – present technology and future challenges. Keynote lectures. In: *ITA-AITES World Tunnel Congress & 33rd ITA General Assembly*, Prague. 22–32.

Zhao, J., and Broms, B. B. (1993). Mechanical and physical properties of the weathered Bukit Timah granite of Singapore. *Proceedings of International Symposium on tardy Soil - Soft Rock*, Athens, 883-890.

Zhao, J., Broms, B. B., Zhou, Y., and Choa, V. (1994). A study of the weathering of the Bukit Timah granite Part B: Field and laboratory investigations. *Bulletin of the International Association of Engineering Geology-Bulletin de l'Association Internationale de Géologie de l'Ingénieur*. 50(1): 105-111.

Zorlu, K., Gokceoglu, C., Ocakoglu, F., Nefeslioglu, H. A., and Acikalin, S. (2008). Prediction of uniaxial compressive strength of sandstones using petrography-based models. *Engineering Geology*. 96: 141-158.